8-2004

How do institutional investors trade

Paul G. J. O'CONNELL
FDO Partners

Melvyn TEO
Singapore Management University, melvynteo@smu.edu.sg
DOI: https://doi.org/10.2139/ssrn.559414

How Do Institutional Investors Trade?[†]

Paul G. J. O'Connell[‡]
FDO Partners LLC
State Street Associates LLC

Melvyn Teo[§]
Singapore Management University
FDO Partners LLC

This version: March 2004

Using a novel, and detailed custody trades dataset, this paper analyzes the trading behavior of institutions. Extant studies have examined the effects of past performance on trading by retail investors, day traders, and futures floor traders. Yet very little work has been done on institutions. We find that unlike other investors, institutions take on more risk following an increase in net profit and loss. However, the responses to a gain and loss are highly asymmetric. Institutions aggressively reduce risk in the wake of losses, but only mildly increase risk in the wake of gains. This asymmetry is more pronounced for experienced and older funds. Further, the performance dependence varies over the calendar year, and manifests itself at the security but not at the portfolio level. We relate these findings to the behavioral theories of narrow framing, dynamic loss aversion, and overconfidence.

JEL Classification Numbers: G10, G11
Keywords: Institutional investors; overconfidence; loss aversion

----

[†]Our thanks are due to State Street Corporation for help in obtaining the data. We also thank Ken Froot, Jeremy Stein, and seminar participants at State Street Associates for helpful suggestions. The views expressed here are ours, and we alone are responsible for any errors or inaccuracies. Melvyn Teo is indebted to the Wharton-SMU Research Center, Singapore Management University, for financial support.

[‡]Corresponding address: 5 Revere Street, Cambridge, MA 02138, USA. Tel. +1 (617) 234-9414. Fax: +1 (617) 864-5548. E-mail: poconnell@fdopartners.com.

[§]Corresponding author: School of Business, Singapore Management University, 469 Bukit Timah Road, S(259756), Tel. +65 6822-0735. Fax: +65 6822-0777. Singapore. E-mail: melvynteo@smu.edu.sg

How Do Institutional Investors Trade?[†]

Abstract

Using a novel, and detailed custody trades dataset, this paper analyzes the trading behavior of institutions. Extant studies have examined the effects of past performance on trading by retail investors, day traders, and futures floor traders. Yet very little work has been done on institutions. We find that unlike other investors, institutions take on more risk following an increase in net profit and loss. However, the responses to a gain and loss are highly asymmetric. Institutions aggressively reduce risk in the wake of losses, but only mildly increase risk in the wake of gains. This asymmetry is more pronounced for experienced and older funds. Further, the performance dependence varies over the calendar year, and manifests itself at the security but not at the portfolio level. We relate these findings to the behavioral theories of narrow framing, dynamic loss aversion, and overconfidence.

JEL Classification Numbers: G10, G11, G30
Keywords: Institutional investors; overconfidence; loss aversion

1. Introduction

The link between risk-taking and past performance has recently come to prominence in the finance literature, and for good reason. On the empirical front, studies have shown that retail investors (Odean, 1988; Barber and Odean, 2000), day traders (Linnainmaa, 2003), futures floor traders (Locke and Mann, 2001; 2003), market makers (Coval and Shumway, 2001), and casino gamblers (Thaler and Johnson, 1990) exhibit performance dependence. On the theoretical front, the resultant behavioral theories of overconfidence, dynamic loss aversion, narrow framing, and disposition offer powerful explanations for financial market anomalies like the equity premium (Barberis, Huang, and Santos, 2001), stock market participation (Barberis, Huang, and Thaler, 2003), momentum (Grinblatt and Han, 2002), and return predictability (Daniel, Hirshleifer, and Subrahmanyam, 2001).

With some exceptions, the bulk of empirical research has looked at the equity trading of retail investors. However, institutional investor asset holdings now dwarf directly-held individual holdings in G7 countries, especially the U.S. and the U.K. As of 1997, the ratio of institutional to direct holdings was 1.5 across G7 households (Davis, 2000).[1] Despite this, virtually no empirical work[2] has been done on this dominant investor class. It may be that institutional investors mimic individual investors in their sensitivity to past performance, but there are good reasons why this might not be the case.

It is natural to think that sophisticated institutional investors might be less susceptible to behavioral biases than retail investors or day traders. In their analysis of brokerage investors in the Israeli market, Shapira and Venezia (2001) find that those who trade professionally are less prone to disposition effects than independent investors. Dhar and Zhu (2002) show that a full one-fifth of their investors are immune to the disposition effect. Attributes that temper the behavioral biases include education, professional

[1] Institutional holdings equal 100 percent of GDP in G7 countries, and 200 percent in the U.S. and U.K. (Davis and Steil, 2001).
[2] One exception is Grinblatt and Keloharju (2000; 2001) who show using trades on Finnish stocks that foreign institutional investors tend to be momentum traders and are less susceptible to holding on to their losses than the Finnish investors. However it remains to be seen whether their findings based on Finnish stocks are representative of the institutional investor class as a whole.

occupation, and income levels. It is fair to say that institutional investors are probably more educated, better trained, and better paid than most retail investors. Further, these investors may have internalized popular investment advice on the importance of not holding on to one's losses. They may also harbor attitudes towards risk-taking different from those of commodity traders and market makers.

Alternatively, there are many non-behavioral reasons why institutions investors may exhibit performance dependence.[3] On one hand, institutions may elect to sell their winners to maintain a desired asset allocation balance, or because the fundamental values they were seeking at the time they put on the trades have been realized. On the other hand, institutions may be constrained by capital requirements. When faced with losses, they have to reduce exposures. Conversely, after a series of gains, they can afford to increase exposures. Related to this, these investors may be mechanically following risk-management driven drawdown rules that specify that exposures be cut once losses exceed a certain cutoff., perhaps with reference to value-at-risk (VaR). Also, institutions may follow momentum strategies (Jegadeesh and Titman, 1993; Grinblatt and Keloharju, 2000). If institutions are net long, a surge in prices simultaneously induces gains and motivates institutions to increase their positions to capture momentum profits. Moreover, there may be tax effects towards the end of the calendar year (Lakonishok and Smidt, 1986; Badrinath and Lewellen, 1991), though such effects are much more relevant in analyzing the behavior of underlying stakeholders such as retail investors. Lastly, managerial performance incentives may be driving the performance dependence. Many managers receive incentive fees that create option-like payoffs based on performance. These option-like payoffs can cause risk taking to fluctuate in response to past performance.

[3] We hasten to add that these explanations, with the exception of risk management concerns, can also apply to individual investors. However, Odean (1998) writes that the strong preference to dispose of winners rather than losers displayed by the retail investors in his dataset cannot be attributed to portfolio rebalancing, subsequent portfolio performance, transactions costs, or tax considerations. Barberis and Thaler (2002) concur that it is hard to account for these effects on rational grounds.

This paper builds on and extends the literature on performance dependence to institutional investors. We ask: Are institutional investor trades influenced by their past gains and losses? If so, what drives this performance dependence? Do institutions behave like retail investors vis à vis their attitudes to risk-taking? Our medium is a proprietary, custody dataset encompassing the complete currency trades of 512 large institutional funds over the period 1994-2002. While some of these funds also manage equities and fixed income securities, there are some good reasons to look in the first instance at their currency activity. First, more so than equity or fixed income trades, currency trading tends to be driven by the fund manager rather than the underlying fund stakeholder. This is especially true in the case where the currencies are being managed as part of a hedging strategy, referred to by practitioners as "currency overlay." Second, forward currency contracts are derivatives in zero net supply. This eliminates the possibility of aggregate capital gains or losses at the level of each currency, which alters the pricing implications that come from theories such as the Grinblatt and Han (2002) model. Third, the currencies traded by institutions are often owned by other institutions who wish to hedge their currency risks. Both institutional parties do not pay capital gains taxes, and only the underlying stakeholders of those other institutions do. Hence, when examining currency trades, we are unlikely to observe any tax-loss selling effects, since these currency trades are twice removed from the underlying stakeholder.[4]

Our main findings are striking. Past performance manifestly affects risk-taking, but the sign and magnitude of this effect differs substantially from what has been observed for individual investors. Unlike other investors, institutional investors do not seem susceptible to disposition effects. Rather, institutions aggressively reduce risk in the wake of losses. Profits do bring some increase in risk-taking, but this increase reverses within a calendar quarter. These results are pervasive across the major currencies, characterizing some 95% of the trading volume in our data.

[4] Strictly speaking this argument only applies to pure currency funds. Nonetheless, the currency trades of bond and equity funds are still once-removed from the underlying stakeholder.

In teasing out an explanation for these patterns, we examine both rational and behavioral stories. Clearly, the story that institutional performance dependence is driven by asset allocation concerns cannot hold as the observed reactions to gains and losses run counter to that predicted by the portfolio rebalancing story.

We find that capital constraints and risk management concerns have difficulty explaining the bulk of the performance dependence we observe. The reaction to losses occurs over a wide range of loss cutoffs. Unless, we make the drastic assumption that cutoff rules take effect more than 40% of the time when losses are incurred, maximum drawdown rules cannot be responsible for the performance dependence. Also, we find a noticeable lack of cross-currency effects. That is, only the P&L from the trades of the same currency matter to risk-taking for that currency, and not the P&L from the trades on other currencies by the same fund. This makes it difficult to forward the capital constraints explanation, which necessarily implies that performance dependence operates at the portfolio level and not only at the account level. Other results suggest that momentum trading cannot adequately account for the performance dependence. Managerial performance incentives also have problems accounting for the performance dependence. The induced convex payoff structures imply that risk-taking should increase and not decrease following losses.

While the evidence is generally not supportive of the capital constraints, stop-loss, momentum, and managerial performance incentives explanations, they fit closely with the behavioral view. In particular, the absence of cross-account effects suggests that institutional investors are narrow framers in the sense of Barberis, Huang, and Thaler (2003) and Kahneman (2003). That is they tend to make their decisions based on information that is most accessible, i.e., past own currency P&L rather than past other currency P&L. Also, the increase in risk-taking following gains is consistent with a generalized overconfidence model (Barber and Odean, 2001) where investors misattribute their past successes to their own abilities. Finally, the decrease in risk-taking following losses is reminiscent of dynamic loss aversion (Barberis, Huang, and Santos, 2001) where investors become more risk averse following losses.

We trace out further evidence supportive of the behavioral view. We find that the performance dependence varies systematically with the calendar period. The effects of gains dominate in the first half of the year while the effects of losses dominate in the second half. It is difficult to explain why cutoff rules matter more in the second half of the year or why capital constraints are binding more for gains in the first half of the year. One simple explanation is that fund managers care more about losses at the end of the year when performance evaluation looms. Moreover, we find that the effects of gains are attenuated for older and more experienced funds. Other researchers have shown that overconfidence also falls with age and experience (Barber and Odean, 2000). Taken together, these results gel with the view that the reaction to gains is driven by overconfidence. Interestingly, we do not find the same effect for losses. Experienced and older funds tend to reduce risk more than rookie or younger funds in the wake of losses. One view is that these funds are more disciplined than other funds and have internalized standard investment advice not to hold on to losses. Similarly, one reason why we do not find disposition effects in our sample is that institutional investors are simply more disciplined and better trained than say retail investors or day traders. Our take on the disposition effect dovetails with that in Dhar and Zhu (2002), Shapira and Venezia (2001), and Grinblatt and Keloharju (2000; 2001).

It is important to emphasize that the results in this paper are not explicitly about the preferences of currency traders or even fund managers per se. Rather they are about the preferences of institutions. The working assumption is that performance contracts, compensation, managerial training, and the like, are all in place to align managerial incentives with what is best for the fund. That is, the traders and managers are acting in the best interest of the funds. Our issue is not with the layer of agency that comes between the manager and the fund. Rather we wish to learn more about the preferences of the institutions through their risk-taking behavior. In this sense, we treat institutions as single entities and leave the agency issues for further research.

The remainder of the paper is organized as follows. Section 2 describes the nature and characteristics of our dataset. Section 3 presents the basic empirical results which link past gains and losses with changes in risk-taking, both unconditionally, and conditional on currency and fund type. Section 4 tests whether the results are driven by institutional investor capital constraints and risk management concerns. Section 5 investigates the possibility that momentum trading and managerial performance incentives are responsible for the observed performance dependence. A discussion of the view that behavioral biases influence their reaction to gains and losses follows in Section 6. Section 7 concludes.

2. Data

The data used in the analysis is provided by State Street Corporation, one of the world's largest investor services providers. State Street clients are primarily large institutional money managers, and the total of all funds serviced by the Corporation at the end of our sample was USD 8.4 trillion, approximately 16 percent of total global assets. Our sample covers the period December 31st, 1993—January 1st, 2003, and comprises over 8 million individual trade records undertaken by some 8,500 anonymous funds. Each record provides us with the currency pair traded, the exchange rate, and the tenor or duration of the contract.

Given the distributional assumptions needed for estimation, quality of the data series is important. Hence the analysis is restricted to the larger funds in the universe, as these tend to have more frequent, continuous trading. Moreover, only trades in the 10 major currencies are included.[5] Mindful of survivorship bias, the requirement for inclusion in our sample is that a fund be in the 95th percentile of trading volume in one or more of six regularly sampled weeks over the nine-year sample period. This criterion selected a subset of 512 funds that account for an average of 72 percent of the volume across the 10 currencies.

[5] The list of currencies is: Danish kroner, Norwegian kroner, Swedish kroner, 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.

There are a number of important fund characteristics to look at. The first is fund life. Although specific information on fund life is not available in the database, an examination of currency holdings makes it clear that most of the funds are not active in the currency markets for the entire sample. Indeed only two percent of the funds have nonzero currency holdings on every day of the sample. Of course, a fund manager may make an active decision to hold no open currency positions, so zero holdings may not imply that a fund is "dead." Recognizing this, one way to proceed is to measure the life of each fund from the first day of nonzero holdings to the last day of nonzero holdings, and then to gauge the likelihood that this is a biased estimate from the incidence of zero holdings during this estimated life. Calculated in this way, the mean fund life is about 4.5 years, while the incidence of zero exposure throughout fund life is only 12 percent, suggesting that the lifespan estimates are reasonable. A second important fund characteristic is base currency, since measured currency risk ought to exclude base-currency holdings. The breakdown by base currency is as follows: U.S. dollar, 67 percent; Australian dollar 12 percent; Canadian dollar 6 percent; euro 3 percent; Japanese yen 3 percent; British pound 3 percent; others 6 percent. Finally, as already mentioned, the underlying type of each fund is important. The database includes comprehensive information on the total holdings of each fund by asset class for the year 2001. Based on this, the funds are classified as fixed income, equity or currency for that year.[6] The resulting categorization comprises 158 fixed income funds, 71 equity funds, and 149 currency funds.

2.1 Basic series

The first step is to construct flow and holdings series for each fund across the currencies. Each day, net flows by currency, fund and tenor are measured.[7] 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 units of foreign currency per dollar. Holdings are built up by cumulating these flows, after adjusting for mark-to-market gains and losses on each day's

[6] Funds with fixed holdings in excess of equity holdings are defined as fixed income funds, and vice versa. Currency funds have no equity or fixed income positions.
[7] 99 percent of the trades value within one year of trade date, so trades with maturity greater than 265 trading days are ignored.

pre-existing positions. For a position with tenor s on date t-1, the marked-to-market gross return between date t-1 and t is f_t^{s-1} / f_{t-1}^{s}, reflecting the fact that it is one day closer to maturity. It is these mark-to-market gains and losses that provide the key profit-and-loss (P&L) series that are used to measure performance. Any currency holdings that do come to maturity—that is, reach a tenor of zero—are treated as delivered, and removed from holdings on value date. This would occur, for example, if a fund purchased and took delivery of spot local currency to facilitate the purchase of an underlying equity or fixed income security. Such transactions are common for fixed income and equity funds, so negative serial correlation at short horizons is likely to be observed in the holdings series for such funds.

With holdings in hand, it is a simple matter to calculate the second key series—a measure of risk exposure. Let $\mathbf{h}_{it}$ be the 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 Σ is the covariance matrix of annualized currency returns constructed from exponentially-weighted daily currency returns.[8] 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.

Figure 1 plots the holdings series for each of our currencies aggregated across all 512 funds, grouped into four rough regions: North America, Japan and Antipodes, Europe and Scandinavia. There is a large amount of variation in the raw holdings numbers, and so to render them comparable, they are measured in units of trading days. For example, if a fund is long $5 million against the euro, and the fund's average daily EUR/USD volume is $1m, then it is counted as having 5 trading days worth of holdings. Figure 1 illustrates that, throughout the sample, funds have tended to be long the dollar and short other currencies. However, towards the end of the sample, this tendency waned considerably.

[8] The exponential decay rate used is 0.998, implying a half-life of decay for past observations of about 350 trading days.

Holdings tell only part of story, however, a fact that becomes abundantly clear when risk is examined. Figure 2 plots the aggregate risk exposure held by the funds in each of the currencies. Notice in particular that the exposure to the Japanese yen and British pound has remained quite high in the recent period. This implies that, individually, the funds in the universe continue to maintain large exposures to these currencies. Some funds are long and some funds are short, with the positions netting out to give an aggregate holding of close to zero. In other words, there is a considerable amount of disagreement across the fund positions. This cross-sectional richness contributes to the statistical power of the data sample.

[Figure 1 and Figure 2 here]

2.2 Persistence

It is well-established that portfolio flows in underlying assets such as equities tend to be persistent (Froot, O'Connell, and Seasholes, 2001). The question arises as to whether the same is true for institutional currency flows. Figure 3 (Panel A) plots the sample autocorrelation function for daily currency risk exposures out to 20 lags, together with 95 percent confidence bands. The functions are plotted for three different levels of aggregation. The first level, "Aggregated by currency and fund," adds up the total risk of all funds across all currencies to arrive at a single time series. The second level, "Aggregated by currency," adds up the total risk across all funds in each currency separately, and shows the autocorrelation estimates for the currency panel. Analogously, the third level, "Aggregated by fund," adds up the total risk across all currencies for each fund, and shows the autocorrelation estimates for the fund panel. At the aggregate and individual currency level, there is evidence of positive serial correlation at the 1-day and 5-day frequencies. Interestingly, however, there is no such persistence at the individual fund level.[9] Individual funds are not persistent in their actions, but funds tend to mimic one another. A substantially similar picture emerges from examination of weekly risk autocorrelations. Overall, this echoes the Froot and Tjornhom (2002) finding of

[9] As mentioned earlier, the negative serial correlation evident at order two arises from the spot trades of fixed income and equity funds.

statistically significant cross-fund lags in equity flows to developed and emerging markets.

Turning to performance, Figure 3 (Panel B) plots similar sample autocorrelation functions for P&L. Here there is no evidence of serial correlation, indicating that the lead-lag effects in risk-taking do not engender persistent performance. Again, the same is true at weekly frequencies. The interesting implication is that managers do not undergo cycles in profitability—for the most part, profits are independent from one period to the next.

[Figure 3 here]

3. Basic Dynamics

In this section, the goal is to size up the degree of performance dependence that is present. We test if there is any link between risk-taking by institutional investors and lagged P&L, and seek to understand the sign of the relationship, if any. Other questions we address include: Is the performance dependence measured economically relevant? Are such effects pervasive across the commonly traded currencies? How does this performance dependence vary across various types of funds (i.e., currency, bond, and equity funds).

The tool we use to address these basic questions is an unrestricted vector autoregression (VAR). The VAR is estimated at the weekly frequency to control for potential day-of-the-week effects. Analogously to the serial correlation analysis presented above, we estimate panel VARs for risk and P&L at the aggregate, the currency, and the fund level. The model allows for heteroskedasticity across currencies and funds, and the lag length for each model is set at 13 weeks, the value selected by the Bayes-Schwartz Information Criterion for the panel fund regression.

Figure 4 shows the essential information that comes out of this exercise. The first column of plots in the figure shows the impact that a unit-standard deviation shock to P&L has on weekly risk, while the second column shows the impact that a unit-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 percent confidence intervals based on the maximum likelihood standard errors are sketched in lighter weight around each function. To calibrate, the one standard deviation P&L shocks at each level of aggregation are \$163m, \$43m, and \$3.4m, while the shocks to annualized risk are \$69m, \$23m, and \$3.2m. The own-equation effects are similar to those conveyed by Figures 3, and so are omitted.

[Figure 4 here]

Performance dependence is manifest in the data. At all levels of aggregation, past performance exerts a positive and statistically significant effect on risk-taking, and the impact persists for between six and eight weeks. For the panel fund regression, a one-standard deviation shock to P&L produces a 3 percent standard deviation change in risk-taking after four weeks. The economic impact is significant too: in dollar terms, the average shock to P&L for a fund is \$3.4m, and this produces an increase in risk which elicits a change in annualized currency risk of \$96,000 over the subsequent four weeks, or an incremental currency holding of \$960,000.[10] Importantly, the serial correlation estimates for P&L calculated earlier make clear that this result is not simply due to persistence in profits or losses.[11] Turning to the second column of plots, there is no appreciable effect in the other direction: as might have been expected, increases in risk-taking do not have a meaningful effect on profits. There is some indication that returns improve with risk-taking, though naturally risk rises in tandem with this.

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

[11] In results not reported, we confirm that the changes in risk-taking arise from active trading rather than simply the passive changes in P&L.

Having investigated the basic relationship between risk-taking and P&L, we now turn to the cross-sectional features of the data. As shown in Table I, we are interested in understanding whether the effects identified are pervasive, in the sense that they apply across currencies and fund types. Looking in more detail at the cross-section also serves as a check on our basic results. If the performance dependence observed in Figure 4 is driven by trading on a few, infrequently traded currencies, then the results thus far are not very interesting as they only apply to a select group of institutional investors.

[Table I here]

Table I shows the effect of the first eight lags of P&L on risk-taking across each currency. The basic pattern observed in the full panel is seen to characterize seven of the ten currencies, the exceptions being Denmark, Sweden, and New Zealand. Trading volume in these currencies is 1.25 percent, 2.43 percent, and 1.46 percent of total volume respectively. Thus the patterns measured earlier apply to the bulk of currency trading in our sample.

[Figure 5 here]

We also perform the same exercise for the various fund types described in Section 2. The impulse responses of risk to shocks in P&L for each fund type are depicted in Figure 5. Currency and bond funds display essentially the same sensitivity to past P&L as was documented earlier for the full group. Equity funds, by contrast, display a somewhat random response to past performance that is statistically insignificant. This accords with the folk wisdom that equity fund managers simply care less about the currency component of their returns. In all fairness, it must also be said that the statistical power of the equity sample is lower, since the number of equity funds, at 71, is about half the number of currency or bond funds in the sample.

Overall, these basic results give rise to three broad interpretations. One view is that the observed performance dependence is mechanically driven by capital constraints. That is when institutions are faced with large losses, they are forced to clamp down on risk taking as they can no longer afford to take up such large positions. Conversely, after institutions rack up an impressive string of wins, they are then able to increase their exposures given their greater asset base. A related view is that institutional investors follow stop-loss rules that require them to cut exposure in the wake of a significant loss. For example, a fund might close out a position if suffers a loss of more than 20%. Such stop-loss behavior would imply that the performance dependence we observe is driven by institutions' reaction to losses rather than gains.

Another view is that the observed performance dependence is motivated by rational concerns of institutions. For example, institutions could be following momentum strategies. When institutions are long, these strategies call for them to buy when currency prices rise and sell when currency prices fall. When institutions are short, these strategies require that they increase their short positions when currency prices fall and reduce their short positions when currency prices rise. In either case, such strategies may mechanically induce the risk and past P&L relationship we observe. This is true whether or not momentum trading of currencies is itself rational (LeBaron, 2002). Also, the observed performance dependence may be a result of the rational response of managers to their performance incentives. Many managers receive incentive fees that create option-like payoffs based on performance. These option-like payoffs can cause risk taking to fluctuate in response to past performance.

Yet, another view is that the observed performance dependence is fuelled by the behavioral biases of institutional fund managers. These behavioral biases include narrow framing, overconfidence, dynamic loss aversion, and disposition. The concept of narrow framing, expounded in Kahneman's (2003) Nobel lecture, explains why people typically reject bets like a 50:50 chance to win \$550 or lose \$500. The idea is that an agent who is offered a new gamble evaluates that gamble to some extent in isolation, separate from her other risks. Barberis, Huang, and Thaler (2003) show that narrow framing can help us understand the stock market participation and equity premium puzzles. Barber and Odean

(2001) argue that driven by overconfidence, single men trade more than single women and lose more money on their trades. Likewise, Glaser and Webber (2003) find that individuals who are more overconfident trade more than those who are less overconfident. On a different note, Barberis, Huang, and Santos (2001) show that dynamic loss aversion can explain the "house money" effect, or the increased willingness to take on more risk following gains, observed among gamblers in casinos and documented by Thaler and Johnson (1990). Other studies have found that retail investors (Odean, 1988), day traders (Linnainmaa, 2003), and futures floor traders (Locke and Mann, 2003) are reluctant to realize their losses, i.e., these investors are prone to the disposition effect. However it remains to see whether institutions are susceptible to these biases. After all, Dhar and Zhu (2002) show that while individual investors exhibit the disposition effect *on average*, fully one fifth of the investors do not. Investor characteristics that temper the disposition effect include income level, professional occupation, and trading experience. It is easy to believe that institutions are immune to these behavioral biases since they are better trained, earn more, and have more trading experience than retail investors.

In the next three sections, we seek to distinguish between these three classes of explanations and in doing so, better understand what motivates institutional investor performance dependence.

4. Do capital constraints and risk management concerns drive institutional investor behavior?

One interpretation of the results in the previous section is that institutional investors face capital constraints. These capital constraints tighten following losses and ease up following gains. Hence these investors mechanically increase risk following an increase in net P&L. Also it may be that institutional investors care a lot about downside risk and hence impose strict maximum drawdown rules which require that they drastically minimize exposures upon suffering a large enough loss. Here, the observed performance dependence is exclusively driven by their reaction to losses.

In this section, we empirically test whether the observed performance dependence is driven by capital constraints and risk management concerns. We approach the issue from several fronts.

First, on one hand, if capital constraints are biting, then the response to gains and to losses should be somewhat symmetric and permanent. A gain of $1 million will allow the fund to permanently increase its currency exposure, while a loss of $1 million will require the fund to permanently reduce its currency exposure. On the other hand, if institutional investors are driven exclusively by stop-loss rules, then their response to gains will be zero, while their response to losses will be significant. Hence it will be useful to examine the effects of gains and losses separately.

Second, if institutional investor performance dependence is driven by stop-loss rules, then it must be that losses only affect risk taking when losses (as a percentage of holdings) are large enough. Funds only cut exposures when losses exceed a certain cutoff. We would not expect small losses (as a percentage of holdings) to have any tangible effect on risk taking. To this end, we re-examine the relationship between risk taking and P&L after conditioning for the level of losses as a percentage of holdings.

Third, any capital constraint or maximum drawdown rule manifests at the fund level. A large loss on the yen forces a fund to cut its exposures on not just the yen, but on its other currencies as well. For the performance dependence to be triggered by capital constraints or cutoff rules, it must be that cross-currency effects are present. To check this, for each currency, we see how funds' risking taking on that currency is affected by the P&L from their other currency trades.

To address the first issue, we distinguish between the dynamic effects of gains and losses. Figure 6 plots separate impulse response functions for gains and losses, estimated from the fund-by-fund data panel.[12] There is in fact a striking difference in the two response functions. Gains produce transitory increases in risk taking that taper off after about six weeks. Beyond that there is evidence of "take-profit" activity as the impulse response function turns statistically negative. By contrast, the effects of losses are both stronger and more permanent. Note that the impulse response function sketched in the lower left-hand corner of Figure 4 is simply an average of these two functions. The implication is that the relatively short-lived average effect illustrated there masks separate effects of gains that appear to be less durable and losses that appear to be more durable.

[Figure 6 here]

The pronounced asymmetry between the effects of a gain and those of a loss, and the transient reaction to gains, suggest that it is unlikely that capital constraints are exclusively responsible for the performance dependence. However, it may be that funds do not always, but nonetheless have the option to (given the relaxation of capital constraints), increase their exposures following gains. This would explain the smaller effects of gains on risk-taking but leaves unanswered why the effects of gains are much less durable than those of losses. Also, since gains do precipitate an increase in risk taking, maximum drawdown or cutoff rules cannot be responsible for all of the observed performance dependence. As discussed earlier, such rules only take effect in the event of large losses.

A natural question to ask at this stage is: How large do losses have to be in order for institutional investors to react to them? The view that institutions react to P&L via maximum drawdown or cutoff rules necessarily implies that this reaction is driven by only the most extreme data points. To test this, we evaluate the effects of a small loss and a large loss on risk taking. A small loss is defined as the loss when net return or (change in P&L / initial holdings) is less than zero but greater than a predetermined (and negative) bound. A large loss is defined as the loss when net return or (change in P&L / initial holdings) is less than a predetermined cutoff. We consider cutoffs of -0.001, -0.0015, -

[12] The results from the other levels of aggregation are similar.

0.002, -0.0025, -0.004, -0.005, and -0.02 which correspond roughly to the 50th, 40th, 30th, 20th, 10th, 5th, and 1st percentiles for negative values of weekly change in P&L / holdings respectively. If the observed reaction to losses is driven by institutional investors following cutoff rules, then it should be that there exists a reasonably large and negative cutoff on returns such that investors do not react to losses smaller in magnitude than this cutoff. In fact this is not what we find.

[Table II here]

Table II presents the results. Over the entire range of cutoffs, investors cut risk whenever they experience a small loss. The reaction of risk to small losses is statistically significant for all cutoffs equal to or below the 40th percentile. Unless we make the drastic assumption that cutoff rules are implemented 40 percent of the time whenever there is a loss, the view that institutional performance dependence is driven by cutoff rules cannot hold. Indeed, the reaction of risk to large losses below the 5th percentile is negative at the first lag and insignificantly positive thereafter. Also the reaction to small losses is stronger than the reaction to large losses for the extreme cutoffs of -0.005 and -0.02, corresponding to a 5th and 1st percentile net return respectively. Hence, we find that the risk taking reaction to losses is robust over a wide range of losses, and cannot be explained by simple cutoff trading rules.[13]

We next test for the presence of cross-currency effects. This will allow us to see if the reaction to gains and losses takes place at the portfolio level or at the account level. If capital constraints are binding then a large loss on the yen account will force a fund to scale back exposures on its other accounts as well. To check this, for each fund and each

[13] One concern is the horizon of the regression variables may be too long to adequately capture stop loss behavior. For example, suppose a fund enters into a EUR/USD transaction, and in the short-term earns a profit of 10% on the trade. If the fund uses relative stop loss rules, then the fund may initiate stop loss activities once profit goes back down to -1% (since this represents a loss of 10% on the most recent high). We will not capture this effect unless the horizon is short enough. Another problem is that we may not be capturing the stop loss reaction to very bad trades if we aggregate over too long a horizon. To mitigate these concerns, we re-do the analysis using daily variables instead of weekly variables. We find that the results are qualitatively very similar. Unless we make the drastic assumption that stop loss rules are triggered more than 50% of the time when a loss occurs, risk management concerns cannot explain the effects of daily losses on daily changes in risk.

currency, we define conjugate P&L as the P&L on the other currencies traded by a fund. Then, for each currency, we estimate the vector autoregression with risk, P&L, and conjugate P&L as state variables. The coefficient estimates on the conjugate P&L lags presented in Table III suggest that cross-currency effects do not drive the performance dependence.

[Table III here]

Note that the coefficients are naturally much smaller than the own P&L coefficients shown in Table I, since conjugate P&L is a much larger quantity on average than own currency P&L. No clear pattern emerges from the conjugate coefficients in Table III. If we focus on the major currencies, there is some mild evidence from the point estimates that portfolio profits increase risk-taking in the British pound, the Australian dollar and Japanese yen, but this doesn't appear to be statistically significant. Only for the euro do we find significant evidence of an effect. Yet, this appears to be a negative one. These results suggest that performance dependence manifests at the account and not at the portfolio level. This, in turn, casts serious doubt on the view that the risk and P&L relationship we observe is driven by capital constraints.

Overall the findings of the section have shed further light on what drives the institutional investor reaction to P&L. We find that the reactions to gains and losses are highly asymmetric. We document a small and transient reaction to gains, and a large and durable reaction to losses. Also, the relationship between risk taking and past losses holds over a wide range of loss cutoffs suggesting that maximum drawdown rules are not responsible for the bulk of the reaction to losses. Further, this relationship manifests at the account and not at the portfolio level. Cross currency effects are noticeably absent. This casts doubt on capital constraints as a viable explanation for the performance dependence.

5. Do momentum strategies and managerial performance incentives explain institutional investor behavior?

There are two other important non-behavioral reasons why we may observe the performance dependence documented in Section 3. First, institutions may engage in momentum trading. In their study of the Finnish market, Grinblatt and Keloharju (2000) find that sophisticated foreign investors tend to be momentum traders while domestic investors tend to be contrarians. What of the institutional investors in our sample? Second, managerial performance incentives may be driving the performance dependence. Many managers receive incentive fees that create option-like payoffs based on performance. These option-like payoffs can cause risk taking to fluctuate in response to past performance.

In this section, we investigate the possibility that the performance dependence is driven by these explanations. The results from the previous section suggest that the momentum story has difficulty explaining the observed performance dependence. One problem is that it does not explain why losses have much greater effects than gains. For the results in Figure 6 to square with a momentum trading story, it must be that institutions believe that momentum is stronger when they are facing losses than when they are facing gains. To further test the view that the performance dependence is driven by momentum trading, we include lags of past currency returns signed by holdings in our baseline currency-by-currency vector autoregressions (Table I). The statistical significances of the P&L lags in the regressions are robust to this adjustment. Hence momentum trading does not drive the observed risk reaction to losses and gains.

The view that managerial performance incentives (which are most likely a function of overall fund performance, unless we assume that within the same fund, there is a manager for the euro account and another manager for the yen account, etc) drive the observed performance dependence implies that such dependence should surface at the portfolio level and not just at the account level. The conjugate currency results (Table III) discussed in the previous section suggest that this is not true. Further, managerial incentives, like bonuses, create *convexity* in payoffs which would tend to give rise to increased risk-taking in the wake of losses. A manager who is down during her performance period is effectively holding an out-of-the-money call option, and so may seek to increase risk in the knowledge that, in a bad outcome, she is no worse off (unless she gets fired) whereas in a good outcome, her option may pay out. This argument holds even if the manager is not an employee, but co-owns or owns the fund. This is because her compensation is likely to be a function of the net inflows into the fund, and many authors have shown that fund flows go overwhelmingly into the best return funds (Guercio and Tkac, 2001; Gruber, 1996) but are slow to leave poorly performing funds, creating again convex payoff structures. Increased risk taking following losses is clearly *not* what we find. Hence, it does not appear that the performance incentives, which may be motivated in turn by the flow / performance relationship for mutual funds or by managerial bonuses, drive our results.

6. Do behavioral biases influence institutional investor behavior?

The results from the previous sections, while inconsistent with the view that institutional investor performance dependence is motivated by capital constraints, risk management concerns, momentum strategies, or managerial incentives, are consistent with several behavioral explanations. First, the reaction to gains and losses (Figure 6) is consistent with dynamic loss aversion where investor risk aversion increases following losses and falls following gains (Barberis, Huang, and Santos, 2001). Second, the increase in risk-taking following gains (Figure 6, top panel) is also consistent with overconfidence among institutional investors. That is they misattribute their recent success to their own abilities and take on greater risk. Third, the conjugate currency results (Table III) are consistent with the concept of narrow framing discussed in Barberis, Huang, and Thaler (2003) and Barberis and Huang (2002), and expounded in Kahneman's (2003) Nobel lecture, where an agent who is offered a new gamble evaluates that gamble to some extent in isolation, separate from her other risks. Our conjugate currency results suggest that institutions frame currency decisions at the account or currency level and not at the portfolio or fund level. For risk taking, past own currency P&L matter but not the past P&L on the firm's other currency accounts. Our results are however not suggestive of the disposition effect as that implies that agents hold on to their losing trades and thereby increase risk after encountering paper losses. The risk and past P&L relationship in the presence of disposition effects should therefore be negative instead of positive as in Figure 4.

In this section, we provide further evidence to pin down and flesh out the behavioral explanations for the observed performance dependence. First, assuming that performance evaluations (i.e., performance reviews and the determination of bonuses) occur at the end of the year, then it is likely that managers become more sensitive to losses and the accumulation of losses in the later half of the year. Hence overconfidence effects (if any) should diminish while dynamic loss aversion effects (if any) should grow over the calendar year.

Figure 7 suggests that this happens. It measures the impulse response functions shown in Figure 6 separately for each half of the calendar year. It is clear that managers are conditionally more risk-tolerant in the first half of the year. Gains in the first half of the year lead to incremental risk-taking, but there is no such evidence in the second half of the year. Correspondingly, losses in the first half produce very little reduction in risk. It is only in the second half of the year that managers systematically cut risk following losses.

[Figure 7 here]

The clear message is that performance dependence varies in a systematic way over the calendar period. This is hard to reconcile with a capital constraints or a maximum drawdown story. It is difficult to understand why capital constraints would produce such a pattern in risk-taking. For this to happen, it must be that in the first half of the year capital constraints are binding more often when there is a gain, and in the second half of the year they are binding more often when there is a loss. It is also difficult to understand why cutoff rules should matter more in the later part of the year. The behavioral stories explain the results in Figure 7 nicely. In the first half the year managers simply care less about losses and the accumulation of losses. Hence overconfidence effects reign. In the second half, when performance evaluation looms, managers become extra sensitive to losses and become even more sensitive to strings of losses. Thus the overconfidence effects make way for dynamic loss aversion effects.

It is true, however, that this calendar effect is consistent with the notion that fund managers are responding rationally to performance-based incentives. If performance is assessed over the calendar year, then as the year draws to a close, the delta of a the incentive option rises towards unity for a manager who is up on the year, and falls towards zero for a manager who is down on the year. This diminishes the reward to risk-taking. However, as discussed in Section 5, such convex payoff structures cannot explain the overall risk reaction to losses, and the conjugate currency results. It appears, then, that although performance incentives are relevant, they are far from the whole story.

Second, according to Barber and Odean (2000) and Dhar and Zhu (2002), older and more experienced retail investors are less overconfident than younger and less experienced retail investors. Locke and Mann (2001) use this fact to empirically discriminate between overconfidence and dynamic loss aversion. We look for a similar pattern among institutional investors. To this end, the sample is split into a formation period - December 31, 1993 to December 31, 1999 - and an evaluation period - January 1, 2000 to January 1, 2003. A fund's age is proxied by the fund's first trade date during the formation period, and fund experience is gauged by the numbers of days during the formation period that the fund actually traded. Then we use a simple two-step procedure. In step one, the sensitivity of each fund to lagged P&L is measured across the evaluation period. Then in step two, the cross-section of coefficients is regressed on fund age and fund experience.

[Table IV here]

Table IV reports the results for the first lag of the regression coefficient on total profits, total gains, and total losses. Both age and experience exert a statistically significant mitigating effect on the total profit coefficient at the first lag. This suggests that the performance dependence we have observed is sensitive to learning, as in the confidence model of Gervais and Odean (2001). More interesting, though, is the fact that, once again, the effect is asymmetric for gains and losses. Age and experience tend not only to decrease the magnitude of the coefficient on lagged gains, but also to increase the magnitude of the coefficient on lagged losses. So the older, wiser funds eschew added risk in the wake of gains, but cut risk more aggressively in the wake of losses.

While the results from this exercise suggest that overconfidence effects are manifest in institutional investors' reaction to gains, they also suggest that older and more experienced funds are more affected by dynamic loss aversion than younger and less experienced funds. This makes intuitive sense given that texts giving investment advice often warn investors against holding on to their losses. Anecdotal evidence suggests that finance practitioners take such "disciplined" trading advice seriously. Experienced and older managers are more likely to have internalized such advice than less experienced and younger managers.

Needless to say, young and inexperienced funds do not necessarily employ young and inexperienced managers. The example of a senior fund manager, with a wealth of trading experience, who starts a new currency fund, comes to mind. Privacy issues with the custody dataset prevent us from conditioning directly on the age and experience of the manager. Our use of fund age and experience is likely to introduce noise into the cross-sectional analysis. Nonetheless, it is remarkable that we still obtain such strong results with the noisy estimate of age and experience.

It is important to square the results with the extant literature on the disposition effect. Odean (1988), Linnainmaa (2003), and Locke and Mann (2003) find that retail investors, day traders, and futures floor traders are susceptible to disposition effects. They tend to hold on to their losers for too long and sell their winners too quickly. Why is it that the institutional investors in our sample do not seem prone to such behavior?

One interpretation is that the disposition effects operate at very short horizons (i.e., daily) as opposed to the weekly or monthly horizons. To check this, we re-estimate the vector autoregression in Figure 6 for daily changes in risk and daily changes in P&L. We find again that investors increase risk following gains and reduce risk following losses. Another interpretation is that investors are prone to the disposition effect but appear otherwise if we only look at their currency accounts. For example, bond funds may be holding on to their loser bonds for too long and selling their winner bonds too quickly. If bond P&L is negatively correlated with currency P&L for these funds, then this may be responsible for the results we find. While we cannot completely rule out this explanation, the fact that our results hold with pure currency funds[14], and that funds seem to frame their risk taking decisions at the currency by currency level (Table III) suggest that that this is unlikely to drive our results. One other interpretation is that institutional investors are less prone to disposition effects simply because they are more disciplined than other investors and have internalized the standard investment advice to not hold on to their losses. This view agrees with our intuition on retail investors and day traders. It also dovetails with the Dhar and Zhu (2002) finding that investors who are better trained, more educated, and more experienced are less prone to disposition effects.

It is worth emphasizing that our results are first and foremost about the preferences of institutions. We assume that performance contracts, compensation, managerial trading, and the like are all in place to align managerial incentives with what is best for the fund. That is managers are acting in the best interest of the funds. While studies like Chevalier and Ellison (1997)[15] have raised issues concerning the layer of agency between the manager and the fund, a detailed analysis of this matter is beyond the scope of this investigation.

[14] All our main results hold with the pure currency funds subsample.

[15] Among their main findings is an incentive by managers to gamble at the end of the calendar year. We find, on the contrary, that managers in our sample tend to be more conservative at the end of the year than at the start of the year (Figure 7). Hence, it is unlikely that the incentive to gamble, which is motivated in turn by the flow / performance relationship for mutual funds, drives our results.

7. Conclusion

The unique nature of our dataset has allowed us to learn much about performance dependence among institutional investors. One could summarize what we have learnt as follows. Past performance manifestly affects currency risk-taking behavior among institutions. But the effects of gains and losses are dramatically different. Gains elicit a mild increase in risk-taking while losses precipitate a large and durable reduction in risk. These effects are not confined to a few select investors. They are pervasive across the major currencies, accounting for more than 95% of the trading volume in the majors.

Risk management concerns or stop-loss rules do not seem to drive such behavior since the reaction to losses occurs for a wide range of loss cutoffs. Further, we find that cross-currency effects are noticeably absent. Investors seem to frame their risk-taking decisions narrowly at the currency by currency level. Since these effects occur at the account level and not at the portfolio level, it is unlikely that capital constraints are at the root of such performance dependence. Moreover, momentum trading cannot account for such behavior; the addition of momentum proxies fails to drive out the importance of past P&L on risk-taking. Also, managerial performance incentives create convex-like payoff structures which should induce managers to increase risk following losses. Since this is not what we find, our results are unlikely to be driven by managerial response to performance incentives.

Finally, these effects vary over the calendar year and across funds with different age and trading experience. The effects of gains dominate in the first half of the year while the effects of losses dominate in the second half. We conjecture that this is related to the performance evaluation cycle for fund managers. Also older and more experienced funds do not increment their risk-taking following gains as much as younger and less experienced funds, and are assiduous in cutting risks once losses occur.

Taken together, our results are consistent with the behavioral explanations of narrow framing, dynamic loss aversion, and overconfidence. Also they are supportive of the view that institutional investors are better trained and more disciplined than retail investors or day traders.

8. References

Badrinath, S., Lewellen W., 1991. Evidence on tax-motivated securities trading behavior. Journal of Finance 46, 369-382.

Barber, B., Odean T., 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. Journal of Finance 55, 773-806.

Barber, B., Odean T., 2001. Boys will be boys: Gender, overconfidence and common stock investment. Quarterly Journal of Economics 141, 261-292.

Barberis, N., Huang M., Santos T., 2001. Prospect theory and asset prices. Quarterly Journal of Economics 116, 1-53.

Barberis, N., Huang M., 2002. A new preference specification that allows for the framing of risks. Unpublished working paper. Stanford University.

Barberis, N., Thaler R., 2002. A survey of behavioral finance. NBER Working Paper 9222.

Barberis, N., Huang M., Thaler R., 2003. Individual preferences, monetary gambles and the equity premium. Unpublished working paper. University of Chicago.

Chevalier, J., Ellison G., 1997. Risk taking by mutual funds as a response to incentives. Journal of Political Economy, December 1997.

Coval, J., Shumway T., 2001. Do behavioral biases affect prices? Unpublished working paper. University of Michigan.

Daniel, K., Hirshleifer D., Subrahmanyam A., 2001. Overconfidence, arbitrage, and equilibrium asset pricing. Journal of Finance 56, 921-965

Davis, E. P., 2000. Implications of the growth of institutional investors for the financial sectors. Discussion Paper PI-0001. The Pensions Institute, Birkbeck College.

Davis, E. P., Steil B., 2001. Institutional investors (Cambridge, MIT Press).

Dhar, R., Zhu N., 2002. Up close and personal: An individual level analysis of the disposition effect. Yale International Center for Finance Working Paper No. 02-20.

Froot, K., O'Connell P. G. J., Seasholes M. S., 2001. The portfolio flows of institutional investors. Journal of Financial Economics 59, 151-193.

Froot, K., Tjornhom J., 2002. Decomposing the persistence of international equity flows. NBER Working Paper No W9079.

Gervais, S., Odean T., 2001. Learning to be overconfident. Review of Financial Studies 14 (1), 1-27.

Glaser, M., Weber M., 2003. Overconfidence and trading volume. CEPR Discussion Paper 3941.

Grinblatt, M., Keloharju M., 2000. The investment behavior and performance of various investor types: A study of Finland’s unique data set. Journal of Financial Economics 55, 43-67.

Grinblatt, M., Keloharju M., 2001. What makes investors trade? Journal of Finance 589-616

Grinblatt, M., Han B., 2002. The disposition effect and momentum. NBER working paper 8734.

Gruber, M., 1996. Another puzzle: The growth in actively managed mutual funds. Journal of Finance 51, 783-810.

Guercio, D. D., Tkac P., 2001. Star power: The effect of morningstar ratings on mutual fund flows. Unpublished working paper. Federal Bank of Atlanta.

Jegadeesh, N., Titman S., 1993. Returns to buying winners and selling losers: Implications for market efficiency. Journal of Finance 48, 65-91.

Kahnemann, D., 2003. Maps of bounded rationality: Psychology for behavioral economics. Forthcoming in American Economic Review.

Lakonishok, J., Smidt S., 1986. Volume of winners and losers: Taxation and other motives for stock trading. Journal of Finance 41, 951-974.

LeBaron, B., 2002, Technical trading profitability in foreign exchange markets in the 1990s, working paper, Brandeis University.

Linnainmaa, J., 2003. The anatomy of day traders. Unpublished working paper, Helsinki School of Economics.

Locke, P., Mann S., 2001. House money and overconfidence on the trading floor. Unpublished working paper, George Washington University.

Locke, P., Mann S. 2003. Do professional traders exhibit loss realization aversion? Forthcoming in Journal of Financial Economics.

Odean, T., 1998. Are investors reluctant to realize their losses. Journal of Finance 53, 1775-1798.

Shapira, Z., Venezia I., 2001. Patterns of behavior of professionally managed and independent investors. Journal of Banking and Finance 25, 1573-1587.

Thaler, R., Johnson E., 1990. Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. Management Science 36, 643-660.

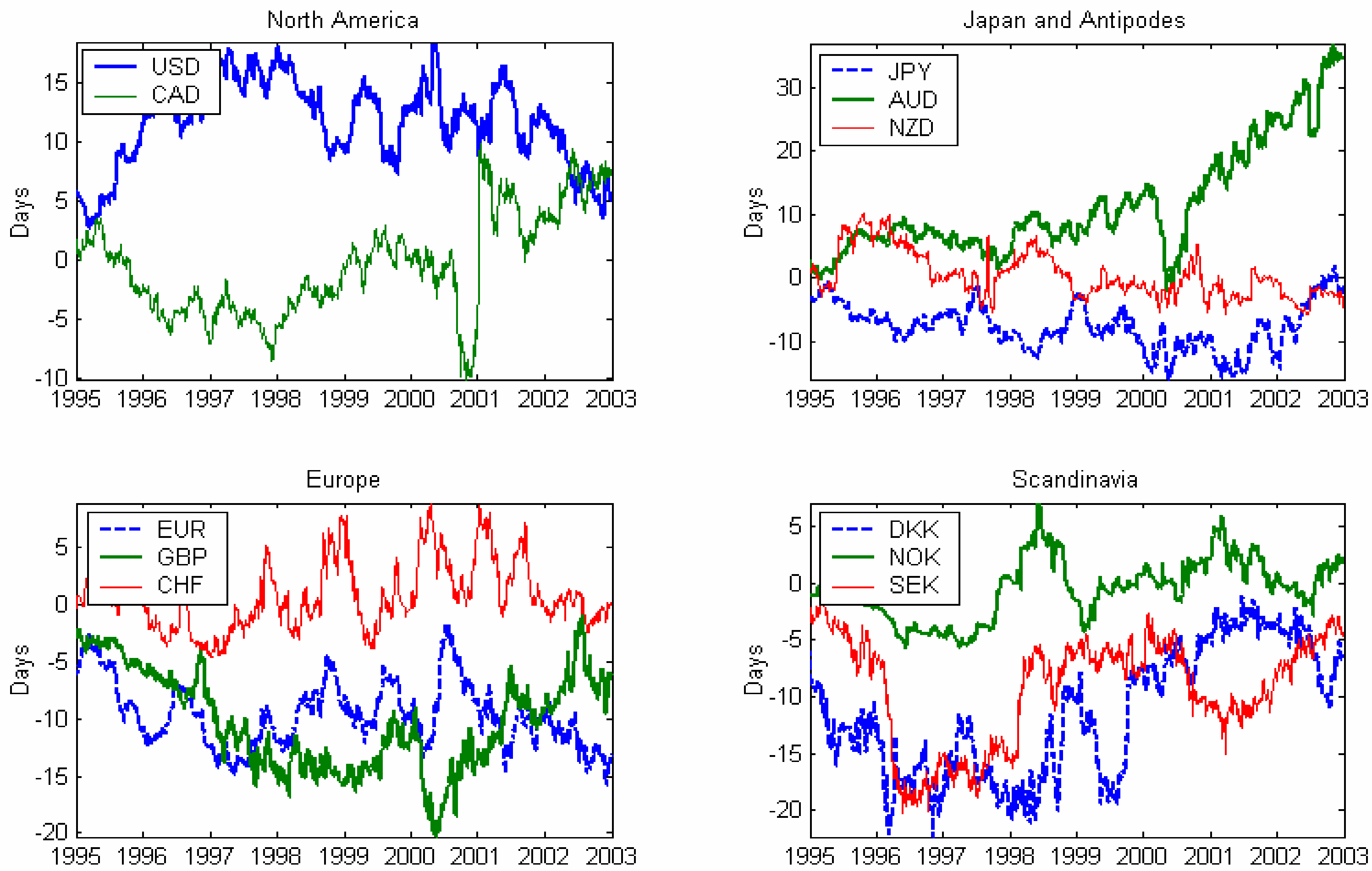

Figure 1: Holdings by currency aggregated across all funds. The sample period is from January 1995 to December 2002.

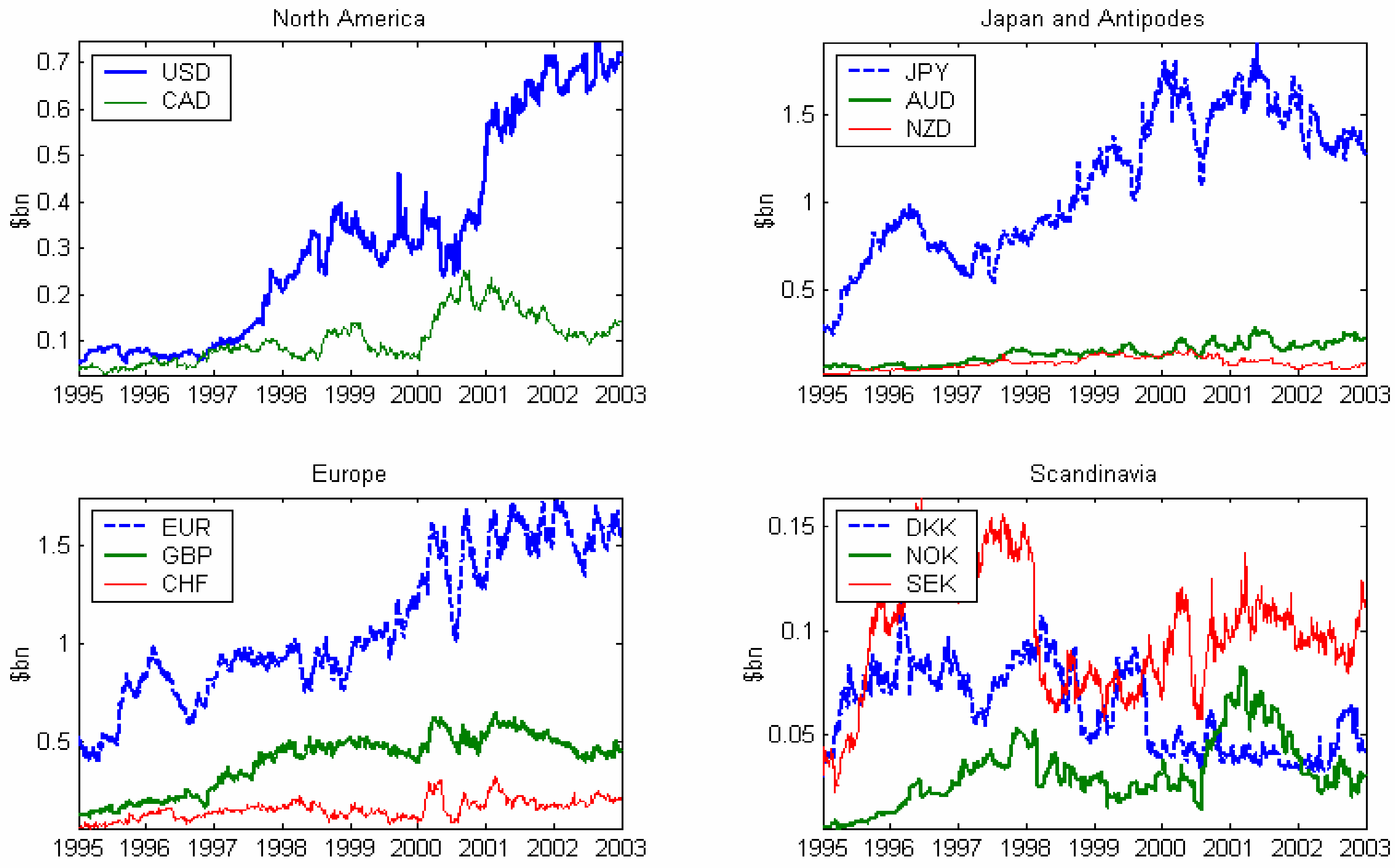

Figure 2: Risk exposure by currency aggregated across all funds. The sample period is from January 1995 to December 2002.

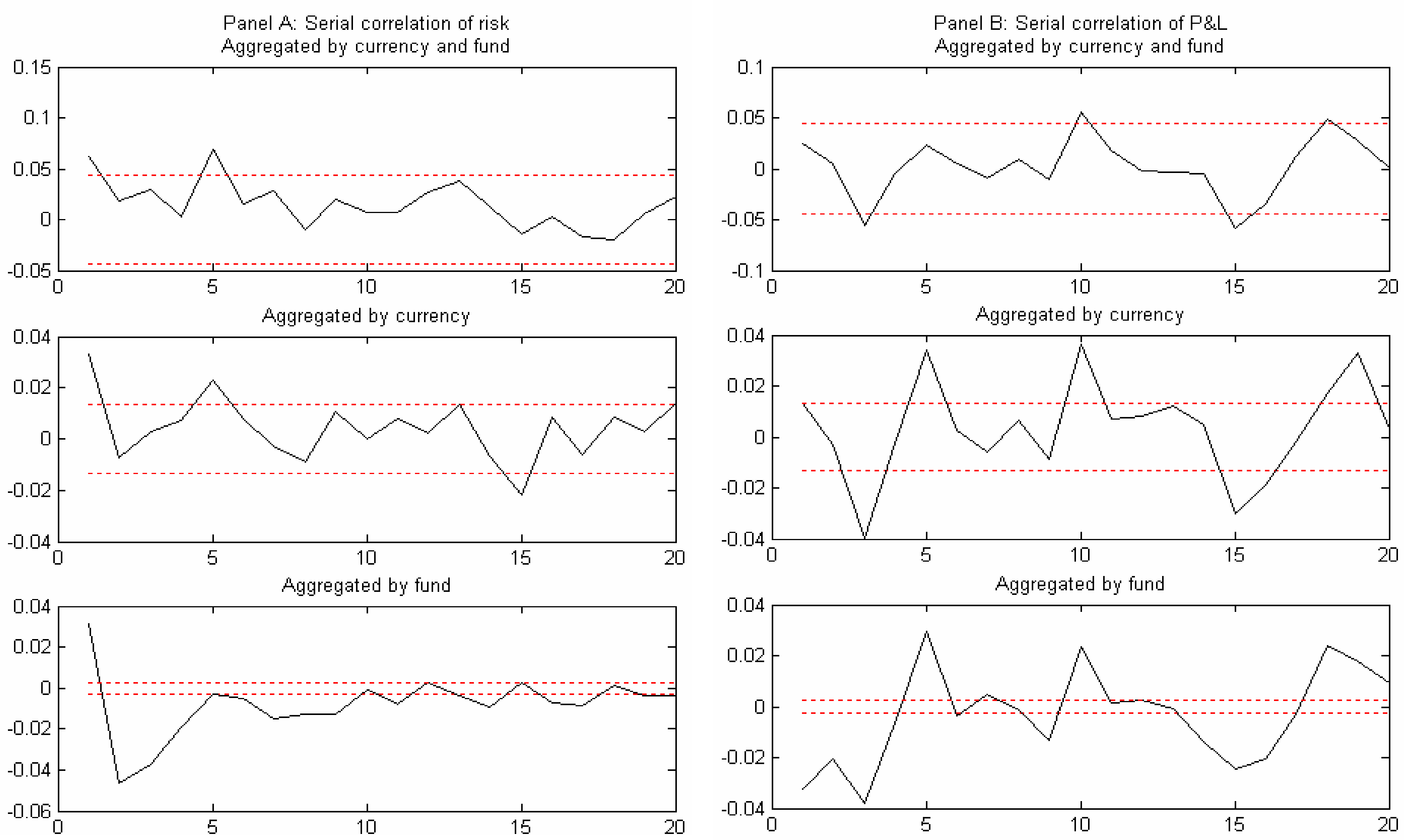

Figure 3: Daily sample autocorrelation functions for risk and P&L aggregates. The sample period is from January 1995 to December 2002. The dotted lines are 95% confidence bounds.

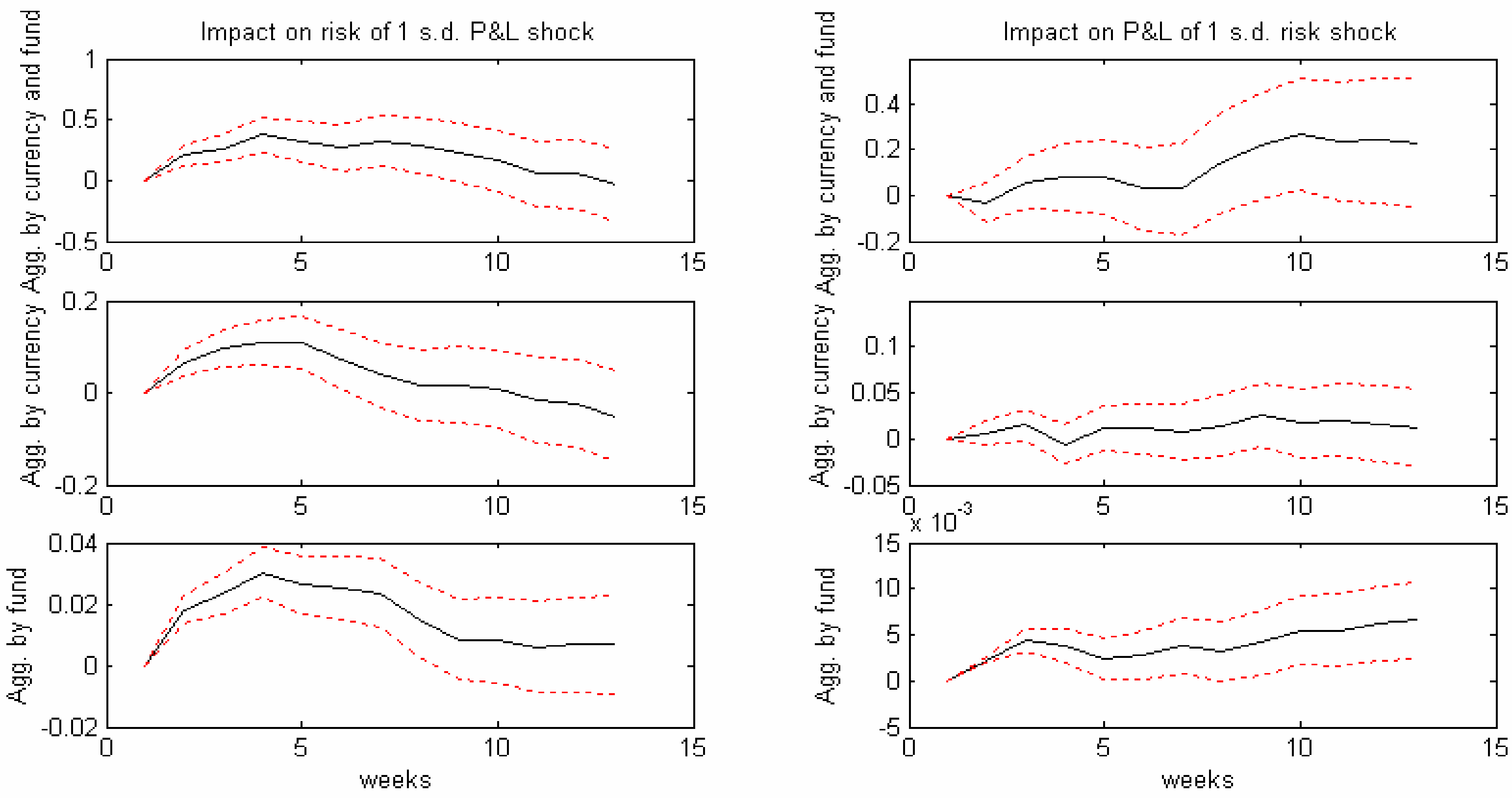

Figure 4: Impulse response functions for shocks to risk and P&L. The sample period is from January 1995 to Deecember 2003. The sample includes 10 currencies and 512 funds. The aggregated by fund and currency panel consists of a series of length T, where T is the length of the sample period. The aggregated 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 lenghts depending on fund life. To generate the impulse response functions, panel VARs for risk and P&l are estimated. The lag length of each VAR is set at 13 weeks, the value selected by the Bayes-Schwartz Information Criterion for the aggregated by 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.

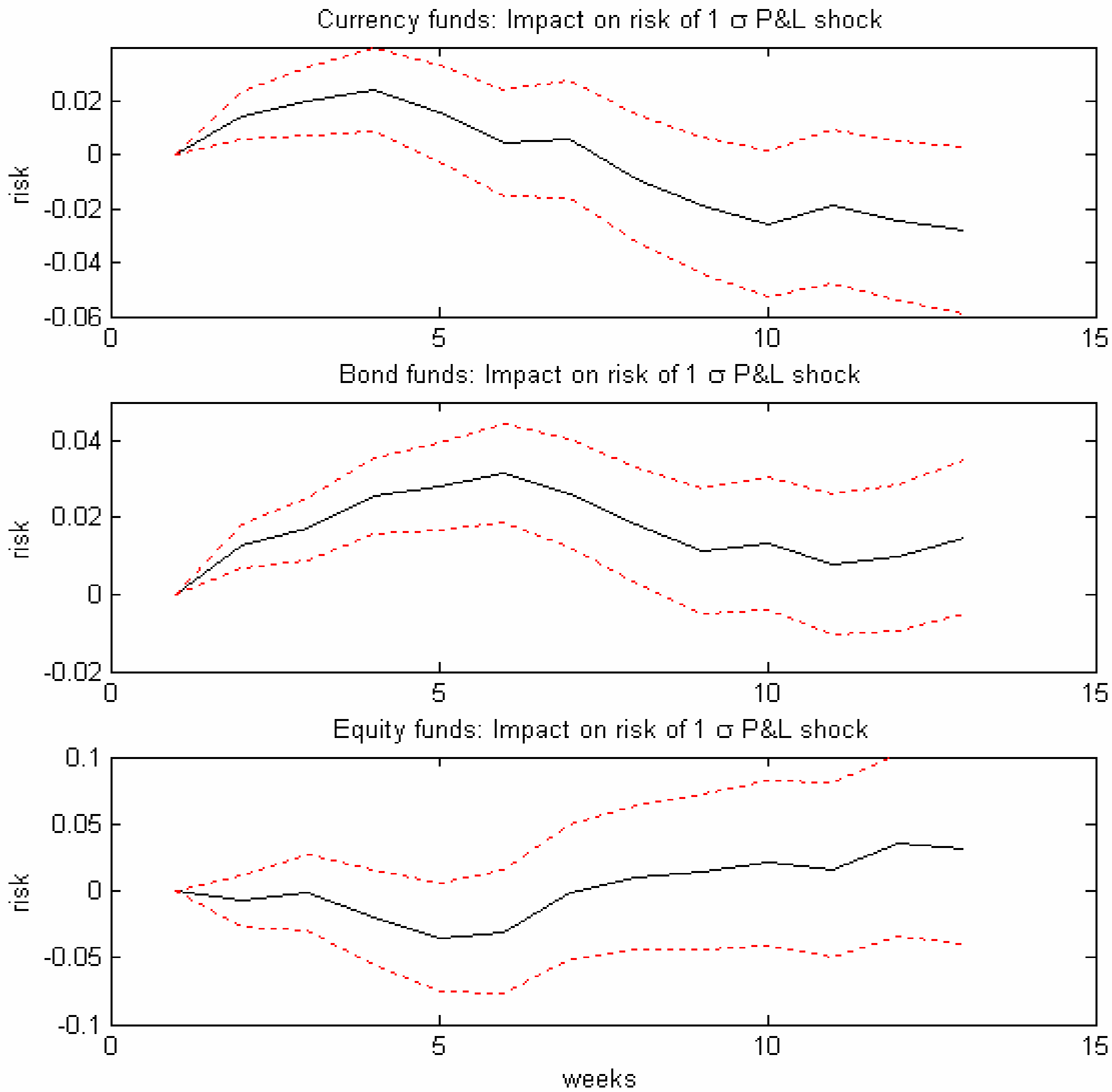

Figure 5: Impulse response of risk to shocks in P&L broken down by fund type. The impulse response functions are generated from a 13-lag bivariate panel VAR for risk and P&L. The sample period is from January 1995 to December 2002. The model allows for heterscedasticity across funds. Estimation is carried 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.

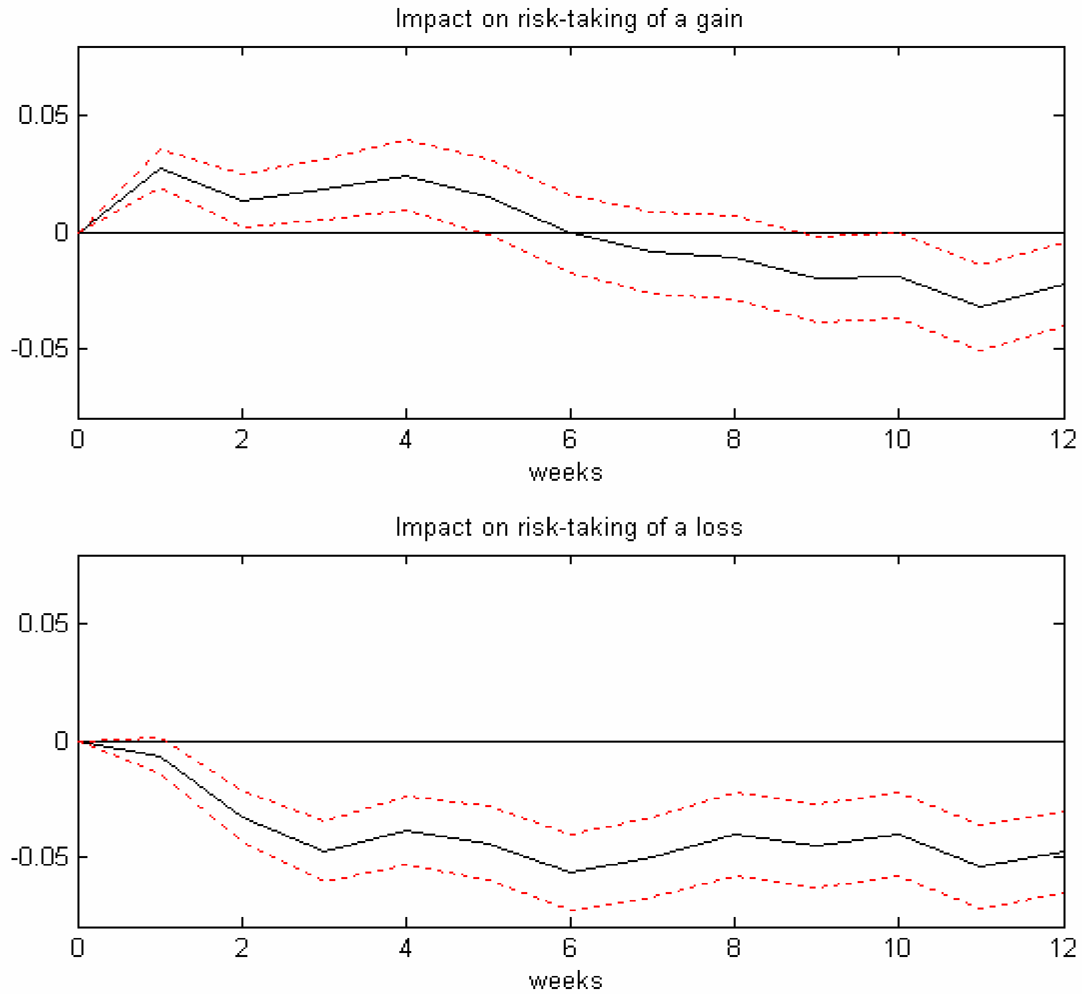

Figure 6: Fund panel impulse response functions for gains and losses. The sample period is from January 1995 to December 2002. To generate the impulse response functions, risk is regressed on weekly lags of P&L conditional on gains and weekly lags of P&L conditional on losses for the fund panel. The regression allows for heteroskedasticity across funds and uses the same lag structure as the VARs in Figure 4. The dotted lines sketched around each function are 90% confidence interval bounds based on maximum likelihood standard errors.

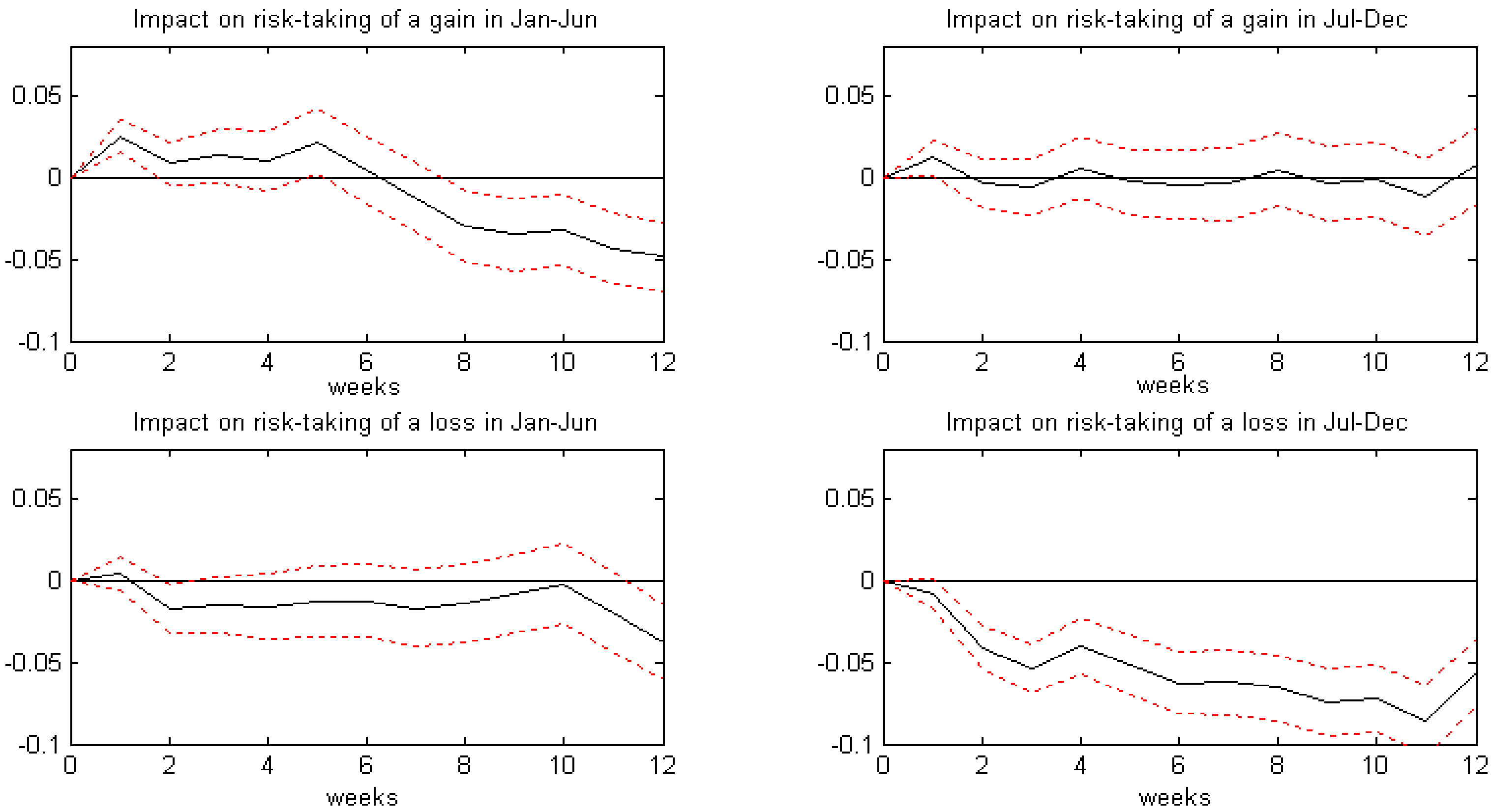

Figure 7: Fund panel impulse response functions for the first and second half of the calendar year. The sample period is from January 1995 to December 2002. The sample is split into the first half of the year (H1) and the second half of the year (H2). To generate the impulse response functions, risk is regressed on weekly lags of risk, weekly lags of P&L conditional on gains and weekly 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 4. The dotted lines sketched around each function are 90% confidence interval bounds based on maximum likelihood standard errors.

Table I

Panel VAR estimates broken down by currency

This table shows the first eight coefficients on lagged P&L from a 13-lag bivariate panel VAR for risk and P&L. The dependent variable is risk. The sample period is from January 1995 to December 2002. The model allows for heterscedasticity across funds. Estimation is carried out by maximum likelihood, stacking all of the funds in the sample. Standard errors are in parentheses. The estimates are shown broken down by currency.

	P&L(t-1)	P&L(t-2)	P&L(t-3)	P&L(t-4)	P&L(t-5)	P&L(t-6)	P&L(t-7)	P&L(t-8)
Denmark	-0.85	1.91	5.12	1.19	1.71	-2.31	-2.89	0.34
	(1.86)	(1.85)	(1.85)	(1.85)	(1.89)	(1.9)	(1.88)	(1.88)
Norway	10.38	12.14	-0.79	3.91	-3.05	-0.58	7.61	24.94
	(8.67)	(8.67)	(8.65)	(8.67)	(8.7)	(8.67)	(8.66)	(8.69)
Sweden	-6.27	-6.02	3.47	-10.15	0.24	5.18	-13.2	-2.34
	(4.54)	(4.52)	(4.51)	(4.51)	(4.55)	(4.54)	(4.52)	(4.53)
Switzerland	9.4	2.99	12.58	10.01	4.84	4.13	5.62	3
	(4.85)	(4.88)	(4.89)	(4.9)	(4.92)	(4.94)	(4.92)	(4.93)
UK	3.3	29.2	26.62	0.82	28.86	10.69	2.11	18.68
	(4.67)	(4.67)	(4.66)	(4.46)	(4.44)	(4.44)	(4.45)	(4.41)
Australia	21.45	23.35	13.18	-12.75	-6.7	22.77	23.72	19.81
	(5.59)	(5.58)	(5.55)	(5.52)	(5.49)	(5.48)	(5.41)	(5.47)
Japan	17.75	14.42	15.33	5.58	-2.01	-5.38	5.98	-7.62
	(4.24)	(4.24)	(4.25)	(4.24)	(4.24)	(4.25)	(4.24)	(4.24)
NZ	-26.89	-6.9	-1.61	-1.48	-7.92	-20.91	-5.52	-5.63
	(5.68)	(5.67)	(5.71)	(5.61)	(5.62)	(5.64)	(5.6)	(5.6)
Canada	10.64	13.87	10.32	1.78	-17.36	-8.61	-5.16	-5.7
	(6.26)	(6.25)	(6.23)	(6.21)	(6.21)	(6.19)	(6.19)	(6.19)
Euro	19.64	10.8	8.23	-3.94	-5.32	1.45	-7.07	-12.67
	(4.27)	(4.26)	(4.26)	(4.27)	(4.28)	(4.28)	(4.26)	(4.26)

Table II

The reaction of risk to losses conditional on the size of the return.

This table shows the first four coefficients on lagged P&L conditional on small negative returns and large negative returns from a 13-lag bivariate panel VAR for risk and P&L. The dependent variable is risk. The independent variables are lagged risk, lagged P&L conditional on a gain, lagged P&L conditional on a small negative return, and lagged P&L conditional on a large negative return. For each negative return cutoff, a small negative return is any return that is greater than the cutoff, while a large negative return is any return that is less than the cutoff. The sample period is from January 1995 to December 2002. The model allows for heterscedasticity across funds. Estimation is carried out by maximum likelihood, stacking all of the funds in the sample. Standard errors are in parentheses. The positions of the cutoffs in the distribution of negative returns are in brackets.

Cutoff return(%)	Small_loss(t-1)	Small_loss(t-2)	Small_loss(t-3)	Small_loss(t-4)	Large_loss(t-1)	Large_loss(t-2)	Large_loss(t-3)	Large_loss(t-4)
-0.1	5.83	24.86	13.56	-8.84	15.52	19.02	8.28	-19.43
[50%tile]	(4.85)	(4.83)	(4.85)	(4.83)	(19.03)	(19)	(18.99)	(18.98)
-0.15	5.4	24.35	14.56	-8.54	20.15	45.31	13.96	4.96
[40%tile]	(4.84)	(4.83)	(4.84)	(4.82)	(12.73)	(12.75)	(12.73)	(12.7)
-0.2	3.97	24.36	13.53	-9.28	15.8	23.15	14.27	-3.98
[30%tile]	(4.95)	(4.93)	(4.95)	(4.93)	(9.68)	(9.69)	(9.68)	(9.66)
-0.25	6.84	27.3	14.62	-10.54	2.55	15.26	11.94	1.32
[20%tile]	(5.19)	(5.17)	(5.19)	(5.17)	(8.09)	(8.09)	(8.08)	(8.07)
-0.4	3.28	20.26	0.6	-10.94	8.08	28.81	25.13	-5.1
[10%tile]	(6.66)	(6.64)	(6.64)	(6.62)	(6.06)	(6.04)	(6.06)	(6.06)
-0.5	-5.7	7.21	0.48	-12.27	10.06	30.47	18.5	-7.67
[5%tile]	(8.56)	(8.56)	(8.55)	(8.53)	(5.47)	(5.45)	(5.47)	(5.46)
-2	55.18	1.49	28.75	-10.4	4.8	25.7	14.41	-8.15
[1%tile]	(26.8)	(26.8)	(26.79)	(26.8)	(4.89)	(4.87)	(4.88)	(4.87)

Table III

Conjugate P&L results by currency

This table shows the first eight coefficients on lagged conjugate P&L from a regression that also has lagged risk and lagged own P&L as regressors. The dependent variable is risk. Conjugate P&L is defined as the profit or loss on all currencies except the regressand currency. The sample period is from January 1995 to December 2002. The model allows for heterscedasticity across funds. Estimation is carried out by maximum likelihood, stacking all of the funds in the sample. Standard errors are in parentheses.

	conjP&L(t-1)	conjP&L(t-2)	conjP&L(t-3)	conjP&L(t-4)	conjP&L(t-5)	conjP&L(t-6)	conjP&L(t-7)	conjP&L(t-8)
Denmark	0.03	-0.02	0.03	0.07	-0.02	0.05	0.03	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Norway	-0.05	0.05	0.02	0.08	0.01	0.14	0	0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Sweden	0.15	-0.04	0.03	0.08	0.01	0.06	0.02	0.07
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Switzerlan	-0.01	-0.05	0.05	0.04	-0.03	0.01	0.03	0.06
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
UK	0.04	0.01	0.06	0.01	0	0.07	-0.03	-0.02
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Australia	0.17	0.14	0.14	0.12	-0.01	0.32	0.12	0.01
	(0.1)	(0.1)	(0.1)	(0.11)	(0.11)	(0.1)	(0.1)	(0.1)
Japan	0.79	-0.33	-0.89	0.66	-1.26	-0.46	-0.32	0.51
	(0.62)	(0.62)	(0.62)	(0.62)	(0.62)	(0.62)	(0.61)	(0.62)
NZ	0.01	0.02	0.01	-0.01	-0.01	0.01	0.01	0
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Canada	0.02	-0.02	0.1	0.1	-0.04	-0.01	-0.01	-0.01
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Euro	-0.68	-0.91	-0.05	0.47	-0.81	1.17	0.34	-0.2
	(0.22)	(0.23)	(0.27)	(0.24)	(0.26)	(0.28)	(0.29)	(0.27)

Table IV

The effects of age and experience on performance dependence

This table illustrates the effect of age and experience on performance dependence. The sample period is from January 1995 to December 2002. The sample is split into two periods: An evaluation period (the last three years of the sample, January 2000 to December 2002) and a formation period (the intial five years of the sample, January 1995 to December 1999). A fund's age is proxied by the length of time since the first day of trading in the formation period sample, and experience proxied by the number of days trading in the formation period. To test sensitivity to these two variables, we use a simple two-step procedure. In step one, the sensitivity of each fund to lagged P&L, lagged P&L conditonal on a loss, or lagged P&L conditional on a gain is measured separately across the evaluation period. Then in step two, the cross-section of coefficients is regressed on age and fund experience. Standard errors in parentheses.

	P&L (t-1)	P&L conditional on gain (t-1)	P&L conditional on loss (t-1)
Age	-1.36	-3.47	0.67
	(0.65)	(1.14)	(1.02)
Experience	-1.71	-5.72	2.49
	(0.91)	(1.56)	(1.39)