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Paul G. J. O'Connell
FDO Partners

Melvyn TEO
Singapore Management University, melvynteo@smu.edu.sg
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Paul G. J. O'Connell and Melvyn Teo*

Abstract

Using a proprietary database of currency trades, this paper explores the effects of trading gains and losses on risk-taking among large institutional investors. We find that institutional investors, unlike individuals, are not prone to the disposition effect. Instead, institutions aggressively reduce risk following losses and mildly increase risk following gains. This asymmetry is more pronounced later in the calendar year and among older and more experienced funds. We show that such performance dependence is consistent with dynamic loss aversion (Barberis, Huang, and Santos (2001)) and overconfidence. In addition, prior institutional gains and losses have palpable implications for future prices.

I. Introduction

The link between risk-taking and short-term past performance receives short shrift in the classical, rational finance literature. As Coval and Shumway (2005) put it, in a setting where fully rational traders have standard Von Neumann-Morgenstern expected utility, profit opportunities are uncorrelated across the trading day, wealth effects are negligible, margin constraints are unimportant, traders' compensation and reputation concerns are neutral, and profits are not related to future trading activity. In other words, past performance should not matter.

Using a proprietary currency trades database, this paper shows that past performance manifestly affects the risk-taking behavior of large institutional managers. However, the sign of the effect differs from what has been observed for

*O'Connell, paul.oconnell@fdopartners.com, FDO Partners LLC, 5 Revere St., Cambridge, MA 02138; and Teo, melvynteo@smu.edu.sg, Singapore Management University, 50 Stamford Rd., Singapore 178899, Singapore. We are particularly indebted to Jeremy Stein and Nick Barberis for many valuable insights and suggestions. We also thank Dennis Bams, Joshua Coval (the referee), Ken Froot, Joel Hasbrouck, Daniel Kahneman, and seminar participants at State Street Associates and the 2004 European Finance Association meetings. We greatly appreciate the help of State Street Corporation in obtaining the institutional trades data and the financial support of the Wharton-SMU Research Center.

retail investors and professional traders. Unlike such investors, the institutional investors in our sample do not seem susceptible to disposition effects. On the contrary, they aggressively reduce risk in the wake of losses and mildly increase risk in the wake of gains. Moreover, any increases in risk-taking are short-lived, reversing themselves within a calendar quarter. These basic results are pervasive across the major currencies and characterize some 91% of the trading volume in our sample.

We consider a host of explanations, including currency hedging activity, margin and capital constraints, stop-loss trading (Osler (2003)), momentum trading, managerial compensation and reputation concerns (Chevalier and Ellison (1997)), and the disposition effect (Odean (1998)), but find evidence suggesting that these explanations cannot account for the bulk of the performance dependence we observe. The fact that the risk-performance relationship is strong for pure currency funds and for long-only positions indicates that currency hedging is not at its root. Margin and capital constraints cannot explain the results, since cross-currency effects within funds are noticeably absent. Stop-loss trading would imply that the risk-performance relationship is driven by large losses, yet the risk reaction to losses persists over a wide range of small losses. Return momentum and herding proxies fail to drive out the explanatory power of past gains and losses on risk-taking. Finally, theories based on compensation concerns and the disposition effect predict the opposite risk reaction to past performance.

Instead, the sign of the effects is more in keeping with the theories of dynamic loss aversion[1] (Barberis, Huang, and Santos (2001)) and overconfidence (Barber and Odean (2001)). The results dovetail with the view that institutional investors are more likely than individual investors to base their sense of self-worth on their ability to invest. Unlike retail investors or professional traders who trade for their own accounts, institutional investors manage other people's money, and their past performance records are often publicly available. Hence, we argue that they are more likely than other investors to derive utility from past performance and to be loss averse. We show that consistent with this, they react strongly to losses occurring at the end of the calendar year, which translate more swiftly to embarrassment for the manager. Also, consistent with an overconfidence explanation, fund age and trading experience attenuate the risk reaction to gains.

In addition, the observed performance dependence has tangible implications for future returns. Because funds with losses are more eager to reduce currency exposure, a one-standard-deviation increase in the losses from long versus short positions, scaled by past trading volume, induces a 3.6% standard deviation or a 2.1 basis point (bp) decrease in returns the next day. Conversely, because funds with gains are more eager to increase exposure, an increase in the gains from long versus short positions precipitates an increase in returns the next day. These price effects are statistically significant (t-statistics = 3.32 and 2.50, respectively), robust to controls for past currency returns, and start to dissipate within a week. They are also stronger for pure currency funds than for other funds. Further,

[1] This is also frequently referred to as the house money effect (see Thaler and Johnson (1990)).

simple long/short trading strategies based on yesterday's gains and losses can generate returns in excess of 7% per year and information ratios close to one. One caveat, however, is that the returns from such strategies may not survive the transaction costs associated with daily rebalancing.

This paper offers fresh insights into the trading behavior of institutional investors and challenges the classical finance view that behavioral biases are "an annoying but essentially harmless anomaly, confined to retail investors and experimental subjects" (Locke and Mann (2005)). In doing so, we build on several themes. Odean (1998), Feng and Seasholes (2005), and Dhar and Zhu (2006) show that retail investors tend to hold onto their losses and quickly cash out their gains. That is, they are prone to the disposition effect. Coval and Shumway (2005) and Locke and Mann (2005) document a similar trading pattern with professional traders at the Chicago Board of Trade (CBOT). We show that the disposition effect results are sensitive to investor type. Unlike other investors, institutional investors are, on average, immune to the disposition effect. They tend to ride their gains and quickly cut their losses. Barberis, Huang, and Santos (2001) propose a model based on dynamic loss aversion that simultaneously explains the equity premium, volatility, and predictability puzzles in finance. Our results are consistent with their model predictions and complement evidence from gambling experiments (Thaler and Johnson (1990)). List (2003) documents that the Thaler (1980) endowment effect diminishes with trading experience, while Haigh and List (2005) show that despite having greater trading experience, CBOT traders tend to suffer from greater myopic loss aversion (Benartzi and Thaler (1995)) than do undergraduates in a laboratory setting. Our results on trading experience resonate with those of List (2003) and challenge those of Haigh and List (2005). Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997) argue that, motivated by career concerns, managers in growth-oriented funds tend to increase volatility in the second half of the year if performance has been poor in the first half of the year. Our tests suggest that behavioral biases can induce an opposite reaction to losses in the nearer term (e.g., at daily and weekly horizons). Our results on price implications corroborate recent evidence by Coval and Shumway (2005) and Frazzini (2006), who show that behavioral biases have tangible implications for future prices. Finally, our findings are supportive of narrow framing amongst institutions, which is comforting in light of the Barberis, Huang, and Thaler (2006) argument that only preferences exhibiting narrow framing are consistent with the equity premium and stock market participation puzzles.

Despite the importance of institutional investors as an investor class, to our knowledge, the only other study that investigates high-frequency trading behavior amongst institutions[2] is Grinblatt and Keloharju (2001). They explore performance dependence among investors (including institutional investors) in the Finnish stock market. Our study differs from theirs in three ways. First, they do

[2]Frazzini (2006) and Wermers (1999) analyze low-frequency mutual fund quarterly equity holdings and find evidence of the disposition effect. We argue that since active currency holdings are further removed from the underlying stakeholders (who, in mutual funds, are typically retail investors) than equity holdings, the currency trades data may be a more suitable place to search for behavioral biases amongst institutional managers.

not distinguish from explanations peculiar to institutions like managerial career concerns. Controlling for these explanations has been crucial in allowing us to isolate any behavioral effects. Second, unlike Grinblatt and Keloharju (2001), we generate impulse response functions from a vector autoregression (VAR) to precisely trace out the evolution of the risk/performance relationship over time. Third and most importantly, in contrast to Grinblatt and Keloharju (2001), we find evidence inconsistent with the disposition effect. The difference in results cannot be simply traced to methodology, as we also employ the logit regressions used in Grinblatt and Keloharju (2001).[3]

The rest of the paper is structured as follows: Section II describes the data. Section III presents the basic empirical results linking risk-taking to past performance. Section IV discusses the various explanations for our findings, while Section V explores the implications for prices. Section VI concludes.

II. Data

The data are provided by State Street Corporation, the world's largest custodian. State Street clients are primarily large global institutional money managers, and the total of all funds serviced by State Street at the end of our sample was \$8.4 trillion, approximately 15% of total global assets. Our sample spans from January 1, 1994 to December 31, 2002, and comprises over eight million individual trade records undertaken by 7,541 anonymous funds.

To construct the risk and P&L series for each fund and each currency, we first derive fund holdings by cumulating flows. Each day, net flows by currency, fund, and tenor are measured. All flows on date t with tenor s are converted to dollars by dividing by the appropriate forward currency exchange rate f_t^s, where f is in units of foreign currency per dollar, adjusted to reflect present value using the one-month U.S. dollar LIBOR interest rate. Spot and forward rates are collected from WM Reuters at the 4:00 PM London close each day. Forward rates are collected for tenors of one, two, three, six, and 12 months, and geometrically interpolated to generate valuation rates for trades of any maturity up to one year. The U.S. dollar LIBOR is also collected from Reuters. If a trade takes place that does not include the U.S. dollar (such as a sterling/yen trade), it is broken down into two separate trades or "legs" against the dollar prior to valuation.

Holdings can then be built up by cumulating these flows, after adjusting for mark-to-market gains and losses on each day's pre-existing positions. Any trades that take place before the start of our database will be missed in the integration of trades up to holdings. However, since over 99% of the trades in our database have a duration or tenor of less than one year, the holdings series will be accurate after the first year of integration. Hence, all the analyses in the paper are done on post-1994 data. To construct holdings, for a position with tenor s on date $t-1$,

[3] Also, Grinblatt and Keloharju (2001) base their disposition results on only the behavior of local Finnish institutions (see their Section I and Table I) that may be less sophisticated (and hence more prone to the disposition effect) than the institutional investors examined in our sample.

the marked-to-market gross return between date $t-1$ and t is f_t^{s-1}/f_{t-1}^s. So, for currency k at time t, holdings are calculated as

$$h_{k,t} = \sum_{s=0}^{S} \left(h_{k,t-1}^s \frac{f_{k,t}^s}{f_{k,t-1}^{s+1}} + b_{k,t}^s - d_{k,t}^s \right),$$

where b is net buying and d captures the spot settlement or delivery, both on date t. Spot delivery occurs when a manager needs currency to buy or sell an underlying asset such as a stock or a bond. With this formula, long positions are signed positively, and short positions are signed negatively. The marked-to-market gain or loss for a day is calculated similarly as

$$\text{PNL}_{k,t} = \sum_{s=0}^{S} h_{k,t-1}^s \left(\frac{f_{k,t}^s}{f_{k,t-1}^{s+1}} - 1 \right).$$

With holdings in hand, it is a simple matter to calculate risk exposure. Let $\mathbf{h}_{it}$ be a vector of currency holdings for fund i on date t. Risk is measured as the standard quadratic form $\mathbf{h}_{it}'\mathbf{\Sigma}\mathbf{h}_{it}$, where $\mathbf{\Sigma}$ is the covariance matrix of annualized currency returns. We calculate $\mathbf{\Sigma}$ as the uncentered second moment of our panel of daily currency returns beginning on January 1, 1994, where the returns are exponentially weighted using a decay factor of 0.998, implying a half-life of about 350 trading days. Note that the relevant $\mathbf{\Sigma}$ matrix differs according to the base currency of each fund. For example, a euro position held by a dollar-based fund entails much more risk than the same position held by a Scandinavian fund, relative to base currency. To cater to this, we calculate separate covariance matrices $\mathbf{\Sigma}_k$ for each base currency k and then compute the relevant quadratic form $\mathbf{h}_{it}'\mathbf{\Sigma}_k\mathbf{h}_{it}$ for each fund. Since $\mathbf{h}$ is always calculated in dollars, risk for all funds is also expressed in dollars, regardless of base currency.

To ensure quality of the data series, the analysis is confined to the larger funds in the universe, as these tend to have more frequent trading. Moreover, only trades in the 10 major currencies[4] are included. Mindful of survivorship bias, the requirement for inclusion in our sample is that a fund be in the 95th percentile of trading volume in at least one of six evenly-sampled weeks over the sample period. The six weeks are weeks 1, 101, 201, 301, 401, and 470 in our 470-week sample. This criterion selected a subset of 512 funds that account for an average of 72% of the volume across the 10 currencies. Our analysis focuses on the behavior of these 512 funds, which have average absolute daily holdings of about \$145 million.[5] Figure 1 plots the absolute holdings by currency aggregated across the 512 funds. It indicates that most of the fund holdings are concentrated in the euro, Japanese yen, British pound, Australian dollar, and Canadian dollar.

The database also includes comprehensive information on the total holdings of each fund by asset class for 2001. Based on this, funds can be classified as fixed

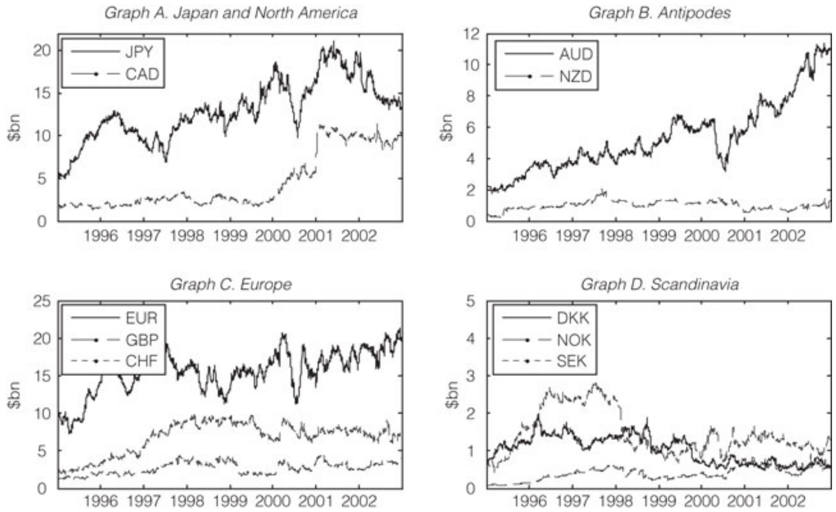
[4]The 10 currencies are the Danish krone, Norwegian krone, Swedish krona, Swiss franc, British pound, Australian dollar, Japanese yen, New Zealand dollar, Canadian dollar, and euro. Prior to 1999, synthetic euro return and flow series are constructed by weighting across the euro member countries.

[5]Nonetheless, we also redo the basic tests on the aggregate risk and P&L series of the remaining funds and obtain similar results. These results are omitted for brevity and are available from the authors.

FIGURE 1

Absolute Value of Holdings by Currency Aggregated Across All Funds

The sample period is from January 1995 to December 2002. JPY denotes Japanese yen, CAD denotes the Canadian dollar, AUD denotes the Australian dollar, NZD denotes the New Zealand dollar, EUR denotes the euro, GBP denotes the British pound, CHF denotes the Swiss franc, DKK denotes the Danish krone, NOK denotes the Norwegian krone, and SEK denotes the Swedish krona. Absolute holding is measured in billions of U.S. dollars.



income, equity, or currency funds. Funds with fixed income holdings in excess of equity holdings are defined as fixed income funds, and vice versa. Currency funds have no equity or fixed income positions. The resulting categorization comprises 158 fixed income funds, 71 equity funds, and 149 currency funds.

An important question to address is the potential influence of currency hedging in our data.[6] Currency trades can arise from passive or active currency management. Passive currency management, also known as currency overlay, arises from the desire to hedge preexisting currency exposure, such as that inherited from underlying holdings of equity or fixed income securities. Active currency management involves taking positions in currencies with a view to earning absolute return from exchange rate movements.[7] Since holdings commingle passive and active trades, and passive exposures are partly driven by exogenous factors, it may be difficult to measure the influence of past currency gains and losses on currency risk-taking. Essentially, the question boils down to whether there is an omitted variable bias stemming from the omission of the determinants of the passive holdings. The answer will depend on whether the omitted determinants—in particular, the returns on underlying equity and fixed income securities—are correlated with currency returns. It turns out that, for the countries we are interested in, the correlation between underlying asset returns and currency returns is quite low. For example, the average correlation between weekly currency returns

[6]We thank Joel Hasbrouck for pointing this out.

[7]The Appendix provides further details on spot and forward currency transactions.

and local currency equity returns across countries is -0.07. The corresponding number for sovereign fixed income securities is 0.09. This suggests that the omitted variable bias, if present, will be relatively muted. For added comfort, in the rest of the analysis, we present separate results for the sample of pure currency funds, which will contain a relatively higher fraction of purely active exposures. In addition, since hedging requires the taking of short positions in foreign currency relative to base currency, we will examine the results for long-only positions of foreign currency, which by definition will be unrelated to hedging.

III. Empirical Results

A. Basic Results

The first order of business is to determine the basic relationship between performance and risk-taking. We are interested in the sign and economic magnitude of the relationship and also in how, if at all, it varies across currencies and funds. The tool we use is an unrestricted VAR, which is first estimated at the weekly frequency to control for potential day-of-the week effects. We estimate panel VARs for changes in risk and P&L at the aggregate level, currency level, fund level, and fully disaggregated level. The model allows for heteroskedasticity across currencies and funds. The lag length L is set at 13 weeks, the value selected by the Bayes-Schwartz Criterion for the fund panel regression.

The aggregate level VAR can be written as:

$$\mathbf{y}_t = \boldsymbol{\alpha} + \sum_{\text{LAG}=1}^{L} \boldsymbol{\Phi}_{\text{LAG}} \mathbf{y}_{t-\text{LAG}} + \boldsymbol{\varepsilon}_t, \tag{1}$$

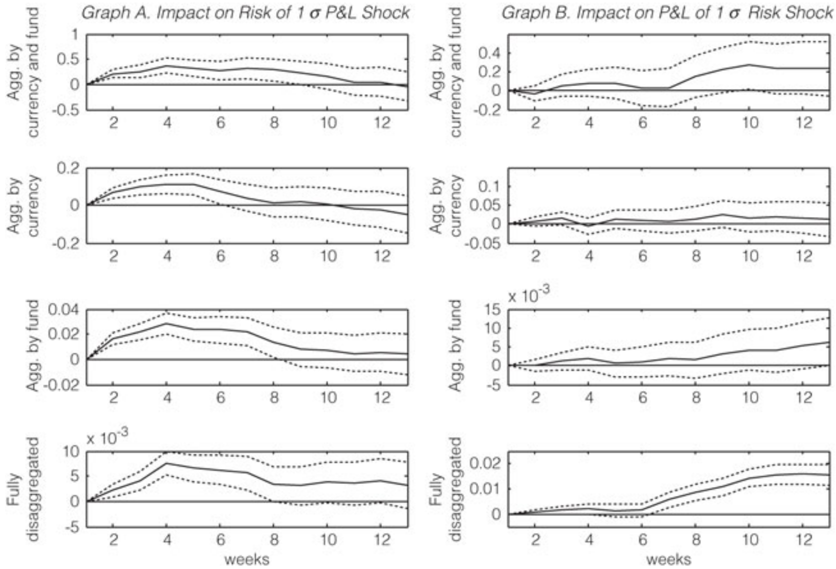
where $\mathbf{y}_t = [\Delta\text{RISK}_t \text{PNL}_t]'$ captures the changes in aggregate risk and profit at time t and $\boldsymbol{\varepsilon}_t = [\boldsymbol{\varepsilon}_t^{\Delta\text{RISK}} \boldsymbol{\varepsilon}_t^{\text{PNL}}]'$ is distributed as $N(0, \boldsymbol{\Omega})$. At the currency level, we estimate a panel version of equation (1) with $\mathbf{y}_{k,t} = [\Delta\text{RISK}_{k,t}\text{PNL}_{k,t}]'$ denoting changes in risk and profit at time t for currency k, and the coefficient matrices constrained to be equal across currencies. At the fund level, we estimate a panel version of equation (1) with $\mathbf{y}_{i,t} = [\Delta\text{RISK}_{i,t}\text{PNL}_{i,t}]'$ denoting changes in risk and profit at time t for fund i, and the coefficient matrices constrained to be equal across funds. We also estimate a fully-disaggregated currency-fund version of equation (1) with $\mathbf{y}_{i,k,t} = [\Delta\text{RISK}_{i,k,t}\text{PNL}_{i,k,t}]'$, and the coefficient matrices constrained to be equal across currencies and funds.

Figure 2 plots the impulse response functions from the VAR. They trace out the effects of past performance on risk-taking and vice versa. The leftmost column shows the impact that a one-standard-deviation shock to P&L has on weekly risk, while the rightmost column shows the impact that a one-standard-deviation shock to risk has on weekly P&L. The effects measured on the vertical axes are also scaled in standard deviation units, and 90% confidence intervals based on maximum likelihood standard errors are sketched around each function. To calibrate, the one-standard-deviation P&L shocks at each level of aggregation are \$163m, \$43m, \$3.4m, and \$1.1m, while the shocks to annualized risk are \$69m, \$23m, \$3.2m, and \$1.6m. The own-equation effects are omitted for brevity.

FIGURE 2

Impulse Response Functions for Shocks to Risk and P&L with Weekly Lags

The sample period is from January 1995 to December 2002. The sample includes the 10 major currencies and 512 funds. The aggregated-by-fund and currency panel consists of a series of length *W* weeks, the number of weeks in the sample period. The aggregated-by-currency panel consists of 10 currency-by-currency series of length *W*. The aggregated-by-fund panel consists of 512 fund-by-fund series of various lengths depending on fund life. The fully disaggregated panel consists of 2,455 fund-by-fund, currency-by-currency series (since not every fund trades every currency) of various lengths. To generate the Cholesky orthogonalized impulse response functions, panel VARs for risk and P&L are estimated with a lag length of 13 weeks, the value selected by the Bayes-Schwartz Information Criterion for the fund panel regression. The VARs allow for heteroskedasticity across currencies and funds. The vertical axes are scaled in standard deviation units of risk and P&L. The dotted lines sketched around each function are 90% confidence interval bounds based on maximum likelihood standard errors.



The leftmost column of impulse response functions in Figure 2 indicates that institutional investors increase risk following good performance. At all levels of aggregation, past performance exerts a positive and statistically significant impact on risk-taking, and the impact persists for six to eight weeks. For the fund panel regression, a one-standard-deviation shock to P&L produces a 3% standard deviation change in risk-taking after four weeks. The economic impact is significant. In dollar terms, a one-standard-deviation shock to P&L for a fund is \$3.4m, and this elicits an increase in annualized risk of \$96,000 over the next four weeks, or an incremental holding of \$960,000.[8] Turning to the rightmost column of plots, there is some indication that the level of profits improves with risk-taking, though not significantly so. Only with the fully disaggregated panel do we find that risk-taking has a positively significant effect on profits.

Having shown that the results are robust to potential day-of-the week effects, we now focus on the daily horizon to obtain a clearer picture of the high-frequency impact of past P&L on risk-taking.[9] Toward this end, we generate

[8]With annualized volatility of approximately 10%, an increase of \$96,000 in risk equates to an increased holding of \$960,000.

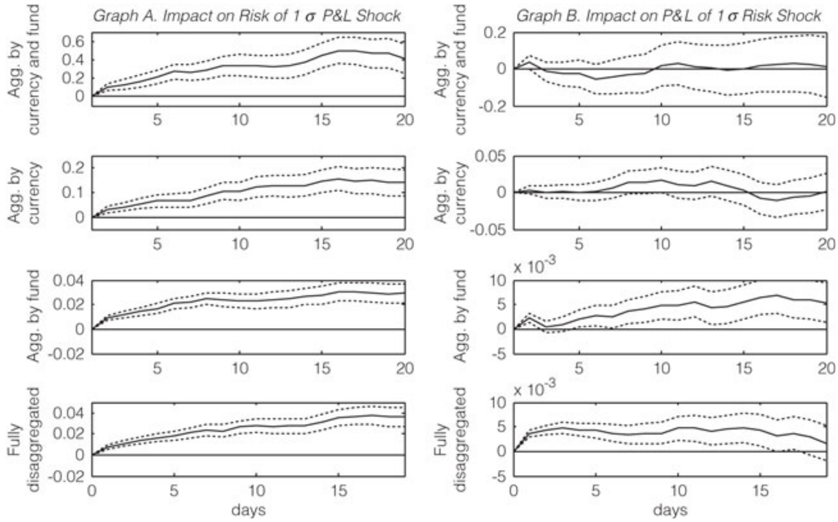
[9]The rest of the analysis will be conducted at the daily frequency, unless noted otherwise, although our results also hold at the weekly frequency.

impulse response functions from the VAR with daily lags, where the lag length L is set at 20 days. The impulse response functions with daily lags displayed in Figure 3 broadly agree with those in Figure 2. They indicate that at all levels of aggregation, a shock to daily P&L increases daily risk-taking. This effect grows over the next 15 days before peaking at around the 15–20 day horizon (i.e., at around the fourth week).

FIGURE 3

Impulse Response Functions for Shocks to Risk and P&L with Daily Lags

The sample period is from January 1995 to December 2002. The sample includes the 10 major currencies and 512 funds. The aggregated-by-fund and currency panel consists of a series of length T days, the number of days in the sample period. The aggregated-by-currency panel consists of 10 currency-by-currency series of length T. The aggregated-by-fund panel consists of 512 fund-by-fund series of various lengths depending on fund life. The fully disaggregated panel consists of fund-by-fund, currency-by-currency series of various lengths. To generate the Cholesky orthogonalized impulse response functions, panel VARs for risk and P&L are estimated with a lag length of 20 days. The VARs allow for heteroskedasticity across currencies and funds. The vertical axes are scaled in standard deviation units of risk and P&L. The dotted lines sketched around each function are 90% confidence interval bounds based on maximum likelihood standard errors.



To check the pervasiveness of the performance dependence, we estimate the fully disaggregated VAR for each currency. Panel A of Table 1 shows the coefficient estimates on the first eight daily lags of P&L for the risk equation. The performance dependence observed in Figure 3 characterizes eight of the 10 currencies, the exceptions being the New Zealand dollar and the Canadian dollar. Since the trading volume in these currencies is 1.12% and 6.98% of the total volume, respectively, the performance dependence applies to the bulk of currency trading in our sample. Specifically, there is evidence of statistically positive P&L lag coefficients (lagged one, two, and three days) at the 10% level for 90.94% of the trading volume (Norwegian krone, Swedish krona, Swiss franc, British pound, Australian dollar, Japanese yen, and euro). Also, we compute F-statistics to test the hypothesis that P&L does not Granger cause risk-taking. We are able to reject the hypothesis at the 5% level for all four major currencies (British pound, Australian dollar, Japanese yen, and euro), which account for 78.71% of the trading volume.

TABLE 1

Regressions on Daily Change in Fund Risk

Table 1 reports maximum likelihood regression coefficients and t-statistics (in parentheses) for 10 regressions, each regression corresponding to a currency, along with the associated F-statistics. The dependent variable is the daily change in risk. The independent variables are the past 20 daily lags of change in risk and the past 20 daily lags of P&L. Only the coefficients and t-statistics for the first eight daily P&L lags are reported for brevity. Coefficients are multiplied by 100. The F-statistics test the hypothesis that the coefficients on the P&L lags are all equal to zero. Panels A and B list regression coefficients and t-statistics for regressions for the full fund sample and the pure currency fund sample, respectively. Coefficients in bold denote statistical significance at the 10% level. ** and * indicate F-statistic significance at the 1% and 5% levels, respectively.

	Dependent Variable: Daily Change in Fund Risk									
Independent Variables	Danish Kroner	Norwegian Krone	Swedish Krona	Swiss Franc	British Pound	Australian Dollar	Japanese Yen	New Zealand Dollar	Canadian Dollar	Euro
Panel A. All Funds										
P&L ($T-1$)	0.082	**1.875**	**0.514**	**0.636**	**0.590**	**0.431**	**0.392**	**−1.14**	**−0.833**	**0.810**
	(1.10)	(4.87)	(2.45)	(2.80)	(2.89)	(1.79)	(1.91)	(−4.23)	(−3.08)	(5.33)
P&L ($T-2$)	0.010	0.144	**0.495**	−0.041	**0.671**	**0.745**	0.248	**−0.720**	0.410	**0.660**
	(0.13)	(0.37)	(2.36)	(−0.18)	(3.29)	(3.10)	(1.21)	(−2.67)	(1.52)	(4.30)
P&L ($T-3$)	−0.055	−0.442	−0.213	−0.261	**0.793**	0.019	0.253	−0.113	0.335	**0.347**
	(−0.74)	(−1.15)	(−1.02)	(−1.15)	(3.88)	(0.08)	(1.23)	(−0.42)	(1.24)	(2.24)
P&L ($T-4$)	−0.035	**1.706**	−0.150	**0.496**	0.127	**0.563**	**0.385**	0.328	**0.783**	0.238
	(−0.47)	(4.43)	(−0.72)	(2.18)	(0.62)	(2.34)	(1.87)	(1.21)	(2.87)	(1.54)
P&L ($T-5$)	0.056	**−0.910**	**0.403**	**0.500**	0.084	−0.058	0.097	**−0.576**	0.041	**0.735**
	(0.75)	(−2.36)	(1.93)	(2.20)	(0.41)	(−0.24)	(0.47)	(−2.14)	(0.15)	(4.85)
P&L ($T-6$)	0.059	−0.091	−0.029	−0.095	0.249	**0.857**	0.154	0.386	**0.478**	0.097
	(0.80)	(−0.24)	(−0.14)	(−0.42)	(1.22)	(3.56)	(0.75)	(1.43)	(1.76)	(0.64)
P&L ($T-7$)	0.112	**0.641**	−0.219	**0.413**	**0.582**	−0.011	**0.385**	−0.163	0.350	0.105
	(1.52)	(1.67)	(−1.05)	(1.82)	(2.85)	(−0.04)	(1.88)	(−0.60)	(1.29)	(0.71)
P&L ($T-8$)	0.015	0.537	−0.008	**0.496**	−0.066	0.101	0.079	0.363	−0.089	−0.111
	(0.20)	(1.40)	(−0.04)	(2.18)	(−0.32)	(0.42)	(0.39)	(1.34)	(−0.33)	(−0.76)
F-statistic	1.05	3.45**	2.05**	2.70**	5.19**	2.47**	1.65*	3.59**	1.96**	4.59**
% of volume	0.96	0.59	2.63	9.02	14.50	5.68	22.52	1.12	6.98	36.00

(continued on next page)

TABLE 1 (continued)

Regressions on Daily Change in Fund Risk

Independent Variables	Dependent Variable: Daily Change in Fund Risk									
	Danish Kroner	Norwegian Krone	Swedish Krona	Swiss Franc	British Pound	Australian Dollar	Japanese Yen	New Zealand Dollar	Canadian Dollar	Euro
Panel B. Pure Currency Funds										
P&L ($T-1$)	**0.426**	**1.929**	**3.532**	**3.480**	**2.023**	0.548	0.479	−**1.481**	−**0.782**	**1.785**
	(1.72)	(3.24)	(7.58)	(6.92)	(5.33)	(1.38)	(1.40)	(−3.59)	(−1.75)	(6.78)
P&L ($T-2$)	0.006	**1.154**	**1.191**	0.160	**1.194**	**0.727**	**0.622**	−**0.717**	0.499	**1.025**
	(0.02)	(1.94)	(2.55)	(0.32)	(3.15)	(1.84)	(1.82)	(−1.74)	(1.12)	(3.82)
P&L ($T-3$)	0.124	0.242	0.155	−0.642	**0.775**	0.646	−0.027	0.216	**0.788**	0.059
	(0.50)	(0.41)	(0.33)	(−1.28)	(2.04)	(1.64)	(−0.08)	(0.52)	(1.76)	(0.23)
P&L ($T-4$)	−0.005	0.742	**1.019**	**1.153**	**0.845**	0.630	**0.804**	0.514	0.708	**0.493**
	(−0.02)	(1.25)	(2.18)	(2.30)	(2.23)	(1.59)	(2.36)	(1.24)	(1.57)	(1.87)
P&L ($T-5$)	0.106	0.869	0.465	**1.412**	0.465	−0.141	−0.295	−0.343	0.520	**1.017**
	(0.43)	(1.46)	(1.00)	(2.81)	(1.22)	(−0.36)	(−0.86)	(−0.83)	(1.16)	(3.89)
P&L ($T-6$)	0.042	0.015	−0.349	−**1.272**	−0.359	0.329	**0.574**	**0.795**	−0.148	−0.147
	(0.17)	(0.02)	(−0.75)	(−2.54)	(−0.95)	(0.83)	(1.68)	(1.92)	(−0.33)	(−0.56)
P&L ($T-7$)	0.225	**1.435**	−0.032	0.301	**0.929**	−0.357	0.026	−0.071	−0.633	**0.833**
	(0.91)	(2.41)	(−0.07)	(0.60)	(2.45)	(−0.90)	(0.08)	(−0.17)	(−1.41)	(3.21)
P&L ($T-8$)	**0.422**	0.783	−0.203	**0.829**	0.370	−0.500	0.021	0.009	−0.316	−0.379
	(1.71)	(1.31)	(−0.43)	(1.66)	(0.98)	(−1.27)	(0.06)	(0.02)	(−0.70)	(−1.42)
F-statistic	0.57	2.51**	4.09**	5.39**	4.59**	1.47	2.53**	3.48**	1.83*	6.30**
% of volume	0.96	0.59	2.63	9.02	14.50	5.68	22.52	1.12	6.98	36.00

As already mentioned, passive currency hedging is unlikely to bias the results, given the low correlation between currency returns and the returns on underlying assets. Nonetheless, it is useful to analyze data from the sample of pure currency funds, since it is likely to have a higher concentration of purely active trading. Panel B of Table 1 reports the coefficient estimates from the currency-by-currency regressions for the pure currency funds sample. The first lag of P&L is positive for eight of the 10 currencies, and there are statistically positive early P&L lags at the 10% level for all four top-volume currencies (Swiss franc, British pound, Japanese yen, and euro). Clearly, the performance dependence is pervasive for the currency funds sample as well.

To complement the pure currency funds analysis, we also estimate the fund level VAR of equation (1) for equity and bond types. The impulse responses of risk to shocks in P&L for each fund type are displayed in Figure 4. Currency and bond funds display qualitatively the same sensitivity to past P&L as with the full group of funds. Equity funds, in contrast, display a negative but somewhat random response to past performance that is statistically insignificant for the most part. This accords with the folk wisdom that equity fund managers care less about the currency component of their returns. To be fair, the statistical power of the equity sample is much lower, since the number of equity funds, at 71, is about half the number of currency or bond funds in the sample.

B. Conditioning on Past Gains and Losses

An important question is whether the impact of gains and losses is symmetric. To investigate this, we estimate the following daily fund level regression with P&L interacted with the positive P&L dummy and the negative P&L dummy:[10]

$$\begin{aligned}(2) \qquad \Delta\text{RISK}_{i,t} = a &+ \sum_{\text{LAG}=1}^{L} b_{\text{LAG}} \Delta\text{RISK}_{i,t-\text{LAG}} \\ &+ \sum_{\text{LAG}=1}^{L} c_{\text{LAG}} \text{POSPNL}_{i,t-\text{LAG}} \\ &+ \sum_{\text{LAG}=1}^{L} d_{\text{LAG}} \text{NEGPNL}_{i,t-\text{LAG}} + \varepsilon_{i,t},\end{aligned}$$

where $i = 1, \ldots, \text{NFUND}$, $t = 1, \ldots, \text{T}$, $L = 20$ days, and $\text{POSPNL} = \max(\text{PNL}, 0)$ and $\text{NEGPNL} = \min(\text{PNL}, 0)$. The rest of the variables are as defined earlier.

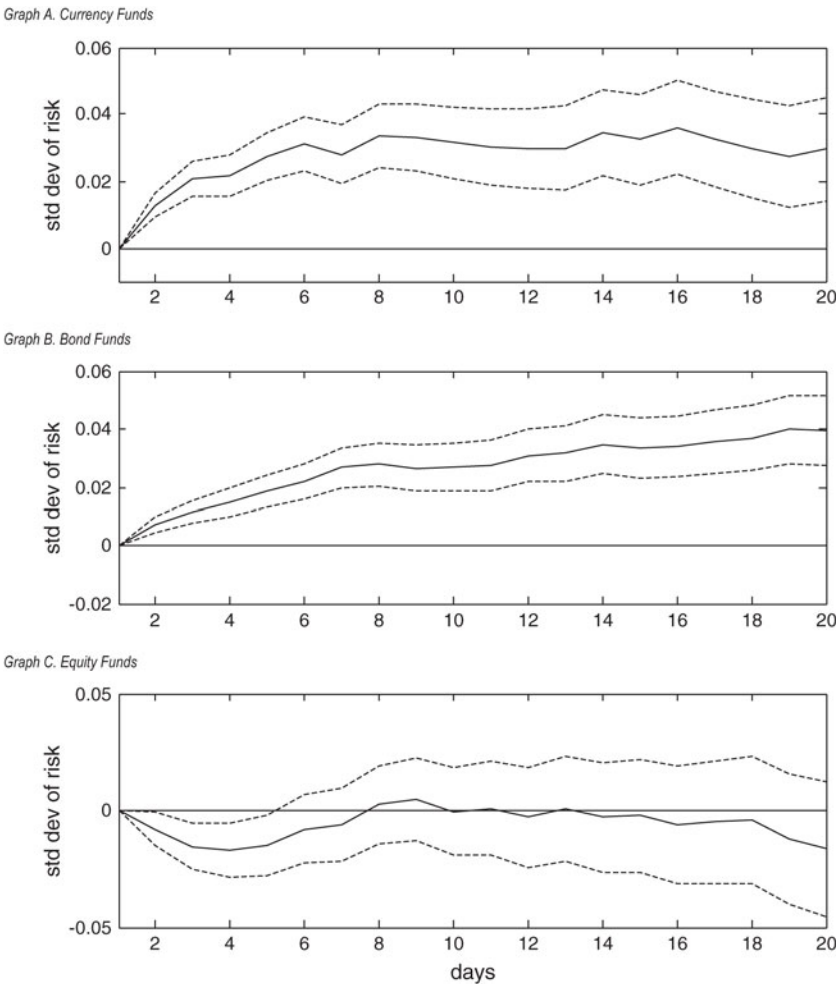
Figure 5 plots separate impulse response functions for gains and losses, estimated from the fund panel. This is done for the full sample of funds (leftmost plots) and the pure currency funds sample (rightmost plots). There is, in fact, a striking difference in the two impulse response functions. Over the full sample of

[10]Since our focus will be on the risk equation in the VAR, we adopt the single equation regression approach for the rest of the paper.

FIGURE 4

Impulse Response of Risk to Shocks in P&L Broken Down by Fund Type
(impact on fx risk of 1 σ fx P&L shock)

The Cholesky orthogonalized impulse response functions are generated from a 20-day-lag bivariate panel VAR for risk and P&L. The sample period is from January 1995 to December 2002. The model allows for heteroskedasticity across funds. Estimation is carried out by maximum likelihood, stacking all of the funds in the sample. The vertical axes are scaled in standard deviation units of risk. The dotted lines sketched around each function are 90% confidence interval bounds based on maximum likelihood standard errors.

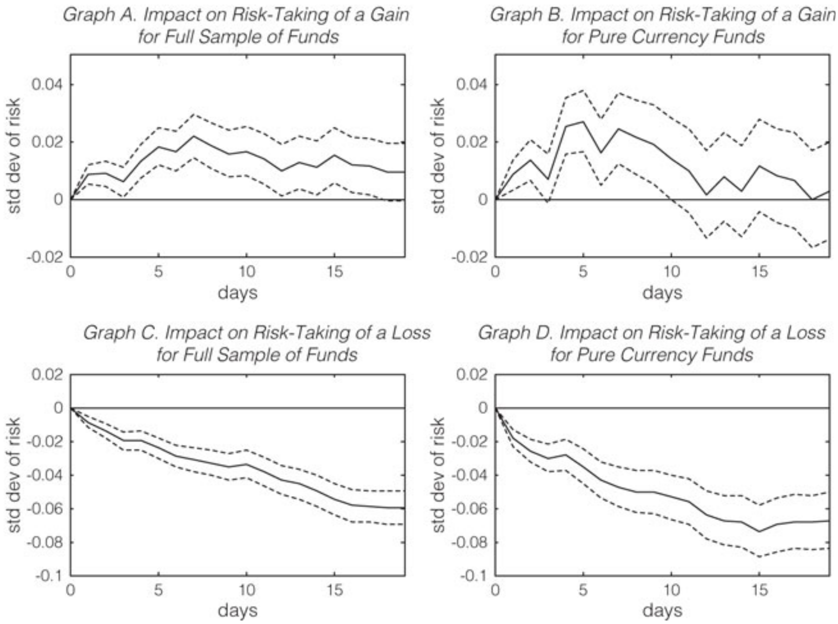


funds, gains produce transitory increases in risk-taking that taper off after about 20 days. In contrast, the effects of losses are both stronger and more durable. Note that the impulse response function located second from the bottom and in the left-most panel of Figure 3 is simply the average of these two functions. The implication is that the performance dependence illustrated in Figure 3 masks separate effects of gains that appear to be weaker and less durable, and losses that appear to be stronger and more durable. The same dichotomous pattern of performance dependence is evident in the pure currency funds sample.

FIGURE 5

Fund Panel Impulse Response Functions for Gains and Losses

The sample period is from January 1995 to December 2002. To generate the Cholesky orthogonalized impulse response functions, risk is regressed on daily lags of P&L conditional on gains and daily lags of P&L conditional on losses for the fund panel. The regression allows for heteroskedasticity across funds and uses the same lag structure as the VARs in Figure 3. The vertical axes are scaled in standard deviation units of risk. The dotted lines sketched around each function are 90% confidence interval bounds based on maximum likelihood standard errors.



The fund level regressions thus far allow for group-wise heteroskedasticity across funds. However, because funds may be trading on the same information, we may need to adjust for cross-sectional covariance across funds. This adjustment requires a balanced panel and forces us to analyze only funds that survive the entire sample period, reducing the sample to just 35 funds. Nonetheless, our basic and conditional results for the fund panel (with cross-sectional covariance across groups) still hold with this small sample of funds.

IV. Discussion

Next, we explore various explanations for the documented performance dependence. The explanations include a mechanical relationship between risk-taking and performance, hedging activities, capital constraints, stop-loss rules, momentum trading, managerial compensation and reputation concerns, the disposition effect, dynamic loss aversion, and overconfidence.

A. Mechanical Relationship between Risk-Taking and Performance

There are concerns that risk-taking may be hardwired to performance. For example, suppose a fund manager holds α_t of her portfolio in the S&P 500 index and $1 - \alpha_t$ in T-bills at the end of period t, where $0 < \alpha_t < 1$. We notice that after positive outcomes (up market periods), the manager appears to "increase" the risk of her portfolio (the beta of her portfolio increases). After negative outcomes, the manager appears to "decrease" the risk of her portfolio.

However, such a mechanical relationship cannot account for our results for three reasons. First, the mechanical relationship is a contemporaneous one. Consider a U.S.-based fund that is long the euro. If the price of the euro rises from end of day $t-1$ to end of day t, the fund registers a gain in day t and risk rises from the end of day $t-1$ to the end of day t. Since we ask whether P&L today explains the change in risk between today and tomorrow, our results are noncontemporaneous. Second, if there is significant positive serial correlation in P&L at the one-day horizon, the mechanical relationship might carry over to the noncontemporaneous setting, but there is no evidence of such daily serial correlation in the data. Third, the mechanical relationship is reversed when a fund is short a currency. To see this, suppose the fund was short USD 1m of euros and the euro depreciates 20% relative to the dollar, so that the fund is now short USD 0.8m of euros. The fund registers a gain, and risk-taking falls at the same time. Since we broadly have as many longs as shorts in our database (there are 227,178 long fund-day observations and 294,361 short fund-day observations), the contemporaneous mechanical effect can go either way. To test the direction of the contemporaneous effect, we estimate the base regression for the fund panel augmented with an additional independent variable: contemporaneous daily P&L. We find that the coefficient on contemporaneous P&L is statistically negative. More importantly, the coefficient estimates on the first few P&L lags are still positive and statistically significant. This is true whether we focus on the full sample or on the pure currency funds sample.

B. Overlay and Hedging

Returning to the issue of whether passive hedging is influencing the results, we replicate the analysis on the subsample of fund-currency observations associated with long currency positions. The basic premise is that overlay strategies typically involve managers being long a foreign investment (e.g., Japanese government bonds) and short the foreign currency (e.g., the yen) relative to base currency. Hence, long currency positions are unlikely to stem from overlay activities. The currency-fund panel impulse response functions for the analysis on long currency positions in Figure 6 suggest that our results are not driven by overlay activities. As with Figure 3, an increase in P&L still exerts a reliably positive effect on future risk-taking. Also, for long currency positions, the effects of a gain are weaker than those of a loss, as suggested by the middle and bottom impulse response functions of Figure 6.

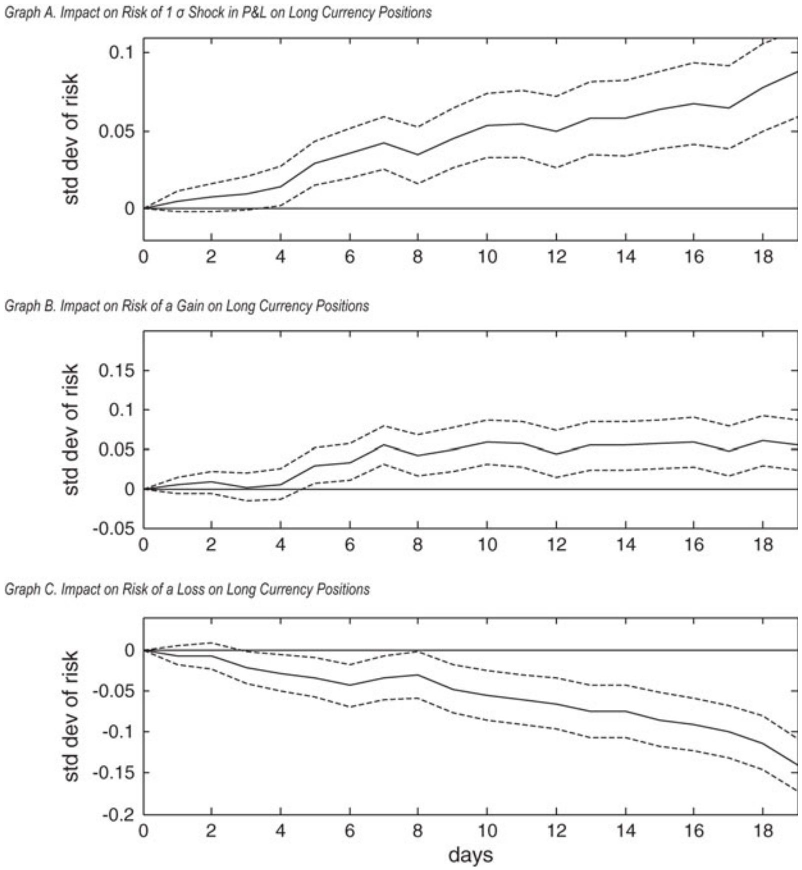
C. Margin and Capital Constraints

Another possible explanation for the observed performance dependence is that margin or capital constraints come into play. When institutions are faced with large losses, they may be forced by binding capital constraints to clamp down on risk-taking. This could explain the strong and durable reaction to losses we

FIGURE 6

Fund Panel Impulse Response Functions for Long Currency Positions

The sample period is from January 1995 to December 2002. To generate the Cholesky orthogonalized impulse response functions in Graph A, risk is regressed on daily lags of P&L for the fully disaggregated currency-fund panel. In Graphs B and C, risk is regressed on daily lags of P&L conditional on gains and daily lags of P&L conditional on losses for the currency-fund panel. The regression allows for heteroskedasticity across currencies and funds and uses the same lag structure as the VARs in Figure 3. The vertical axes are scaled in standard deviation units of risk. The dotted lines sketched around each function are 90% confidence interval bounds based on maximum likelihood standard errors.



witness in Figure 5. However, when capital or margin limits are in place, cross-currency effects on risk are apt to arise. Because such limits operate at the fund level and not just at the account level, for each currency and each fund, past gains and losses on one currency should also affect risk-taking in other currencies in the fund.[11] To test this, we augment the independent variables in the risk equation of equation (1) with past 20 lags of daily P&L from the other currencies (which we term conjugate currency P&L):

[11] The recent demise of the U.S. hedge fund Amaranth Advisors LLC, where the losses on its natural gas positions affected risk-taking in its other positions, is an extreme example of capital constraints at work. See "End of the Road for Dollars 6bn-Loser Amaranth," *Financial Times* (September 27, 2006).

$$\Delta\text{RISK}_{i,k,t} = a^k + \sum_{\text{LAG}=1}^{L} b^k_{\text{LAG}} \Delta\text{RISK}_{i,k,t-\text{LAG}} + \sum_{\text{LAG}=1}^{L} c^k_{\text{LAG}} \text{PNL}_{i,k,t-\text{LAG}} + \sum_{\text{LAG}=1}^{L} d^k_{\text{LAG}} \text{CONJPNL}_{i,k,t-\text{LAG}} + \varepsilon_{i,k,t}, \tag{3}$$

where $\text{CONJPNL}_{i,k,t} = \sum_{j \neq k} \text{PNL}_{i,j,t}$, $i = 1, \ldots, \text{NFUND}$, $k = 1, \ldots, \text{NCURR}$, $t = 1, \ldots, T$, $L = 20$ days. Then, we estimate the equation (3) regressions with daily lags. In results available upon request, we find that cross-currency effects are noticeably absent and do not drive the performance dependence. This also lends support to the idea that institutional managers narrowly frame their decisions at the account level and not at the fund level. Narrow framing is, in turn, consistent with preferences like those proposed by Barberis, Huang, and Santos (2001), where an agent's decision utility must depend on the outcome of the gamble over and above what that outcome implies for total wealth risk.[12]

D. Stop-Loss Activities

A related view is that institutional investors follow risk-management-motivated stop-loss rules that require them to cut exposure in the wake of a significant loss (Osler (2003)). For example, a fund might close out a position if it suffers more than a 20% loss on the position. Stop-loss trading may therefore explain the strong negative reaction of risk to losses. For stop-loss rules to drive our results, it must be that the reaction to losses is dictated by the most extreme losses. There should exist a large loss cutoff such that there is no risk reaction for all losses smaller in magnitude than the cutoff. To test this, we estimate the following regression for various loss cutoffs and for each currency with daily lags:

$$\Delta\text{RISK}_{i,k,t} = a^k + \sum_{\text{LAG}=1}^{L} b^k_{\text{LAG}} \Delta\text{RISK}_{i,k,t-\text{LAG}} + \sum_{\text{LAG}=1}^{L} c^k_{\text{LAG}} \text{POSPNL}_{i,k,t-\text{LAG}} + \sum_{\text{LAG}=1}^{L} d^k_{\text{LAG}} \text{SNEGPNL}_{i,k,t-\text{LAG}} + \sum_{\text{LAG}=1}^{L} e^k_{\text{LAG}} \text{LNEGPNL}_{i,k,t-\text{LAG}} + \varepsilon_{i,k,t}, \tag{4}$$

[12]See Section 4.2 of Barberis, Huang, and Thaler (2006) for further discussion.

where $i=1,\ldots,\text{NFUND}$, $k=1,\ldots,\text{NCURR}$, $t=1,\ldots,T$, $L=20$ days, and SNEGPNL equals NEGPNL for losses smaller in magnitude than the cutoff and equals zero otherwise, while LNEGPNL equals NEGPNL for losses larger in magnitude than the cutoff and equals zero otherwise. The regressions are estimated at the fully disaggregated level, as it is harder to detect stop-loss trading, if any, in aggregated data. We use a wide range of loss cutoffs including the 50th, 60th, 70th, 80th, 90th, and 95th loss percentiles to detect stop-loss behavior. Despite the extensive battery of tests, for all currencies, we cannot find a loss cutoff such that the coefficient on SNEGPNL is statistically insignificant and the coefficient on LNEGPNL is statistically significant. In fact, for all currencies where the positive risk/past performance relationship holds (see Table 1), the coefficient on SNEGPNL is significant for all cutoff levels. Hence, stop-loss rules are unlikely to drive the reaction to losses that we observe.

E. Correlated Profit Opportunities

Prior studies have found that institutions engage in momentum trading and buy into well-performing stocks (Griffin, Harris, and Topaloglu (2003), Badrinath and Wahal (2002)). It is easy to see why momentum trading may induce the observed reaction to past performance. Suppose an institution that follows momentum strategies is long a currency. If the subsequent returns are high, the institution racks up gains and increases its long exposure in line with its momentum strategy. Conversely, when subsequent returns are low, the institution suffers losses and reduces its long exposure to the currency in line with the momentum strategy. A similar relationship exists when a momentum trader is short a currency. However, momentum does not explain the asymmetry between the risk reaction to gains and losses. For momentum to account for the asymmetry we observe, it must be that funds adopt momentum strategies more often when they face losses than when they face gains. It is difficult to understand why the impetus for momentum trading would vary systematically with the sign of past performance. Nonetheless, to test whether our findings are driven by momentum, we estimate the following currency-by-currency, fund panel regression with daily lags:

$$(5)\quad \Delta\text{RISK}_{i,k,t} = a^k + \sum_{\text{LAG}=1}^{L} b^k_{\text{LAG}}\Delta\text{RISK}_{i,k,t-\text{LAG}} + \sum_{\text{LAG}=1}^{L} c^k_{\text{LAG}}\text{PNL}_{i,k,t-\text{LAG}} + \sum_{\text{LAG}=1}^{L} d^k_{\text{LAG}}\text{RET}_{k,t-\text{LAG}}\text{SIGN}(\text{HOLD}_{i,k,t-\text{LAG}}) + \varepsilon_{i,k,t},$$

where $i=1,\ldots,\text{NFUND}$, $k=1,\ldots,\text{NCURR}$, $t=1,\ldots,T$, $L=20$ days, and RET is currency return, HOLD is currency holdings, and $\text{SIGN}(X)$ is the sign of variable X. The results indicate that momentum trading does not drive the observed reaction of risk to past performance. Most of the signed return lags are insignificantly different from zero, while the coefficients on the P&L lags are qualitatively similar to those in Table 1.

F. Manager's Compensation and Reputation Concerns

Institutional reputation concerns may induce performance dependence. To minimize the impact of negative investment outcomes on their reputation, institutions tend to follow each other's trades or herd (Wermers (1999), Sias (2004)). To explore the effects of herding in our sample of institutional investors, we augment the regressors in the currency-by-currency, fund panel regressions with the fraction of institutions increasing exposure to the currency minus the average fraction of institutions increasing exposure to currencies. This variable is the risk analog of the herding ratio in equation (2) of Sias (2004). The results from this exercise suggest that herding is tangential to the risk/past performance relationship. None of the coefficients on the herding variable lags are statistically significant.

Managerial compensation concerns may also generate performance dependence. Because manager compensation is often viewed as a convex function of performance (Chevalier and Ellison (1997), Del Guercio and Tkac (2008)), funds tend to cut risk following bouts of good performance and increase risk following bouts of poor performance (Chevalier and Ellison (1997), Elton, Gruber, and Blake (2003)). However, such compensation effects cannot explain our results, as they predict the exact opposite of what we find in Figure 5. Moreover, such incentive effects should operate at the portfolio level and not just at the currency level. Yet, we fail to detect cross-currency effects within funds. This suggests that managerial concerns do not drive the short-term performance dependence that we uncover.

G. Disposition Effect

A large body of work finds that individuals, including retail and professional investors, are prone to the disposition effect (Odean (1998), Linnainmaa (2003), Locke and Mann (2005), and Coval and Shumway (2005)). In addition, Grinblatt and Keloharju (2001) show that local institutional investors in the Finnish market are also afflicted by the disposition effect. If the investors in our sample are similarly affected, then they should not reduce risk following losses (by holding onto their losses) and should reduce risk following gains (by selling their winners). Yet, we find that they cut risk following losses and ramp up risk following gains. Our results challenge Grinblatt and Keloharju's (2001) findings and suggest that disposition results in the literature are sensitive to investor type.

To better square our surprising disposition results with the extant literature, and to facilitate comparison, we adopt the methodology of Odean (1998) and compare the proportion of losses realized (PLR) with the proportion of gains realized (PGR). The analysis relies on daily aggregated buys and sells. One advantage of aggregation is that we control for investors who break up their trades over the course of a day. We assume that currencies are bought and sold at closing prices. Following Odean (1998), each day that an offsetting daily flow occurs, we compare the price of that currency to its average purchase price to determine whether that currency is sold or bought for a gain or a loss. An offsetting flow occurs when the fund is net long the currency and sells the currency, or when the fund is net short the currency and buys the currency. Each currency that is held by the fund for that day but does not experience an offsetting flow is considered to be a paper (unrealized) gain or loss (or neither). On days when no offsetting flows take place for a fund, no gains and losses, realized or paper, are recorded.

First, we aggregate the number of realized gains, paper gains, realized losses, and paper losses over time and across funds. The PGR is the ratio of the aggregated realized gains over the aggregated realized and paper gains. The PLR is the ratio of the aggregated realized losses over the aggregated realized and paper losses. The hypothesis is that there is no disposition effect or PLR $\geq$ PGR. Hence, the null hypothesis is PLR $<$ PGR. The results of this test are presented in Panel A of Table 2. Over the full sample, we find that PLR is 0.2333, while PGR is 0.2304. The difference in proportions (PLR minus PGR) is positive and statistically significant[13] at the 1% level. This starkly contrasts with Odean (1998), who finds that the difference in proportions for his sample of retail investors is statistically negative. Unlike his retail investors, the institutional investors in our sample do not seem prone to the disposition effect. The analysis here nicely corroborates our findings with the VAR. Mindful once again of the potential influence of passive hedging, we also replicate the analysis for pure currency funds and find even stronger results. The difference in proportions for the pure currency funds sample is about 2.8 times that for the full sample of funds.

The aggregate analysis counts each realized gain, realized loss, paper gain, and paper loss on the day of an offsetting flow as separate independent observations. This assumption may not hold. Daily flows may be correlated across time within each fund if funds are offloading large positions over several days or may be correlated across funds if funds are trading on the same information. In Panel B of Table 2, we relax the assumption that flows are independent across time for each fund and calculate the average fund PLR and PGR. Only funds with non-zero denominators for both PLR and PGR are included in the analysis, giving us a sample of 498 funds and 144 pure currency funds. We find that inferences remain unchanged with the fund-level PLR and PGR comparison. In Panel C of Table 2, in addition to relaxing the assumption of independence across time, we also try to control for dependence across funds. Daily flows in a currency are counted only if no more than two other funds have flows of the same sign for the same currency that day. Thus, we ensure that daily flows in the same direction for more than three funds are not counted. This control for correlated fund flow gives us a sample of 292 funds and 74 pure currency funds with non-zero denominators

[13]The standard error used to calculate the t-statistics in the aggregate analysis is

$$\sqrt{\frac{\mathrm{PGR}(1-\mathrm{PGR})}{n_{\mathrm{RG}}+n_{\mathrm{PG}}}+\frac{\mathrm{PLR}(1-\mathrm{PLR})}{n_{\mathrm{RL}}+n_{\mathrm{PL}}}},$$

where n_{RG}, n_{PG}, n_{RL}, and n_{PL} are the number of realized gains, paper gains, realized losses, and paper losses, respectively.

TABLE 2

Proportion of Gains and Losses Realized

Table 2 compares the proportion of gains realized (PGR) to the proportion of losses realized (PLR), where PGR is the number of realized gains divided by the number of realized gains plus the number of paper (unrealized) gains, and PLR is the number of realized losses divided by the number of realized losses plus the number of paper (unrealized) losses. Buys and sells are aggregated each day for this analysis. In Panel A, realized gains, paper gains, realized losses, and paper losses are aggregated over time (1995–2002) and across all funds or across all pure currency funds in the sample. For the full sample of funds, there are 217,583 realized gains, 726,949 paper gains, 201,798 realized losses, and 663,035 paper losses. For the pure currency sample of funds, there are 68,029 realized gains, 193,252 paper gains, 64,066 realized losses, and 174,234 paper losses. The *t*-statistics test the null hypothesis that the differences in proportions are equal to zero assuming that all realized gains, paper gains, realized losses, and paper losses result from independent decisions. In Panel B, realized gains, paper gains, realized losses, and paper losses are aggregated over time (1995–2002) for each fund. The average PLR and PGR are reported as well as the average difference in proportions across all funds or across all pure currency funds. The *t*-statistics test the null hypothesis that the differences between fund level PGR and PLR is equal to zero assuming independence of gains and losses at the fund level. In Panel C, the analysis is similar to that in Panel B except that the daily flows in a currency are counted only if no more than two other funds have flows of the same sign for the same currency on that day. This controls for the dependence in PGR and PLR across funds. ** and * indicate significance at the 1% and 5% levels, respectively.

	All Funds	Pure Currency Funds
Panel A. Aggregate Level		
PLR	0.2333	0.2688
PGR	0.2304	0.2604
Difference in proportions (PLR − PGR)	0.0029**	0.0084**
t-statistic	4.74	6.78
Panel B. Fund Level		
Average PLR across funds	0.3337	0.4417
Average PGR across funds	0.3274	0.4316
Average difference in proportions	0.0063**	0.0101**
t-statistic	3.12	2.80
Panel C. Fund Level (controlling for dependence in PGR and PLR across funds)		
Average PLR across funds	0.2528	0.3018
Average PGR across funds	0.2313	0.2490
Average difference in proportions	0.0215*	0.0528*
t-statistic	2.03	2.45

for PGR and PLR. For this sample of funds, we find that PLR is again statistically higher than PGR.[14]

Since Grinblatt and Keloharju (2001) find evidence of the disposition effect with their sample of institutional investors, it will be important to reconcile our results with theirs. To this end, we replicate their logit regression methodology on our sample of institutional investors. To investigate the determinants of the sell-versus-hold decision, we regress a sell-versus-hold dummy variable (that takes a value of one when an investor sells a currency and a value of zero otherwise) on lags of currency returns, a large loss dummy, and a small loss dummy.[15] The variables are signed appropriately so that all inferences can be made as if investors are long currencies. As in Table I of Grinblatt and Keloharju (2001), currency returns

[14] The standard error for the average difference in the fund-level PLR and PGR is

$$\frac{1}{K}\sqrt{\sum_{i=1}^{K}\left[\frac{\mathrm{PGR}_i(1-\mathrm{PGR}_i)}{N_{\mathrm{RG}i}+N_{\mathrm{PG}i}}+\frac{\mathrm{PLR}_i(1-\mathrm{PLR}_i)}{N_{\mathrm{RL}i}+N_{\mathrm{PL}i}}\right]},$$

where $N_{\mathrm{RG}i}$, $N_{\mathrm{PG}i}$, $N_{\mathrm{RL}i}$, and $N_{\mathrm{PL}i}$, are the account level number of realized gains, paper gains, realized losses, and paper losses, respectively.

[15] We define a large loss as a loss larger in magnitude than the median loss and a small loss as a loss smaller in magnitude than the median loss.

for day 0, -1, -2, -3, -4, $[-19, -5]$, $[-39, -20]$, $[-59, -40]$, $[-119, -60]$, $[-179, -120]$, and $[-239, -180]$ are included among the regressors as controls. The coefficient estimates on the small and large loss dummies for the full sample are displayed in Panel A of Table 3. They suggest that for nine out of the 10 currencies, a loss increases the probability that an institutional investor will sell versus hold a currency. This sharply contrasts with Grinblatt and Keloharju (2001), who find that a loss induces the institutional investors in their sample to hold rather than to sell (i.e., the coefficient estimates on their loss dummies are statistically negative). Our results cannot be explained by the effects of overlay or hedging, as they persist with the pure currency funds sample (see Panel B, Table 3). Further, we redo the analysis on the sell-versus-buy decision and find similar results (see Panels C and D, Table 3). The logit regression results indicate that the difference between our findings and those of Grinblatt and Keloharju (2001) on the disposition effect cannot be traced to methodology. Rather, we argue that by focusing on the currency trades that better capture the active component of institutional investor trading, we obtain very different results on the disposition effect. The institutional investors in our sample appear sophisticated enough to avoid one of the most common trading pitfalls facing individual investors—the disposition effect. In contrast, the local Finnish institutional investors, whom Grinblatt and Keloharju (2001) base their disposition results on, do not appear to be as sophisticated.

H. Dynamic Loss Aversion and Overconfidence

While our results cannot be traced to the explanations we have so far considered, they are consistent with the theories of dynamic loss aversion[16] (Barberis, Huang, and Santos (2001)) and overconfidence (Barber and Odean (2001)).

Barberis, Huang, and Santos (2001) show that if i) investors receive utility from changes in the value of their financial wealth and not just from consumption; ii) investors are loss averse (i.e., they are more sensitive to losses in financial wealth than to gains); and iii) they become more loss averse if their previous investment results have been poor, then investors can exhibit the kind of performance dependence uncovered in this paper. These investors take on more risk following gains because the prior gains cushion the effects of any future losses, and they cut back on risk following losses because after being burnt by the initial loss, they are more sensitive to additional setbacks. While Barberis, Huang, and Santos (2001) leverage on features central to the prospect theory of Kahneman and Tversky (1979), their predictions sharply differ from those of the disposition effect because they do not assume that investors integrate outcomes from sequential gambles. Their conclusions dovetail with the risk-taking behavior of Cornell students in gambling experiments (Thaler and Johnson (1990)) and of television game show participants (Gertner (1993)). In addition, their model simultaneously explains the equity premium, volatility, and predictability puzzles in finance. To our best knowledge, this is the first study that documents evidence from financial

[16]This is also commonly referred to as the "house money" effect (Thaler and Johnson (1990)).

TABLE 3

Logit Regressions on Sell versus Hold Decision and Sell versus Buy Decision

Table 3 reports, in each panel, maximum likelihood regression coefficients and *t*-statistics (in parentheses) for 10 Logit regressions, each regression corresponding to a currency. In Panels A and B, the dependent variable is based on a dummy variable that obtains the value of one when an investor sells a currency. Each sell is matched with all the currencies in the investor's portfolio that are not sold the same day. In these "hold" events, the dummy variable obtains the value of zero. All same-day trades on the same currency are netted. In Panels C and D, the dependent variable is an analogously defined dummy that takes a value of one for "sell" events and a value of zero for "buy" events. The independent variables include lags of currency returns (with positive and negative returns represented separately) and two capital loss dummies associated with small and large capital losses. Currency returns for day 0, -1, -2, -3, -4, $[-19, -5]$, $[-39, -20]$, $[-59, -40]$, $[-119, -60]$, $[-179, -120]$, and $[-239, 180]$ are included among the regressors, as in Table 1 of Grinblatt and Keloharju (2001). Only the coefficient estimates and *t*-statistics for the loss dummies are reported for brevity. ** and * indicate significance at the 1% and 5% levels, respectively.

Independent Variables	Danish Kroner	Norwegian Krone	Swedish Krona	Swiss Franc	British Pound	Australian Dollar	Japanese Yen	New Zealand Dollar	Canadian Dollar	Euro
Panel A. All Funds (dependent variable: Sell vs. Hold dummy)										
Large loss dummy	−0.015**	0.014*	0.026**	0.135**	0.039**	0.083**	0.153**	0.032**	0.046**	0.043**
(loss > median loss)	(−3.59)	(2.08)	(5.86)	(23.62)	(7.26)	(16.97)	(28.75)	(5.14)	(9.62)	(8.07)
Small loss dummy	0.013**	0.022**	0.031**	0.112**	0.056**	0.022**	0.104**	0.038**	0.031**	0.135**
(loss ≤ median loss)	(5.06)	(5.66)	(11.06)	(32.35)	(17.79)	(7.36)	(30.64)	(10.47)	(10.66)	(41.68)
Panel B. Pure Currency Fund (dependent variable: Sell vs. Hold dummy)										
Large loss dummy	−0.022*	−0.006	0.039**	0.137**	0.059**	0.006	0.206**	0.024*	0.035**	0.018
(loss > median loss)	(−2.17)	(−0.53)	(3.95)	(13.06)	(5.43)	(0.57)	(20.79)	(2.00)	(3.54)	(1.87)
Small loss dummy	0.005	0.004	0.027**	0.045**	0.048**	−0.011	0.084**	0.016*	0.016**	0.104**
(loss ≤ median loss)	(0.80)	(0.70)	(4.34)	(6.67)	(7.63)	(−1.72)	(13.45)	(2.28)	(2.64)	(17.44)
Panel C. All Funds (dependent variable: Sell vs. Buy dummy)										
Large loss dummy	−0.077*	0.032	0.297**	0.100**	0.268**	0.184**	0.175**	0.325**	0.165**	0.043**
(loss > median loss)	(−2.42)	(0.45)	(16.59)	(8.02)	(38.02)	(16.88)	(25.70)	(10.91)	(13.98)	(8.83)
Small loss dummy	0.133**	0.192**	0.231**	0.110**	0.251**	0.207**	0.141**	0.310**	0.287**	0.196**
(loss ≤ median loss)	(7.34)	(3.07)	(20.24)	(14.52)	(59.93)	(28.58)	(33.63)	(18.30)	(36.55)	(70.02)
Panel D. Pure Currency Fund (dependent variable: Sell vs. Buy dummy)										
Large loss dummy	−0.147	0.157	0.320**	0.083**	0.335**	0.169**	0.207**	0.247**	0.040	0.076**
(loss > median loss)	(−1.55)	(1.69)	(12.03)	(4.86)	(29.01)	(9.71)	(19.13)	(6.28)	(1.85)	(8.28)
Small loss dummy	0.073	0.264**	0.212**	0.091**	0.264**	0.205**	0.146**	0.259**	0.137**	0.181**
(loss ≤ median loss)	(1.17)	(3.56)	(12.77)	(8.70)	(38.35)	(18.45)	(22.28)	(11.87)	(8.10)	(33.79)

markets consistent with the Barberis, Huang, and Santos (2001) model of dynamic loss aversion.

We argue that institutional fund managers are prone to dynamic loss aversion precisely because a large part of their self-esteem and industry standing is tied to their portfolios' past performance. According to Barberis, Huang, and Santos (2001), investors are loss averse because they may interpret a loss as a sign that they are second rate investors, dealing their ego a painful blow, and they may feel humiliated in front of friends when the word leaks out. Institutional investors are more likely than retail investors to care about whether they are viewed as "second rate investors." Just as we expect a defense attorney to be fairly adept at cross-examining witnesses and building cases, we also expect a fund manager to be fairly skilled at investing. It is therefore more humiliating for a fund manager to be labeled "a second rate investor" than for a retail investor (e.g., a lawyer) to be labeled as such. Further, unlike professional investors who trade for their own accounts (e.g., CBOT traders), institutional investors manage "other people's money," so their shortcomings are more apparent than is true for private investors. Institutional investors' past performance records are often publicly available, either through fund prospectuses or data vendors. Hence, it is more likely that the "word leaks out" to friends and acquaintances in the industry when institutional managers perform badly. Consequently, institutional managers are more likely than individual investors to derive utility from past performance and to be loss averse.

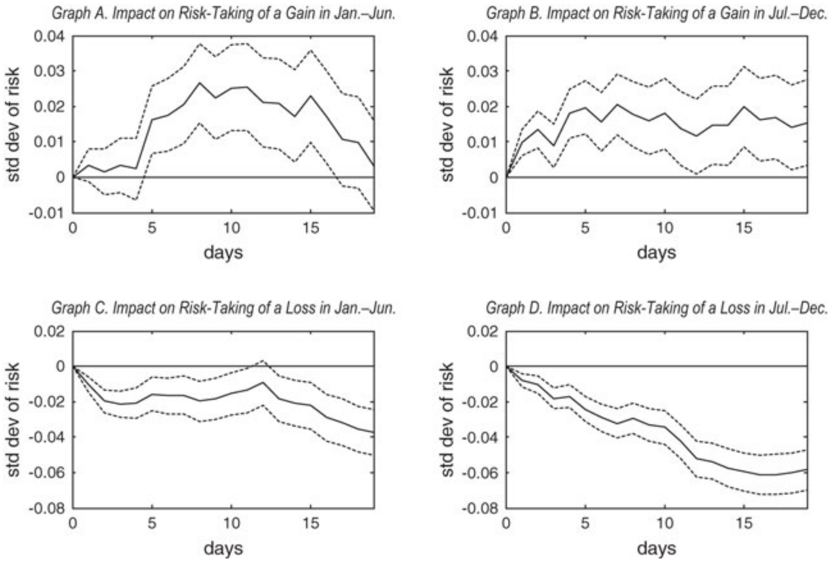
If the results are driven by dynamic loss aversion, then we would also expect that losses matter more at the end of the calendar year, since fund performance is typically evaluated at annual horizons. For example, a mutual fund is often evaluated on the spread between the fund's annual return (measured over the calendar year) and the return on its benchmark. Losses near the end of the calendar year translate more swiftly to embarrassment for a fund manager. To gauge the sensitivity of the performance dependence to calendar time, we stratify the results by calendar time. That is, we plot separate impulse response functions for each half of the calendar year. The impulse response functions evaluate the risk-taking response to a gain and to a loss. The results from this exercise are displayed in Figure 7 and indicate that while the effects of gains do not differ substantially between calendar halves, the effects of prior losses are much stronger in the second half than in the first half of the calendar year. Gains in both halves elicit mild increases in risk, while only losses in the second half induce strong and statistically significant reductions in risk. These results are consistent with the view that the institutional risk reaction to prior losses is driven by dynamic loss aversion.

The risk reaction to gains is also consistent with an overconfidence explanation (Barber and Odean (2001), Glaser and Weber (2007)). If institutional managers are overconfident, prior gains may cause them to misattribute their success to their own abilities and to take on more risk as a result. To further test the overconfidence story, we gauge the sensitivity of the performance dependence to fund age and trading experience. According to Barber and Odean (2000) and Dhar and Zhu (2006), older and more experienced retail investors are less overconfident than their younger and less seasoned counterparts. Hence, if the risk reaction to gains is driven by overconfidence, then we should find that it attenuates with

FIGURE 7

Fund Panel Impulse Response Functions for the First and Second Half of the Calendar Year

The sample period is from January 1995 to December 2002. The sample is split into the first half of the year (H1) and the second half of the year (H2). To generate the Cholesky orthogonalized impulse response functions, risk is regressed on daily lags of risk, daily lags of P&L conditional on gains, and daily lags of P&L conditional on losses for each fund, for each subsample. The regression allows for heteroskedasticity across funds and uses the same lag structure as the VARs in Figure 3. The vertical axes are scaled in standard deviation units of risk. The dotted lines sketched around each function are 90% confidence interval bounds based on maximum likelihood standard errors.



age and trading experience. To check this, we divide the sample into a formation period (January 1995 to December 1999) and an evaluation period (January 2000 to December 2002). We define fund age as the number of days since the first trading day in the formation period, and define trading experience as the number of trading days in the formation period. Then, we employ a simple two-step procedure. First, the sensitivity of each fund to lagged P&L is measured across the evaluation period via equations (1) and (2) with weekly lags. We use the weekly version of the regressions, as the positive relationship between P&L and risk (see Figure 3) extends beyond the first daily lag. Second, the cross-section of coefficients for the first weekly lag of P&L is regressed on fund age and trading experience. Only funds that are live at some point in the formation period and that have at least two years of holdings data in the evaluation period are included in the analysis. This gives us a sample of 178 funds, of which 63 are pure currency funds.

Table 4 reports the sensitivity of the coefficients on the first lag of PNL, the first lag of POSPNL, and the first lag of NEGPNL to fund age and trading experience. Fund age and trading experience[17] exert mitigating effects on the net profit coefficient at the first lag. These effects are statistically significant at the

[17] Of course, young and inexperienced funds do not necessarily employ young and inexperienced managers. Privacy issues with the State Street Bank custody dataset prevent us from conditioning

5% level for the full sample and statistically significant at the 10% level for the currency funds sample. We find that, for both the full sample and pure currency funds sample, these mitigating effects are driven mainly by the risk reaction to gains. Young and inexperienced funds increase risk more after a gain than old and seasoned funds. Moreover, this pattern is statistically significant at the 5% level for both fund samples. Perhaps reflecting an increased tendency for the disposition effect amongst younger and less experienced funds (see Odean (1998)), the coefficient estimates on NEGPNL indicate that younger and less experienced funds also cut risk less after a loss, though this effect is not statistically significant at the 10% level. Note that while the unconditional reaction to losses dominates the unconditional reaction to gains (see Figure 5), there is no requirement that the risk reaction to losses is more sensitive to age and experience than is the risk reaction to gains. Indeed, because of the attenuation effect of age and experience on behavioral biases like overconfidence and disposition, one could argue from the results of the sensitivity analysis[18] that the risk reaction to gains is consistent with the overconfidence story expounded by Barber and Odean (2001) and Gervais and Odean (2001), while the risk reaction to losses is inconsistent with the disposition effect.

TABLE 4

Sensitivity of Performance Dependence to Fund Age and Trading Experience

Table 4 illustrates the sensitivity of performance dependence to fund age and trading experience. The sample is from January 1995 to December 2002. The sample is split into an evaluation period (January 2000 to December 2002) and a formation period (January 1995 to December 1999). Fund age is proxied by the length of time since the first day of trading in the formation period. Fund experience is proxied by the number of trading days in the formation period. To test sensitivity to these variables, we use a simple two-step procedure. In step one, the sensitivity of each fund to the first weekly lagged P&L (PNL), lagged P&L conditional on a gain (POSPNL), or lagged P&L conditional on a loss (NEGPNL) is measured separately over the evaluation period. In step two, the cross-section of coefficients is regressed separately on standardized fund age and trading experience. Only funds that are live at some point in the formation period and that have at least two years of holdings data in the evaluation period are included in the analysis. This gives us 178 funds, of which 63 are pure currency funds. The *t*-statistics are in parentheses. ** and * indicate significance at the 1% and 5% levels, respectively.

	Dependent Variable: Coefficient on		
Independent Variable	PNL($t-1$)	POSPNL($t-1$)	NEGPNL($t-1$)
Panel A. Full Sample			
Fund age	−5.71*	−12.46**	4.94
	(−2.53)	(−3.09)	(1.46)
Fund experience	−5.67*	−12.30**	5.02
	(−2.52)	(−3.05)	(1.48)
Panel B. Pure Currency Fund Sample			
Fund age	−7.29	−17.32*	7.17
	(−1.93)	(−2.36)	(1.07)
Fund experience	−6.68	−16.13*	7.83
	(−1.76)	(−2.18)	(1.18)

directly on the age and experience of the manager. Since our use of fund age and experience is likely to introduce noise to the analysis, it is remarkable that we still obtain significant results.

[18]One concern is that our approach is not robust to the errors in variables problem. This is because the P&L betas used in the cross-sectional regression are themselves estimated. To allay such concerns, we also estimate the equation (2) regression augmented with the interaction of fund age and trading experience with P&L. Our inferences do not change with this alternative specification.

V. Implications for Prices

The performance dependence results become more interesting if they have implications for future prices. In Section V we explore the effects of prior institutional gains and losses on currency prices. The results in Section III indicate that, conditional on an initial long position, institutional investors will be eager to buy following gains and eager to sell following losses. The effects are reversed conditional on an initial short position. If institutions take liquidity when they trade, then the P&L on long positions minus the P&L on short positions may positively forecast returns. Since the effects of gains on risk-taking are weaker than those of losses, then P&L on long positions minus P&L on short positions should more positively forecast returns when conditioning on losses than when conditioning on gains. Moreover, any changes in returns should subsequently reverse themselves, as they are not driven by changes in fundamentals. To test this, we estimate the following regression:

$$\text{RET}_{k,t} = a + \sum_{\text{LAG}=1}^{L} b_{\text{LAG}}\text{RET}_{k,t-\text{LAG}} + \sum_{\text{LAG}=1}^{L} c_{\text{LAG}}\text{PPNL}_{k,t-\text{LAG}} + \sum_{\text{LAG}=1}^{L} d_{\text{LAG}}\text{NPNL}_{k,t-\text{LAG}} + \varepsilon_{k,t}, \tag{6}$$

where $\text{RET}_{k,t}$ is daily currency return for currency k at day t, $\text{PPNL}_{k,t}$ is the difference between the sum of daily P&L on long positions and the sum of daily P&L on short positions, conditional on gains, and $\text{NPNL}_{k,t}$ is the analogous difference, conditional on losses. Both $\text{PPNL}_{k,t}$ and $\text{NPNL}_{k,t}$ are scaled by the past 60-day moving average of dollar trading volume on currency k so as to better assess the impact on currency returns.[19] The underlying intuition is that for currencies with higher trading volume, a greater dollar increase in risk-taking is needed to generate the same impact on returns. Note that conditional on all positions being long positions, PPNL and NPNL are just the POSPNL and NEGPNL variables defined in Section III.B, respectively, but scaled by trading volume. As in the previous analysis, we present results from maximum likelihood regressions allowing for groupwise (grouped by currency) heteroskedasticity. Since our a priori intuition suggests that the return implications of risk-taking are likely to be ephemeral in nature, we focus on regressions with the maximum daily lag L set at one day and at five days. For completeness, we also perform univariate regressions with daily return as the dependent variable and with the first daily lags of PPNL and NPNL as independent variables.

The coefficient estimates on the PPNL and NPNL variables are reported in Table 5 for both the full sample of funds and the pure currency funds sample. The univariate regression estimates indicate that consistent with our intuition, both PPNL and NPNL positively forecast the next day's currency return. Moreover, the

[19]We thank the referee for this excellent suggestion. We also try scaling P&L with the past 240-day moving average of trading volume and obtain qualitatively similar results.

return implications of NPNL are stronger than those of PPNL. Perhaps unsurprisingly, when we include controls for past returns in the regressions, the coefficient estimate on the first lag of PPNL often loses its statistical significance, while that on the first lag of NPNL maintains its statistical significance. For the full sample, the coefficient estimates from the equation (6) regression with a maximum lag of one day indicate that a unitary increase in PPNL induces a 10.1 bp increase in currency return the next day, while an increase in NPNL by the same amount induces a 13.3 bp increase in currency return the next day. Both these effects are statistically significant at the 5% level. Since the standard deviation in daily currency returns is 59.4 bps while that for NPNL is 0.159, a one-standard-deviation increase in losses[20] (scaled by trading volume) precipitates a 3.6% standard deviation or 2.1 bp decrease in currency return the next day as institutions reduce risk-taking in the wake of those losses. In addition, the negative coefficient estimates on PPNL and NPNL in the regressions with a maximum lag of five days suggest that these performance dependence effects start to dissipate within a week,[21] consistent with them not being driven by changes in fundamentals. It is also noteworthy that the effects of performance dependence on prices are even stronger with the pure currency funds sample. In addition, we note that while the past performance and risk-taking relationship appears to extend beyond a few weeks, the past performance and price relationship is much more transient (extending not more than a week). One possible reason for this dissonance is that the market anticipates and quickly prices in the actions of institutional investors even though flows take time to materialize. For example, if the market experiences a surge in demand for a currency, it may anticipate further demand for that currency going forward. This may occur whether or not the market is aware of the impetus for the additional demand, which in our case arises from changes in risk-taking amongst institutions. Indeed such a phenomenon has been documented by Froot, O'Connell, and Seasholes (2001), who show that international equity prices are bid up in anticipation of future international equity flows. When those flows fail to materialize, returns fall.

To gauge the economic significance of the impact of past institutional P&L on currency prices, we evaluate the returns from simple long- and short-trading strategies based on PPNL and NPNL. Every day, we sort our set of 10 currencies by yesterday's PPNL or NPNL. Then, we buy the top N currencies and short the bottom N currencies where $N \in \{1, 2, 3\}$. Our set of long/short strategies are reminiscent of those investigated by Okunev and White (2003) and Neely, Weller, and Dittmar (1997). For each strategy, we report the annualized return, the associated t-statistic, the information ratio, and the percentage of days where return is greater than zero. To adjust for risk, we take as a benchmark the equally-weighted average return of the 10 currencies (following Okunev and White (2003)) and evaluate the alphas of the strategies relative to that benchmark. As with the previous analysis, we present results for the full sample of funds and for the pure

[20] An increase in losses implies a decrease in NPNL and vice versa.

[21] In results not reported, we replicate the analysis in Table 5 with weekly variables and confirm that the price impact dissipates within a week. None of the weekly PPNL and NPNL lags reliably predict weekly currency returns.

TABLE 5

Regressions on Daily Currency Returns

Table 5 reports maximum likelihood coefficient estimates and *t*-statistics (in parentheses) for regressions on daily currency percentage return for the currency panel from January 1995 to December 2002. The independent variables are *L* lags of PPNL, NPNL, and currency return. PPNL is aggregated currency P&L conditioned on gains and scaled by past-60-day moving average of currency volume. NPNL is aggregated currency P&L conditioned on losses and scaled by past-60-day moving average of currency volume. Aggregated P&L is the difference between the sum of P&L across all long positions and the sum of P&L across all short positions in the currency. The standard errors allow for groupwise (grouped by currency) heteroskedasticity. ** and * indicate significance at the 1% and 5% levels, respectively.

			Full Sample of Funds with Currency Return Lags								Pure Currency Funds Sample with Currency Return Lags					
	Univariate		max lag $L = 1$			max lag $L = 5$			Univariate		max lag $L = 1$			max lag $L = 5$		
PPNL($t-1$)	0.086**		0.068		0.101*	0.065		0.080	0.290**		0.202		0.219	0.198		0.071
	(3.19)		(1.72)		(2.50)	(1.49)		(1.73)	(3.01)		(1.62)		(1.76)	(1.45)		(0.48)
PPNL($t-2$)						−0.018		0.021						−0.186		−0.085
						(−0.41)		(0.44)						(−1.37)		(−0.57)
PPNL($t-3$)						0.039		0.078						−0.037		0.159
						(0.88)		(1.68)						(−0.27)		(1.06)
PPNL($t-4$)						−0.040		0.005						−0.046		0.042
						(−0.92)		(0.12)						(−0.34)		(0.28)
PPNL($t-5$)						0.028		0.041						0.273*		0.397**
						(0.63)		(0.89)						(1.99)		(2.66)
NPNL($t-1$)		0.102**		0.108**	0.133**		0.138**	0.164**		0.462**		0.501**	0.509**		0.587**	0.671**
		(3.92)		(2.78)	(3.32)		(3.18)	(3.60)		(4.81)		(3.97)	(4.02)		(4.24)	(4.44)
NPNL($t-2$)							−0.007	0.031							−0.059	0.083
							(−0.16)	(0.69)							(−0.43)	(0.54)
NPNL($t-3$)							−0.062	−0.033							−0.239	−0.188
							(−1.43)	(−0.73)							(−1.72)	(−1.23)
NPNL($t-4$)							−0.126**	−0.085							−0.038	0.073
							(−2.91)	(−1.85)							(−0.27)	(0.48)
NPNL($t-5$)							0.102*	0.134**							0.047	0.014
							(2.35)	(2.93)							(0.33)	(0.09)
R^2	0.0004	0.0006	0.0004	0.0006	0.0008	0.0010	0.0019	0.0023	0.0005	0.0009	0.0005	0.0010	0.0012	0.0015	0.0017	0.0026

currency funds sample. We also report separate results for the first half and second half of the sample period to evaluate the performance of the strategies over time.

The performance attributes reported in Table 6 reveal that simple P&L-based strategies can achieve annualized returns of greater than 7% over the sample period. Further, such returns are statistically significant at the 1% level for all strategies with $N > 1$. Equally impressive are the information ratios that come close to, or exceed, one. Again, this is especially true for strategies where $N > 1$. Consistent with the stronger risk reaction to losses documented in Section III, the returns from strategies based on losses are higher than those from strategies based on gains. For instance, the NPNL-based strategy over the full sample with $N = 1$ achieves a return of 10.73% per year (t-statistic = 2.59), while the analogous PPNL-based strategy achieves a return of 7.39% per year (t-statistic = 1.82). Risk does not appear to explain the high returns. The estimated alphas from the one-factor model are all very similar to the annualized returns, suggesting that the betas with the equally-weighted currency return benchmark are low in magnitude. Turning to the performance of the portfolios over the sample period, we find that the strategies perform better in the second half of the sample period than in the first half. All 12 of the long/short strategies generate statistically significant returns (at the 5% level) in the second half, while only three strategies generate statistically significant performance (at the 5% level) in the first half. One view is that the State Street data better capture institutional investor trades in the second half of the sample period. Another view is that the influence of institutional investors as a group in foreign exchange markets has grown.

One caveat, however, is that the strategies typically require very high turnover, since the portfolios are rebalanced daily. Consequently, the returns reported in Table 6 may not survive adjustments for transactions costs. For example, the annual turnover for the NPNL-based strategy over the full sample with $N = 3$ is 146.75.[22] That is, the long/short portfolio is turned over 146.75 times over the course of a year or once over the course of 1.63 days. Assuming a round-trip transactions cost of 5 bps (as in Levich and Thomas (1993) and Osler and Chang (1995)), this implies that transactions cost reduces annualized returns by 14.7%.[23] Clearly, the portfolio returns may not survive the high transactions costs associated with daily rebalancing.[24] Nonetheless, the analysis in Table 6 suggests that information on past institutional P&L may be useful for enhancing strategies in foreign exchange space. More importantly, the results indicate that past institutional P&L impacts prices in an economically significant way and complement those of Coval and Shumway (2005) and Frazzini (2006), who show that behavioral biases have implications for prices.

[22]The annual turnover figures for the other strategy portfolios are similar in magnitude. The analysis assumes that there are 240 trading days in a year.

[23]Note that the transactions costs associated with turning over the long and short portfolio once is 10 bps.

[24]To reduce turnover, we experimented with strategies based on past week PPNL and NPNL. None of these strategies generated statistically significant returns, consistent with the documented transient impact of P&L on prices (see Table 5).

TABLE 6

Simple Long- and Short-Trading Strategies Based on Past P&L

Every day, the 10 currencies in the sample are sorted based on yesterday's aggregate P&L scaled by the past-60-day moving average of volume. Performance attributes from three strategies are reported. The first strategy buys the top currency and shorts the bottom currency. The second strategy buys the top two currencies and shorts the bottom two currencies. The third strategy buys the top three currencies and shorts the bottom three currencies. Alpha is measured relative to the equal-weighted return average of the 10 currencies. Aggregate P&L is the sum of P&L for all long positions minus the sum of P&L for all short positions. In Panels A and B, P&L is summed across all funds. In Panels C and D, P&L is summed across all pure currency funds. The sample period is from January 1995 to December 2002. The *t*-statistics are in parentheses. ** and * indicate significance at the 1% and 5% levels, respectively.

	Buy Top, Short Bottom Currency			Buy Top 2, Short Bottom 2 Currencies			Buy Top 3, Short Bottom 3 Currencies		
	Full Sample Period	1st Half	2nd Half	Full Sample Period	1st Half	2nd Half	Full Sample Period	1st Half	2nd Half
Panel A. Full Sample of Funds (currencies sorted on yesterday's P&L/volume conditional on a gain)									
Annualized return (%)	7.39	1.50	13.26*	9.50**	5.03	13.96**	8.96**	7.39*	10.52**
	(1.82)	(0.27)	(2.26)	(3.13)	(1.16)	(3.31)	(3.59)	(2.05)	(3.04)
Annualized alpha (%)	7.15	1.26	13.05*	9.33**	4.77	13.85**	8.87**	7.28*	10.45**
	(1.76)	(0.22)	(2.24)	(3.09)	(1.10)	(3.29)	(3.55)	(2.02)	(3.02)
Information ratio	0.62	0.13	1.09	1.06	0.55	1.59	1.22	0.98	1.46
% of days > 0	50.89	49.26	52.52	51.37	51.56	51.18	52.38	52.33	52.42
Panel B. Full Sample of Fund (currencies sorted on yesterday's P&L/volume conditional on a loss)									
Annualized return (%)	10.73**	5.82	15.63**	10.01**	9.77*	10.26*	8.94**	6.70	11.18**
	(2.59)	(0.98)	(2.72)	(3.18)	(2.14)	(2.36)	(3.46)	(1.78)	(3.17)
Annualized alpha (%)	10.81**	6.20	15.55**	10.12**	10.03*	10.27*	9.03**	6.89	11.21**
	(2.62)	(1.05)	(2.71)	(3.22)	(2.20)	(2.36)	(3.50)	(1.83)	(3.17)
Information ratio	0.88	0.47	1.31	1.08	1.03	1.13	1.18	0.85	1.52
% of days > 0	51.51	50.02	53.00	51.13	51.75	50.50	51.46	51.66	51.27
Panel C. Currency Funds Sample (currencies sorted on yesterday's P&L/volume conditional on a gain)									
Annualized return (%)	7.03	2.94	11.12*	9.94**	8.24*	11.64**	7.82**	6.03	9.61**
	(1.78)	(0.52)	(2.00)	(3.55)	(2.08)	(2.94)	(3.34)	(1.83)	(2.88)
Annualized alpha (%)	6.71	2.46	10.92*	9.76**	7.96*	11.53**	7.67**	5.83	9.50**
	(1.71)	(0.44)	(1.98)	(3.50)	(2.02)	(2.92)	(3.28)	(1.78)	(2.86)
Information ratio	0.60	0.25	0.96	1.21	1.00	1.41	1.13	0.88	1.38
% of days > 0	51.22	50.22	52.23	51.27	51.27	51.27	52.57	54.54	50.60
Panel D. Currency Funds Sample (currencies sorted on yesterday's P&L/volume conditional on a loss)									
Annualized return (%)	10.13*	7.03	13.23*	8.15**	7.05	9.24*	7.36**	4.75	9.97**
	(2.51)	(1.20)	(2.37)	(2.81)	(1.69)	(2.30)	(3.11)	(1.40)	(3.02)
Annualized alpha (%)	10.25*	7.60	13.11*	8.26**	7.31	9.27*	7.43**	4.88	10.00**
	(2.54)	(1.31)	(2.35)	(2.86)	(1.76)	(2.31)	(3.14)	(1.44)	(3.02)
Information ratio	0.85	0.58	1.14	0.96	0.81	1.10	1.06	0.67	1.45
% of days > 0	51.03	49.64	52.42	50.12	49.93	50.31	51.90	51.66	52.14

VI. Conclusion

In classical finance theory, behavioral biases neither affect risk-taking behavior nor have any implications for prices. This paper challenges that view on both counts. In contrast to the prevailing literature on individuals (retail investors and professional traders), we show that large institutions are not prone to the disposition effect. Instead, they take on more risk following gains and scale back on risk following losses. Our results are not driven by mechanical relationships, hedging activities, capital constraints, stop-loss rules, momentum trading, herding, or managerial career concerns. Instead, they are consistent with dynamic loss aversion and overconfidence. To our best knowledge, we are the first to provide market evidence supporting the dynamic loss aversion model of Barberis, Huang, and Santos (2001). Moreover, the performance dependence has economically and statistically significant implications for future prices. Because institutional investors are more eager to cut risk following losses, the losses from long versus short positions negatively forecasts the next day's currency return. Conversely, because institutional investors are more eager to increase risk following gains, the gains from long versus short positions positively forecast the next day's currency return. These price effects are not driven by fundamentals, as they start to dissipate within a week.

Appendix. Currency Transactions

To see how the various types of active and passive spot and forward transactions are represented in our data, it is worthwhile to look at some sample trades. Table A1 shows some hypothetical foreign exchange transactions of the kind that appear in our database[25] Fund A buys \$1 million of underlying Japanese government bonds (JGBs) in July 2003 and sells them in December 2003. In order to actually settle the funds for the JGB, the spot transactions shown in Panel A of Table A1 are executed. If the fund decides to passively hedge the currency exposure implicit in the JGB holding using Fund B as an overlay manager, it will result in the transactions shown in Panel B of Table A1. There, a 100% hedged position is initiated by selling the full amount of yen out to three months in the forward market. In October, the hedging position is rolled forward by just over two months using a foreign exchange swap. In December, when the JGB is sold, the hedge is lifted using a closing spot trade. Since the yen appreciated over the period, there is a currency gain on the holding of the JGB equal to \$90,956.54. The hedging trades offset most of this, since collectively they lose \$85,549.07. The example in Panel C of Table A1 is more straightforward. There, Fund C wishes to take an active position in the Mexican peso in July 2003 and does so by means of an outright forward contract. In August, the peso position is closed using a spot trade, generating a loss of \$48,271.36 due to peso depreciation.

In seeking to understand the relationship between risk-taking and past gains and losses, active currency trades are of the most relevance, since they are independently motivated. In other words, it is the kind of trades conducted by Fund C that we wish to focus on. Unfortunately, our database contains no information on whether a trade is active or passive. This means that it is not possible to distinguish between the spot trades of

[25]Note that these hypothetical trades are dated after the end of our sample. We do this to make transparent the fact that we treat the actual trades in our database with full confidentiality.

TABLE A1

Hypothetical Foreign Exchange Trade Records

Table A1 shows examples of the hypothetical trade records in our database. Fund A purchases yen in the spot market in order to buy an underlying asset (e.g., a Japanese government bond) on 7/17/2003. Fund B then hedges the currency exposure of Fund A passively using a 100% hedge ratio and a three-month forward contract. On 10/8/2003, the hedging position is swapped forward by another two months. On 12/16/2003, the fund sells the underlying, and closes the passive currency hedged. Fund C uses a forward contract to take exposure to the Mexican peso for one month.

Fund	Currency Bought	Currency Sold	Amount Bought	Amount Sold	Trade Date	Value Date	Transaction Type	FX P&L
Panel A. Spot Transactions Associated with Purchase of Underlying Asset								
Fund A	JPY	USD	117,370,000.00	1,000,000.00	15-Jul-03	17-Jul-03	Spot	90,596.54
Fund A	USD	JPY	1,090,596.54	117,370,000.00	16-Dec-03	18-Dec-03	Spot	
Panel B. Passive Hedging Transactions by Overlay Manager Associated with Fund A								
Fund B	USD	JPY	1,003,068.94	117,370,000.00	15-Jul-03	15-Oct-03	Forward	
Fund B	JPY	USD	117,370,000.00	1,072,033.69	08-Oct-03	15-Oct-03	Swap	–85,549.07
Fund B	USD	JPY	1,074,113.56	117,370,000.00	08-Oct-03	18-Dec-03		
Fund B	JPY	USD	117,370,000.00	1,090,697.89	16-Dec-03	18-Dec-03	Spot	
Panel C. Outright Exposure to Currency								
Fund C	MXN	USD	20,944,000.00	2,000,000.00	15-Jul-03	14-Aug-03	Forward	–48,271.36
Fund C	USD	MXN	1,951,728.64	20,944,000.00	12-Aug-03	14-Aug-03	Spot	

Funds A, B, and C, nor between the forward trades of Funds B and C, even though they are motivated by very different considerations. For this reason, we do not work at the trade-by-trade level, as is often done in the literature. Instead, we sum up all open positions held by a fund to yield aggregate holdings series that reflect net exposure in each currency. For example, the trades conducted by Fund B in Table A1 give rise to a net short position of 117,370,000 yen over the period from July 15, 2003 to December 16, 2003. The discounted dollar value of this short yen position, which we sign negatively and which varies from day to day with the yen/dollar forward exchange rate and the U.S. interest rate, is the aggregate holdings series we focus on. Importantly, however, the trades of Funds A and B contained in this aggregation are unlikely to bias our results in any way, as discussed in the main text.

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