A Natural Experiment in Portfolio Management*

Stephan Kranner
WU Vienna University of Economics and Business

Neal Stoughton
WU Vienna University of Economics and Business and Vienna Graduate School of Finance

Josef Zechner
WU Vienna University of Economics and Business and Vienna Graduate School of Finance

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Abstract

The Portfolio Management Program (PMP) in Vienna Austria has been in existence for more than ten years. This paper analyzes the ten year performance (2004-2014) of the three competing funds with the objective of using this controlled setting to test two behavioral theories of funds management. We test both the tournament effect and the disposition effect, as well as looking at a selection of demographic variables. Consistent with tournament theory, the funds behave as predicted with trailing funds shifting into idiosyncratic risks that leading funds cannot mimic. The paper also documents a definitive reverse disposition effect, whereby losing assets are more likely to be sold than winning assets. We identify a group size effect where larger managerial teams are more cautious and have lower risk adjusted returns. These results show that managerial behavior in the partly controlled setting of academic guidance can vary greatly from what has been found with retail investors.

1 Introduction

Student-run investment portfolios have been an important component of the educational environment in business schools since Lafayette College established the first fund in 1950. As of 2007 several hundred million dollars were under management by teams of university students in more than 300 institutions worldwide.[1] The first non-US student-run fund was established in 1987 at the University of British Columbia in Canada. Partly modeled on that fund, three portfolios were established in 2004 in Vienna Austria in the form of the *Portfolio Management Program* (PMP), which is a privately sponsored program organized at

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[1]See Lawrence (2008).

the WU Vienna University of Economics and Business with students from that university as well as two others nearby.

This paper analyzes the portfolio management decisions of these three PMP funds over the first ten years (2004-2014) of their existence. Not only are the portfolio performances analyzed, but also two important theories of investment management are tested and documented. We are able to do this because the PMP represents a natural experiment with data available about actual decisions and with real monetary consequences.

We begin with a demographic analysis of managerial attributes. These variables include group size, gender, and educational background. We find that gender effects do not show up in risk-taking or risk-adjusted performance. However we find that group size matters and smaller groups have higher risk-adjusted performance while taking more idiosyncratic risk.

The first behavioral test is related to the theory of tournaments. According to this theory funds at an intermediate date that are trailing have incentives to take on more risk than those that are in the lead. We are able to focus on this effect in a controlled natural experiment since there is a well-defined termination date at which time the current generation of managers exits and is replaced by a new generation of managers. This turnover date occurs exactly once a year. Considering that there are only a small number of funds (3), and only ten annual tournaments, we find good support for not only the main tournament hypothesis, but also several related behavioral effects. Specifically we find that decomposing risk-chasing into idiosyncratic as well as systematic risk, there are tendencies for the winning funds to shift away from idiosyncratic into systematic risk before the termination date. This makes sense as it is easier for the trailing funds to mimic systematic risk, but this is not of concern to the leading funds. The trailing funds tend to move away from systematic risk into idiosyncratic risk, as theory predicts.

The second test is related to the disposition effect. This behavioral theory posits that investors are loss-averse and hence are more reluctant to sell losers than winners, everything else held the same. Because of our specific pricing data and the records of asset sales and purchases, we are able to test this within a natural experiment as well. Here we find strong evidence of a *reverse disposition effect*, i.e., these student-run funds have a greater propensity to sell their losing assets as compared to the winners. We hypothesize that the annual managerial turnover aspect of this program allows the current generation of managers to focus better on current information without being burdened as much by regret about past decisions, as compared to individual investors. We find that this reverse disposition effect is robust to many control variables, such as volatility, length of holding period, and magnitude of accrued gains and losses. It is not that these controls do not matter, they do, but the reverse disposition effect survives. Further there is an aspect of similarity of asset disposition between groups, which may be due to the fact that although mandates differ and money is managed separately they attend common classes and otherwise interact socially.[2]

Before we discuss these results within the relevant literature it is useful to provide some background information about the organization of the PMP. The program was begun in 2003 based on considerable interest of two finance professors in Vienna and the sponsor of a local private foundation. Three portfolios

[2]The trading facility is in a shared room for instance.

were initially set up with 1 million euros of real money in total and were raised to 1 million euros each by 2008. The funds were each given separate mandates which has governed their investment strategy to this day. The *ZZ* fund is managed in an "entrepreneurial" fashion with a focus on cash flow yield.[3] It has a wide latitude to invest in many different asset classes, including emerging market bonds, currencies, non-deliverable forwards, global equities, commodities and structured products that are offered over the counter by investment banks. The so-called *Yale* fund is modeled after the prominent Yale endowment. It has a mandate consisting of strategic asset allocation weights that are derived from the annual reports of the endowment at Yale University. Further the emphasis is on active management and manager selection, as discussed in Swensen (2009). The third portfolio, the *Harvard* fund has a mandate to conform loosely to the strategic asset allocation weights of the endowment at Harvard university. A more explicit constraint is that this fund should invest 70% in passively managed assets such as index tracking products.

The format of funds management involves overlapping generations. The program is typically two years in length for all students. The first year involves serving as an "analyst" whereby the students are allowed to self select into the respective funds. They serve an apprentice year by performing research assignments identified in consultation with the managers of their fund, who are in the second year of the program. Near the end of the academic year, the analysts are promoted to become managers of the same fund and they then assume managerial responsibility for the asset management decisions. Acceptance into the PMP is highly competitive and is determined by a board consisting of professors and research associates at the university as well as tutors and personnel from the cooperating partner. Students are allowed first to self-select into their preferred fund when they begin their first term as analysts. If there is oversubscription then a random reallocation procedure is used to ensure equal numbers in the analyst team.

At the conclusion of the program, many students have graduated to take positions at prominent banks and other money management institutions within Europe, including those of the partner itself. The program is also listed as a formal course at the WU university. Students receive course credit and there are weekly meetings at which students from one group present their findings and decisions and are critiqued by students of other groups, as well as the professors and tutors. Students receive a grade which is partly based on both absolute and risk-adjusted performance of their own portfolio, as well as how they do in their presentations and exercises at the weekly sessions. While we do not have the data on how starting salaries of the graduates are correlated with individual fund performance, it seems natural to us that such questions would arise at job interviews and be a relevant consideration for prospective employers.

We should also emphasize that there are two main features that distinguish the PMP program from the majority of other programs: (1) there are three separately managed portfolios that are competing with one another; and (2) the students are given a very large investment universe to analyze and explore, not only domestic equities, but many other asset classes and products that are not typically available to small retail investors.

The literature on student-run investment portfolios is quite meager. There are no studies that conduct the sort of analysis of performance and trading behavior that we do, either at the micro level (i.e., for a

[3]The name ZZ comes from the name of the asset management firm, ZZ Vermögensverwaltung, which is a cooperating partner of the PMP.

specific university) or at the macro level (by looking across universities). The most recent survey of student-run funds is due to Lawrence (2008). He conducts an extensive survey from universities around the world and discusses a number of trends and the size and variety of fund structures across institutions. As he identifies, the most common situation is where a portion of the university endowment is delegated to student managers as opposed to professional management. He also discusses the role of faculty and the interaction with investment professionals. Referring to this study, Stumbaugh (2012) discusses what form a potential database could take that would aggregate data across universities. The motivation for this design exercise is to encourage competitions between student managed funds.

There are several papers that discuss the specific features and experiences of locally run student managed funds at the universities of the authors. Schill (2008) is a case study of the Monticello fund, run by MBA students at the Darden School of the University of Virginia. The case focuses on a very specific decision, the question of which of six potential stocks the new managers of the fund should invest in. Drawing upon the experiences of the student funds at Brigham Young University Sudweeks, Seaberg, Davis, Prieto, and Sain (2012) discuss the pedagogy of the program and how it interfaces with the traditional set of educational experiences such as coursework. Motivated by the student-run fund at the University of California, Long Beach, Ammermann, Runyon, and Conceicao (2011) posits a technical trading rule, backtests it and argues that this is the type of strategy that such funds should adopt. Bruce and Greene (2013) is a recently published hands-on textbook about student managed portfolios, which addresses students that are currently engaged in a portfolio management program. Besides the information of the investment philosophy and the organizational structure of various real world student managed funds, it mainly provides a comprehensive toolkit for the actual fund management that serves as a guideline for students.

Effects on group size in the context of mutual funds have been found also by Bär, Kempf, and Ruenzi (2011). The two behavioral aspects that we focus on here, the tournament effect and the disposition effect have long histories in the academic literature. The most prominent finance papers in the tournament literature are those of Chevalier and Ellison (1997) and Brown, Harlow, and Starks (1996). We employ some similar tests to Brown, Harlow, and Starks (1996) although we have more frequent data which enables us to extend their test templates to other, more specific aspects of strategic tournament play such as those identified in the model of Chen, Hughson, and Stoughton (2013). The disposition effect was first discussed in the finance context by Shefrin and Statman (1985) who argued that psychology could be responsible for this form of loss averse behavior and found suggestive evidence from individual decisions as well as mutual fund trades. A very important database of individual retail trades was analyzed in Odean (1998) and the disposition effect identified by the same type of tests that we employ here. Nicolosi, Peng, and Zhu (2009) uses this same data set to analyze the experiential practices of individual investors. Other relevant papers are those of Ben-David and Hirshleifer (2012), who conduct a probit test of the disposition effect, Jin and Scherbina (2010), who find a reverse disposition effect as we do but with respect to mutual funds with managerial turnover and Hartzmark (2013) who not only considers the disposition effect but also a "rank effect" whereby individuals and mutual funds might have a greater tendency to sell the position with the most extreme capital gains and losses in their portfolio. Behavioral finance theories and the academic evidence are summarized in Barberis and Thaler (2003).

The detailed performance analysis, both absolute and risk-adjusted takes place in section 2. Our demographic analysis appears in 3. We perform tests for the tournament effect in section 4 and the disposition effect in section 5. Section 6 concludes the paper.

2 Portfolio Analysis

This study comprises ten years of portfolio data from the three student-run portfolios in the Portfolio Management Program. The major data set is a unique series of portfolio net asset values that was compiled on a weekly basis and retained over the life of the funds. These weekly NAVs as well as asset cash flow distributions were used for the total return series for each of the funds.[4] In addition, we have hand collected the asset purchase and sell dates along with the associated asset prices from Bloomberg. In the benchmark analysis that follows below, we also use Bloomberg pricing data to compute weekly returns. We begin the discussion of the portfolios by considering their performance both on an absolute as well as risk-adjusted basis, while accounting for intertemporal variations in styles. This is important as the composition of the management team changed from year to year.

2.1 Performance and Benchmarks

We illustrate the total return performance of the three portfolios in comparison to a benchmark. All of our analyses are done using weekly return data.[5] Figure 1 shows what 1 Euro invested on May 24, 2004 would have grown to at the end of the ten year period. Of the three portfolios the one following the ZZ investment philosophy would have returned almost 200% after eight years. At the end of the ten year period, its performance was up by about 130%. The other two student-run portfolios following the investment philosophies of Yale and Harvard tracked very closely over this period of time and were up by about 75%. For comparison purposes we have selected a benchmark representing a global market, which is the MSCI All Country world index. This index consists of equities both in developed as well as developing countries. Compared to this index, the ZZ portfolio experienced strong outperformance over the ten year period, while Harvard and Yale had better cumulative performance over the first 9 years, falling back into conformity by May 2014.

[4]Because of changes in the manner in which the portfolios are accounted for in Austria, we had to make certain adjustments to obtain the "before tax" return series. For the initial period, taxes were not applicable to the portfolio returns. For the period 06/2012–06/2014, we added back the taxes paid by each fund in a straightforward manner. For a short period, 06/2011–06/2012, we had to follow a more complicated procedure of imputing the tax to be added back since the portfolios were held in pooled accounts. We took the dividend yields of the MSCI AC World and the largest emerging market bond fund held by the groups, which were 2.8% and 4.2%, respectively. We assumed a 40/60 allocation for the ZZ fund and a 60/40 allocation for the YALE and HARVARD group with a statutory tax rate of 25%. The method of tax adjustment does not affect our main results as in an earlier version of the paper we made no adjustments and achieved the same empirical results.

[5]The pricing of the student-run funds is done on a weekly basis.

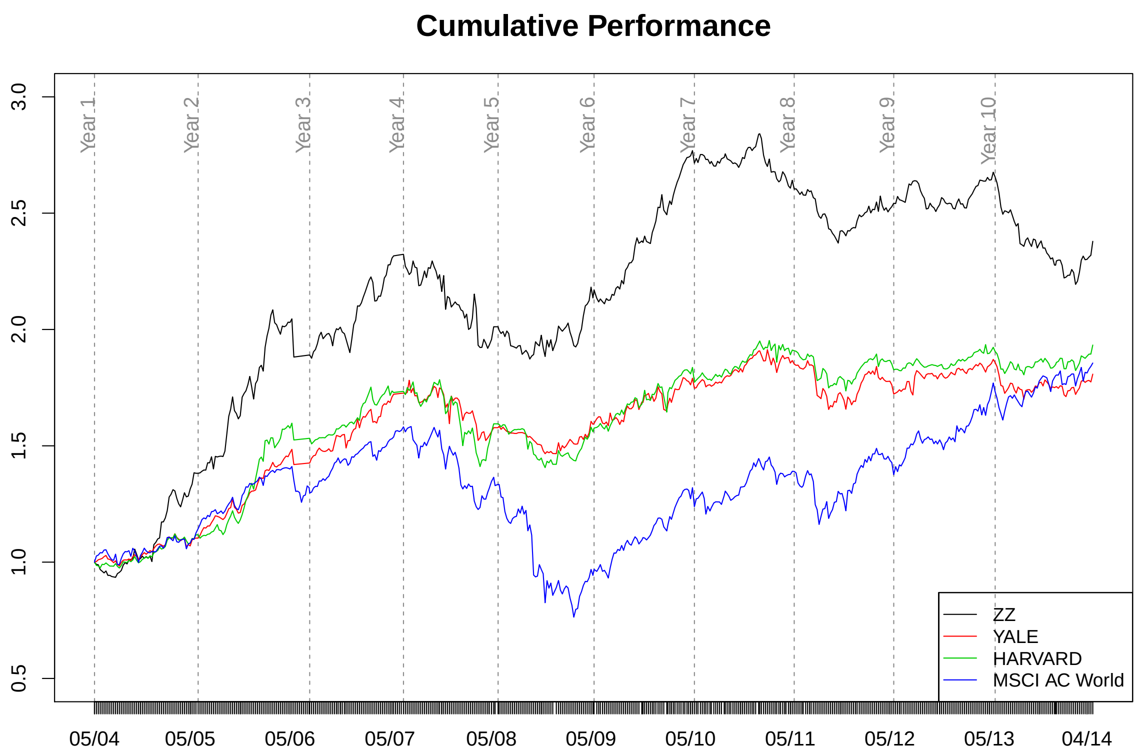

Figure 1: Cumulative performance of the PMP portfolios and the MSCI AC World

For analytical purposes we also have established an additional set of style benchmarks. Because the students were given wide latitude to invest globally across many asset classes, we selected an additional seven indexes for comparison. These indexes are listed in Table 1. These include domestic (European) equity, US equity, emerging markets equities, global bonds, emerging market currencies, commodities and a rate of return index representing cash held in Germany.

	Ticker	Name	Asset Class
Benchmarks			
1	SXXR	STXE 600 NRt	Equity (Domestic)
2	SPTRTE	S&P 500 EUR TR	Equity (US)
3	MSDEEEMN	MSCI Emerging Markets Daily Net	Equity (EM)
4	JPEIGLBL	JPMorgan EMBI Global Total Ret	Bond (EM)
5	MXEF0CX0	MSCI EM Currency	Currency (EM)
6	RICIGLTR	Rogers International Commodity	Commodity
7	GRGYSHRT	Bundesbank Germany Avg Govt Bond	Cash
Market			
8	NDEEWNR	MSCI AC World Index Daily Net	Market

Table 1: Benchmark overview

Figure 2 shows how these benchmarks compare in terms of aggregate performance over the same ten year period. It is apparent that the MSCI emerging market equity index had the strongest overall performance while commodities were weakest.

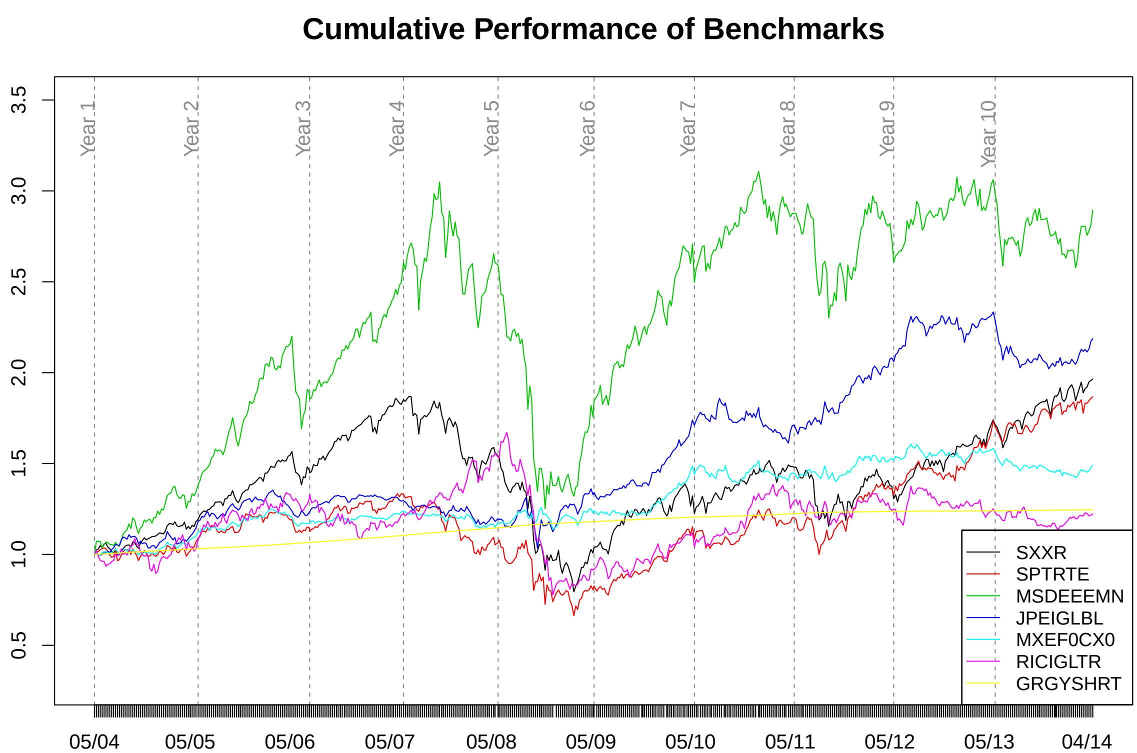

Figure 2: Cumulative performance of benchmarks

Recall that the Harvard and Yale PMP funds are supposed to use as models the respective university endowments. Figure 3 compares the performance of the 3 PMP portfolios with the actual Yale and Harvard endowments on the basis of annual data at the end of the fiscal year. While the 2 student-run portfolios mimicking the Yale and the Harvard investment philosophy slightly underperform their real endowment benchmarks, the ZZ portfolio was actually ahead over the first 9 years.

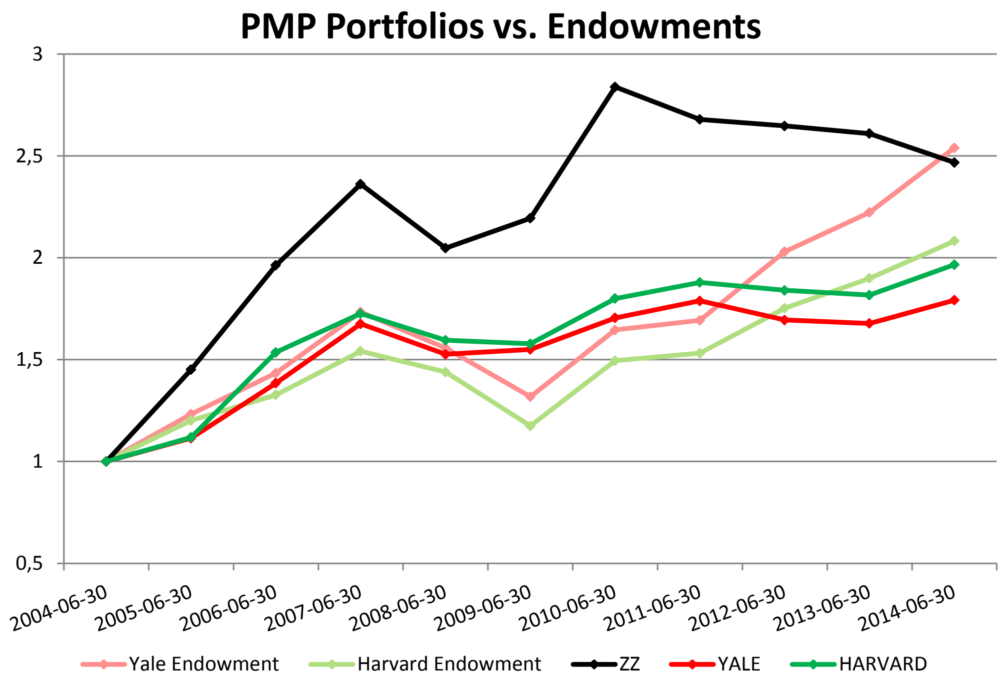

Figure 3: Cumulative performance of the PMP portfolios and the actual YALE and HARVARD endowments (in EUR)

2.2 Risk Adjusted Performance

We now compute the risk-adjusted performance both in terms of a Sharpe ratio as well as the alpha relative to the global market index.

We compute Sharpe ratios using the volatility of the weekly returns, σ_i. Excess returns are computed on a weekly basis by deducting the riskfree rate, $r_{f,t}$, from the fund returns, $r_{i,t}$. We use the short-term German Bund yields as a riskfree rate (GRGYSHRT). We used the following formula: $SR_i = \frac{r_{EX,i}}{\sigma_i}$, where $r_{EX,i} = \Sigma_{t=1}^{n} r_{i,t} - r_{f,t}$, where n is the number of time periods over which the Sharpe ratio is computed (e.g., weeks during a year).

We display Sharpe ratios for each of the 10 years and for the total period in Table 2. The six risky indexes are also provided. While there was considerable variation over time, the Sharpe ratio over the total period for the ZZ fund was 0.60, the Harvard fund 0.48, and the Yale fund 0.42. The overall market had a Sharpe ratio of 0.25. Out of the indexes the JP Morgan total return bond fund was best with a Sharpe ratio of 0.54.

	Years										Total
	1	2	3	4	5	6	7	8	9	10	Period
PMP											
ZZ	2.32	1.91	2.25	–	0.43	2.80	–	–	0.79	–	0.60
YALE	0.92	2.89	2.13	–	–	0.69	0.63	–	1.07	–	0.42
HARVARD	1.15	2.62	1.52	–	–	0.96	0.73	–	0.91	0.15	0.48
Benchmarks											
SXXR	1.36	2.52	2.64	–	–	0.85	1.44	–	2.48	1.19	0.27
SPTRTE	0.27	0.34	1.59	–	–	1.90	0.64	0.50	2.22	0.86	0.23
MSDEEEMN	1.80	2.86	2.69	–	–	1.78	0.97	–	1.10	–	0.42
JPEIGLBL	1.10	0.02	0.82	–	0.44	2.91	–	1.92	1.14	–	0.54
MXEF0CX0	1.01	0.30	0.25	–	0.22	1.71	–	0.42	0.38	–	0.23
RICIGLTR	–	1.16	–	1.53	–	0.61	1.39	–	–	–	–
Market											
NDEEWNR	0.74	1.70	2.22	–	–	1.74	0.86	–	2.29	0.66	0.25

Table 2: This table presents the annualized Sharpe ratios for each year along with the total over the 10 year period. In the table the entry "–" indicates a period where the *ex post* value was negative.

Next we regress the excess return of the 3 PMP portfolios on the excess return of the "market" (MSCI AC World). That is we run the following regression:

$$r_{EX,i,t} = \alpha_i + \beta_i r_{EX,MSCI,t} + \epsilon_{i,t}$$

Columns Year1 to Year10 represent the 10 manager years, whereas the Total column shows the results for the whole 10 year period. Table 3 indicates the values of alpha for each year and the "beta" (market coefficient) for the ZZ portfolio. For the purpose of each year, weekly excess returns are used to obtain the yearly beta. The alphas are annualized. First note that the market factor loadings are rather small. For instance the average over the ten years is only 0.235. This reflects the fact that the fund holdings are not closely related to equities, except for the second year. The alphas are marginally positively significant in two out of the ten years and significantly negative in the last year.

	Year1	Year2	Year3	Year4	Year5	Year6	Year7	Year8	Year9	Year10	Total
alpha	0.276^{+}	0.081	0.152	-0.148	0.112	0.132^{+}	-0.079	-0.031	0.020	-0.138^{+}	0.055^{+}
	(0.144)	(0.124)	(0.112)	(0.173)	(0.104)	(0.068)	(0.058)	(0.062)	(0.052)	(0.075)	(0.033)
market	0.142	1.447^{***}	0.310	0.248^{+}	0.175^{***}	0.318^{***}	0.210^{**}	0.125^{*}	0.090	0.365^{***}	0.235^{***}
	(0.165)	(0.183)	(0.187)	(0.146)	(0.043)	(0.064)	(0.066)	(0.047)	(0.065)	(0.101)	(0.029)
R^2	0.014	0.566	0.062	0.061	0.260	0.328	0.167	0.122	0.037	0.206	0.115
Adj. R^2	-0.005	0.557	0.039	0.040	0.245	0.314	0.150	0.105	0.018	0.190	0.113
Num. obs.	53	50	44	47	50	52	52	52	53	52	522

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 3: This table shows the alpha and the beta coefficients of the regression of the ZZ excess returns on the market excess returns for each of the 10 years and the total period. The lower number in parenthesis shows the standard error.

The same risk-adjusted performance panel is now exhibited for the Yale portfolio in Table 4. By contrast, the factor loadings are larger on an annual basis, although when using a constant factor loading over the entire time period, the exposure is reduced on average. The alpha is significantly positive in one out of the ten years.

	Year1	Year2	Year3	Year4	Year5	Year6	Year7	Year8	Year9	Year10	Total
alpha	0.026	0.117^{*}	0.107	-0.086	0.018	-0.033	0.011	-0.074	0.015	-0.048	0.027
	(0.048)	(0.056)	(0.101)	(0.151)	(0.067)	(0.083)	(0.057)	(0.069)	(0.066)	(0.074)	(0.026)
market	0.474^{***}	0.799^{***}	0.482^{**}	0.260^{*}	0.099^{***}	0.459^{***}	0.313^{***}	0.425^{***}	0.256^{**}	0.249^{*}	0.264^{***}
	(0.056)	(0.083)	(0.169)	(0.127)	(0.028)	(0.078)	(0.065)	(0.053)	(0.082)	(0.099)	(0.022)
R^2	0.588	0.658	0.163	0.085	0.211	0.406	0.315	0.566	0.160	0.112	0.217
Adj. R^2	0.580	0.651	0.143	0.065	0.194	0.394	0.301	0.557	0.144	0.094	0.215
Num. obs.	53	50	44	47	50	52	52	52	53	52	522

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 4: This table shows the alpha and the beta coefficients of the regression of the YALE excess returns on the market excess returns for each of the 10 years and the total period. The lower number in parenthesis shows the standard error.

Likewise Table 5 indicates the alpha and market factor loadings for the Harvard portfolio. As this portfolio has a higher passive component, it is not surprising that the market factor is closer to one than the Yale and ZZ portfolios. There is no statistically significant risk-adjusted performance in any of the ten years.

	Year1	Year2	Year3	Year4	Year5	Year6	Year7	Year8	Year9	Year10	Total
alpha	0.052	0.156	0.051	-0.004	0.031	-0.021	0.015	-0.047	0.023	-0.009	0.031
	(0.061)	(0.103)	(0.079)	(0.119)	(0.076)	(0.076)	(0.064)	(0.059)	(0.044)	(0.064)	(0.025)
market	0.323^{***}	0.954^{***}	0.337^{*}	0.634^{***}	0.203^{***}	0.524^{***}	0.426^{***}	0.352^{***}	0.069	0.292^{**}	0.329^{***}
	(0.069)	(0.152)	(0.132)	(0.100)	(0.031)	(0.072)	(0.074)	(0.045)	(0.055)	(0.086)	(0.021)
R^2	0.298	0.452	0.135	0.470	0.468	0.513	0.400	0.551	0.030	0.186	0.315
Adj. R^2	0.284	0.441	0.114	0.458	0.457	0.503	0.388	0.542	0.011	0.170	0.314
Num. obs.	53	50	44	47	50	52	52	52	53	52	522

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 5: This table shows the alpha and the beta coefficients of the regression of the HARVARD excess returns on the market excess returns for each of the 10 years and the total period. The lower number in parenthesis shows the standard error.

2.3 Style Analysis

Next, we apply a Sharpe style analysis (Sharpe, 1992) to the portfolio returns using the six risky factor portfolios. That is we utilize the following regression:

$$r_{i,t} = \alpha_i + \sum_{j}^{6} \beta_{ij} f_{j,t} + \epsilon_{i,t},$$

where $f_{j,t}$ represents the returns on the benchmark index j. To capture the aspect that the portfolios are mimicked by the benchmarks, we include the standard constraints that the factor loadings are nonnegative, $\beta_{ij} \geq 0$. Because we know from experience that there are a lot of unique assets held, the remaining amount, $1-\sum \beta_{ij}$, may be thought of as residual holdings that are orthogonal to all the six risky benchmarks employed. Of course some of this could be in the form of cash, but more generally these constitute evidence of strategies not adequately explained by any benchmark.

Table 6 shows the results of a constrained regression for the ZZ portfolio. First notice that there is an improvement in the R^2 relative to the case of the aggregated market. Second there is some time variation in the exposures to the various asset classes. There is substantial exposure to emerging market equities, emerging market bonds and emerging market currencies. Exposure to European and US equity markets are reduced. This is in keeping with the mandate of these portfolio managers. The remaining alpha is never statistically significant in any of the years. The uniqueness percentage is substantial and often larger than 50%. The second year was somewhat special with a negative residual weight which could have been due to substantial leverage.

ZZstyle	Year1	Year2	Year3	Year4	Year5	Year6	Year7	Year8	Year9	Year10	Total
Intercept											
alpha	0.231	-0.023	0.174	-0.2	0.135	0.127	-0.068	-0.055	0.023	-0.091	0.057
	(0.156)	(0.119)	(0.129)	(0.184)	(0.111)	(0.074)	(0.056)	(0.067)	(0.051)	(0.067)	(0.032)
Benchmarks											
Equity (Domestic)	0	24.91	0	0	2.25	0.41	0	0	0	0	0
Equity (US)	0	7.77	5.41	0	9.23	4.45	0	7.48	0	0	0
Equity (EM)	26.43	61.97	14.24	22.78	0.16	17.56	17.87	5.27	0	27.68	17.69
Bond (EM)	5.74	31.86	0	2.43	0.83	8.24	3.17	15.71	13.9	21.91	0.99
Currency (EM)	0	21.33	25.41	12.53	12.56	0	15.35	0	17.75	0	23.03
Commodity	8.26	6.37	0	18.51	5.64	8.4	0	0	0	2.42	1.63
R2											
R2	0.13	0.69	0.07	0.21	0.28	0.4	0.32	0.23	0.24	0.48	0.2
Cash											
1-sum	59.57	-54.21	54.93	43.75	69.33	60.94	63.61	71.54	68.36	48	56.67

Table 6: This table shows the weights of the ZZ style anaylsis for each of the 10 years and the total period. The lower number in parenthesis (for alpha) shows the standard error.

Table 7 now indicates the same figures for the Yale portfolio. It is apparent that Yale is exposed more to European and emerging market equities and less so to emerging market bonds and currencies. There is also a small exposure to commodities. Implied unique asset holdings are even more substantial than the ZZ portfolio. The positive alpha is reduced considerably in comparison with the single factor market model.

YALEstyle	Year1	Year2	Year3	Year4	Year5	Year6	Year7	Year8	Year9	Year10	Total
Intercept											
alpha	-0.011	0.05	0.07	-0.155	0.061	-0.022	0.003	-0.032	0.007	-0.033	0.035
	(0.052)	(0.049)	(0.105)	(0.165)	(0.069)	(0.087)	(0.06)	(0.055)	(0.07)	(0.078)	(0.024)
Benchmarks											
Equity (Domestic)	41.13	12.26	0	4.81	7.92	5.44	16.18	2.93	16.32	8.27	10.82
Equity (US)	0	7.87	0	0	0	0	4.55	0	0	0	0
Equity (EM)	9.37	39.94	46.11	12.7	3.2	31.58	9.84	36.78	12.66	15.1	14.56
Bond (EM)	0	0	12.66	0	0	0	0	0	7.12	1.01	0
Currency (EM)	13.97	0	0	0	1.1	0	0	0	0	0	2.43
Commodity	0	10.2	0	24.21	1.11	6.23	2.73	0	0	2.45	2.26
R2											
R2	0.65	0.8	0.33	0.19	0.3	0.51	0.34	0.8	0.23	0.16	0.3
Cash											
1-sum	35.53	29.73	41.23	58.28	86.66	56.76	66.71	60.29	63.91	73.18	69.94

Table 7: This table shows the weights of the YALE style anaylsis for each of the 10 years and the total period. The lower number in parenthesis (for alpha) shows the standard error.

Finally Table 8 shows that the Harvard portfolio is more exposed to emerging market equities, less so to domestic (European) equities and to emerging market currencies. Substantial uniqueness occurs here as well, except for year 4.

HARVARDstyle	Year1	Year2	Year3	Year4	Year5	Year6	Year7	Year8	Year9	Year10	Total
Intercept											
alpha	0.037	0.061	0.034	-0.074	0.074	-0.026	0	-0.011	0.028	-0.003	0.035
	(0.067)	(0.1)	(0.08)	(0.13)	(0.068)	(0.074)	(0.066)	(0.053)	(0.046)	(0.067)	(0.023)
Benchmarks											
Equity (Domestic)	22.67	10.75	0	0	9.74	0	20.19	3.91	0	16.01	6.96
Equity (US)	2.46	4.33	0	21.14	0	0.84	0	0	0	0	0
Equity (EM)	0	57.01	36.02	25.93	10.55	41.18	24.85	26.27	7.62	12.88	22.13
Bond (EM)	17.46	0	0	0	3.41	2.95	0	0	0	0	0
Currency (EM)	11.16	0	0	29.14	1.69	0	0	0	11.05	0	4.3
Commodity	0	3.43	1.69	16.26	2.51	7.3	0	4.68	0	2.73	1.97
R2											
R2	0.35	0.6	0.34	0.53	0.64	0.65	0.45	0.73	0.14	0.26	0.4
Cash											
1-sum	46.25	24.48	62.28	7.52	72.1	47.72	54.95	65.14	81.33	68.38	64.63

Table 8: This table shows the weights of the HARVARD style anaylsis for each of the 10 years and the total period. The lower number in parenthesis (for alpha) shows the standard error.

In summary, we have looked in detail at the overall and risk-adjusted performance of the three student-run portfolios. We find that the portfolios can be understood with a six factor risky set of risky styles along with the returns to a cash account in Euros. Emerging markets is an important component explaining returns for all of the portfolios while the ZZ portfolio is more exposed to bonds and currencies than the other two. Finally there remains a relatively large alpha even after these types of risk-adjustments for the ZZ portfolio, although given the rather short time series, it is not statistically significantly positive.

3 Demographics

We now perform a cross-sectional analysis of these performance attributes of the portfolios and on some demographic information that was retained from the student records. All students were chosen from a competitive pool of applicants, so we have information on their gender, age, nationality, and educational background for instance. We merged these personal data with group composition to perform the following analysis. In this analysis we use demographics to explain the alpha, the beta and the idisyncratic volatility of the market regression from section 2: $r_{EX,i,t} = \alpha_i + \beta_i r_{EX,MSCI,t} + e_{i,t}$

Table 9 lists the various demographic variables. The size of the group is between one and six students. The female variable records the percentage of the group composition who are women. The TUstudent variable refers to the percentage of students who are attending a degree program at the Technische Universität Wien, which is a university that specializes in more technical, mathematically inclined programs. Finally the NOdegree variable is the percentage of students who applied for the program without having yet graduated with a degree.[6]

Demographic Effects

Variable	Description
groupsize	size of the group in absolute figures (e.g. 1-6)
female	relative amount of female students in a group in percentage points
TUstudent	relative amount of TU students in a group in percentage points
NOdegree	relative amount of students without a degree in a group in percentage points (100% equals no degree)

Table 9: This table shows the variables used in the demographic regressions

3.1 Effect of Demographics on Alpha

We use the following regression model to analyze the effect of demographics on the annualized alpha coefficients for all 3 PMP groups over the 10 year time horizon:

$$\alpha_{t,i} = a_i + b_1(groupsize)_{t,i} + b_2(female)_{t,i} + b_3(TUstudents)_{t,i} + b_4(NOdegree)_{t,i} + e_{t,i}$$

where $i = \{$ZZ, YALE, HARVARD$\}$ and $t = \{1, 2, \ldots, 10\}$ years.

[6]This typically would be for students who were still in progress for an undergraduate degree at the start of their time in the program.

	Model 1	Model 2
(Intercept)	0.083	0.080
	(0.108)	(0.110)
groupsize	-0.031°	-0.034°
	(0.016)	(0.017)
female	-0.075	-0.038
	(0.075)	(0.084)
TUstudent	0.076	0.108
	(0.121)	(0.130)
NOdegree	0.105	0.123
	(0.082)	(0.085)
groupYALE		-0.037
		(0.043)
groupZZ		0.011
		(0.042)
R^2	0.223	0.261
Adj. R^2	0.099	0.068
Num. obs.	30	30

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\circ}p < 0.1$

Table 10: This table shows the results of the regression of the annualized Alphas of the 3 PMP portfolios (LHS) on the demographic variables and the group dummy (RHS).The lower number in parenthesis shows the standard error.

Table 10 presents the results of an analysis of all three portfolios for 10 years, i.e., 30 annual results. Aside from the demographic variables discussed above, there are dummies for being in the Yale group and the ZZ group. Therefore the intercept represents the effect of being in the Harvard group and the coefficients on the dummies are the differences to this group. In Table 10 the groupsize coefficient is significant for both models and indicates a negative impact on alpha, i.e. the bigger the group size the lower the alpha. This suggests that groups take less active positions. The adjusted R^2 is higher when groups are not included in the model (no impact due to group). These results find some correspondence with the literature in mutual funds. For instance Bär, Kempf, and Ruenzi (2011) document that there is some (weak) evidence that performance is lower for team managed mutual funds.

3.2 Effect of Demographics on Beta

We use the following regression model to analyze the effect of demographics on the beta coefficients for all 3 PMP groups over the 10 year time horizon:

$$\beta_{t,i} - 1 = a_i + b_1(groupsize)_{t,i} + b_2(female)_{t,i} + b_3(TUstudents)_{t,i} + b_4(NOdegree)_{t,i} + e_{t,i}$$

where $i = \{\text{ZZ, YALE, HARVARD}\}$ and $t = \{1, 2, ..., 10\}$ years. We use $\beta_{t,i} - 1$ to measure the β-deviation from the market ($\beta_m = 1$).

	Model 1	Model 2
(Intercept)	0.132	0.123
	(0.305)	(0.317)
groupsize	-0.078	-0.085
	(0.047)	(0.050)
female	0.136	0.182
	(0.212)	(0.243)
TUstudent	-0.658°	-0.650°
	(0.343)	(0.375)
NOdegree	-0.526^{*}	-0.513^{*}
	(0.231)	(0.245)
groupYALE		-0.014
		(0.124)
groupZZ		0.050
		(0.122)
R^2	0.343	0.351
Adj. R^2	0.238	0.181
Num. obs.	30	30

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\circ}p < 0.1$

Table 11: This table shows the results of the regression of the Betas of the 3 PMP portfolios (LHS) on the demographic variables and the group dummy (RHS).The lower number in parenthesis shows the standard error.

The results in Table 11 show that groups with more students in technical degree programs and groups with more students without a degree take significantly less systematic risk. Here we do not find, unlike Bär, Kempf, and Ruenzi (2011) that group size matters.

3.3 Effect of Demographics on Idiosyncratic Volatility

The following transformation is used to get the demeaned idiosyncratic volatility for all 3 PMP groups over the 10 year time horizon:

$$\Delta\sigma(\epsilon_{weekly,i})_{t,i} = \sigma(\epsilon_{weekly,i})_{t,i} - \bar{\sigma}(\epsilon_{weekly,i})$$

We use the following regression model to analyze the effect of demographics on the annualized demeaned idiosyncratic Volatility:

$$\Delta\sigma(\epsilon_{weekly,i})_{t,i} * \sqrt{(52)} = a_i + b_1(groupsize)_{t,i} + b_2(female)_{t,i} + b_3(TUstudents)_{t,i} + b_4(NOdegree)_{t,i} + e_{t,i}$$

where $i = \{$ZZ, YALE, HARVARD$\}$ and $t = \{1, 2, \ldots, 10\}$ years.

	Model 1	Model 2
(Intercept)	0.056	0.051
	(0.036)	(0.034)
groupsize	-0.009	-0.012^{*}
	(0.005)	(0.005)
female	-0.025	-0.009
	(0.025)	(0.026)
TUstudent	-0.058	-0.065
	(0.041)	(0.040)
NOdegree	-0.005	-0.004
	(0.027)	(0.026)
groupYALE		0.005
		(0.013)
groupZZ		0.030^{*}
		(0.013)
R^2	0.160	0.327
Adj. R^2	0.025	0.151
Num. obs.	30	30

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\circ}p < 0.1$

Table 12: This table shows the results of the regression of the idiosyncratic volatility of the 3 PMP portfolios (LHS) on the demographic variables and the group dummy (RHS).The lower number in parenthesis shows the standard error.

In Table 12 we obtain significance for demographic variables only in the second model. Here we find that the ZZ group takes significantly more idiosyncratic volatility than YALE and HARVARD. Additionally, the groupsize variable is significant and shows a negative sign, i.e. the bigger the group size the lower is unsystematic risk. The adjusted R^2 is higher when groups are controlled for. This is most consistent with Bär, Kempf, and Ruenzi (2011).

3.4 Effect of Demographics on Total Volatility

The following transformation is used to get the demeaned volatility for all 3 PMP groups over the 10 year time horizon:

$$\Delta\sigma(r_{weekly,i})_{t,i} = \sigma(r_{weekly,i})_{t,i} - \bar{\sigma}(r_{weekly,i})$$

We use the following regression model to analyze the effect of demographics on the annualized demeaned total volatility:

$$\Delta\sigma(r_{weekly,i})_{t,i} * \sqrt{(52)} = a + u_i + b_1(groupsize)_{t,i} + b_2(female)_{t,i} + b_3(TUstudents)_{t,i} + b_4(NOdegree)_{t,i} + e_{t,i}$$

where $i = \{$ZZ, YALE, HARVARD$\}$ and $t = \{1, 2, ..., 10\}$ years.

	Model 1	Model 2
(Intercept)	0.077°	0.072°
	(0.039)	(0.037)
groupsize	-0.012°	-0.015^{*}
	(0.006)	(0.006)
female	0.000	0.020
	(0.027)	(0.028)
TUstudent	-0.099^{*}	-0.102^{*}
	(0.044)	(0.043)
NOdegree	-0.022	-0.019
	(0.029)	(0.028)
groupYALE		0.001
		(0.014)
groupZZ		0.029°
		(0.014)
R^2	0.265	0.397
Adj. R^2	0.147	0.240
Num. obs.	30	30

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\circ}p < 0.1$

Table 13: This table shows the results of the regression of the total volatility of the 3 PMP portfolios (LHS) on the demographic variables and the group dummy (RHS).The lower number in parenthesis shows the standard error.

Similarly to the case of idiosyncratic risk the size of the group and the ZZ group indicator are significant. Additionally technically trained students seem to take less risk.

In summary, we find that the major demographic variable that shows up in performance and risk taking is the size of the group. Here it seems that a larger group takes less overall risk and this tends to show up in lower risk-adjusted performance. There are also some differences when there are more technically inclined students. However we find no evidence at all that there are any gender effects on the returns data of our student managed funds.

4 Tournaments

As previously mentioned, one of the unique aspects of the Portfolio Management Program in Vienna is that there have been three groups of students competing since inception. Further each portfolio is managed by a disjoint group of students who have a well-defined starting and ending date, after which the portfolio management is turned over to the next generation. This setting is ideal for identifying the tournament effect whereby losing funds take more risk to try and surpass winning funds by the end of the management year.

4.1 Total Risk

Table 14 shows the pattern of rankings at the end of each cohort year. The ZZ group finished first the most times (five out of ten years), while Harvard was next, with four top finishes. The Yale group only finished first in one year.

	Rank		
	1	2	3
Group			
ZZ	5	2	3
YALE	1	5	4
HARVARD	4	3	3

Table 14: The contigency table relates the final ranking (after one management year) with the group dummy.

Table 15 relates the ranking at the intermediate date (after three quarters) with the ranking at the end of the managerial year. In 7 out of 10 cases the group that was in the lead through the third quarter also finished first at the turnover date. In two out of 10 cases, the fund in second place overtook the first place fund by the end of the year. Hence we can see that there is evidence of reversals of fund orderings in the data.

	Rank (Q3)		
	1	2	3
Rank at the End			
1st	7	2	1
2nd	3	5	2
3rd	0	3	7

Table 15: The contigency table relates the ranking after Q3 with the final ranking (after one management year).

Following Brown, Harlow, and Starks (1996) we evaluate the changes in risk-taking in the fourth quarter of the manager year versus the first three quarters. We then relate this change to the relative ranking of the funds at the end of the first three quarters. That is, we define σ_{Q4} to be the standard deviation of weekly returns in the last quarter and σ_{Q1-Q3} as the standard deviation in the first three quarters. We define the normalized volatility ratio as

$$VR = \frac{\sigma_{Q4}}{\sigma_{Q1-Q3}} - 1.$$

Table 16 illustrates the contingency table involving the three funds. This shows that the fund that is highest ranked in the third quarter only had the highest risk ratio in the fourth quarter one out of ten years. The fund that was ranked lowest had the highest risk ratio six out of ten times. It also appears that funds that were ranked lowest had a risk ratio distribution skewed towards high risk taking as compared to medium or low risk taking. On the other hand, funds in the middle tended to have a very flat distribution of risk taking. Using a Chi-squared test for independence between return rank and volatility ratio rank gives a value of $\mathrm{X}^2 = 6$, with a p-value of 0.1991, which means that the null hypothesis cannot be rejected at a conventional significance level.

	Rank (Q3)		
	1	2	3
Risk in Q4			
high	1	3	6
middle	5	3	2
low	4	4	2

Table 16: This contingency table relates the ranking after the first 3 quarters with the risk taken in the fourth quarter, which is measured in terms of total volatility.

4.2 Idiosyncratic Risk

According to tournament theory, the trailing funds at the end of the third quarter should not only try and increase their risks relative to what they took in the first three quarters, they should do so in a way that is not easily mimicked by the winning fund. To test for this, we run the following regressions on third and fourth quarter fund returns on the MSCI AC world index (our market portfolio):

$$r_{i,Q1-Q3} = \alpha_i + \beta_{i,Q1-Q3} r_{m,Q1-Q3} + \epsilon_{i,Q1-Q3}, \tag{1}$$

$$r_{i,Q4} = \alpha_i + \beta_{i,Q4} r_{m,Q4} + \epsilon_{i,Q4}. \tag{2}$$

We then compute the residual risks from this regression, $\sigma_{i,\epsilon,Q1-Q3}$ and $\sigma_{i,\epsilon,Q4}$ and the normalized idiosyncratic volatility ratio:

$$IVR = \frac{\sigma_{i,\epsilon,Q4}}{\sigma_{i,\epsilon,Q1-Q3}} - 1.$$

Table 17 shows the contingencies between the ranks at the end of the third quarter and the idiosyncratic risk ratio. We see that these results mirror what was already seen in terms of total risk. The highest ranked funds have the lowest risk ratio almost all the time and the frequency of the highest risk ratio is associated with the lowest ranked funds. The Chi-squared test statistic for independence between ranks and idiosyncratic risks yields a value of $\mathrm{X}^2 = 6.6$ with associated p-value equal to 0.1586.

	Rank (Q3)		
	1	2	3
Risk in Q4			
high	1	3	6
middle	4	3	3
low	5	4	1

Table 17: This contingency table relates the ranking after the first 3 quarters with the risk taken in the fourth quarter, which is measured in terms of idiosyncratic volatility.

The results involving return rankings and volatility ratios are illustrated in Figure 4. These are box plots of the return ranking and volatility ratios. The thick line represents the median, the box refers to the 25%

and 75% quantiles and the thin lines reflect the minimum and maximum values. On the left panel we see that there is basically no change in the risk ratio for the highest ranked funds in terms of total risk, while there is increasing risk for both the mid ranked fund and the lowest ranked fund. The right panel shows a similar rank and risk effect for idiosyncratic volatility, except now we notice that the highest funds are actually *reducing* their risks in the last quarter, while the mid and low ranks tend to keep their risks at about the same level. Interestingly, this is the exact prediction obtained by Chen, Hughson, and Stoughton (2013) in their model with three fund tournaments.

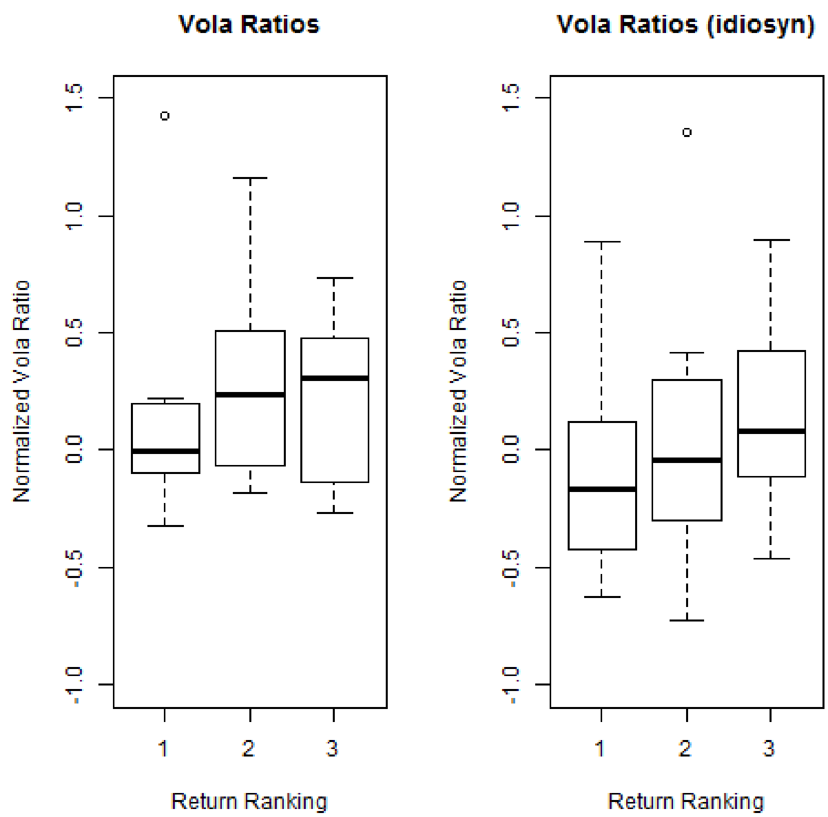

Figure 4: Boxplot of the volatility ratios explained by ranking

These results are also borne out in a linear regression framework with dummy variables representing the return ranks as in Table 18.

	Total	Idiosyncratic
Intercept	0.246^{+}	0.136
	(0.135)	(0.152)
Rank1	-0.121	-0.240
	(0.190)	(0.215)
Rank2	0.051	-0.081
	(0.190)	(0.215)
R^2	0.031	0.045
Adj. R^2	-0.041	-0.025
Num. obs.	30	30

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 18: This table shows the results of the regression of the volatility ratios (LHS) on the ranking (RHS). The lower number in parenthesis shows the standard error.

In Chen, Hughson, and Stoughton (2013) they demonstrated a lock-in effect whereby with three funds the leading fund might not necessarily reduce risk if its lead was not substantial. Therefore, we add an interactive term to the regression framework, by defining the lead ratio as in

$$\text{LeadRatio} = \frac{r_{1,Q1-Q3} - r_{2,Q1-Q3}}{r_{1,Q1-Q3} - r_{3,Q1-Q3}},$$

where $r_{1,Q1-Q3}$, $r_{2,Q1-Q3}$, $r_{3,Q1-Q3}$, are the respective returns of the first, second and third ranked funds over the first three quarters. The interpretation is that this is the relative difference between the first and second fund in relation to the difference between the first and third fund. We then perform the following regression relating the total volatility ratio to the ranks and the interactive term:

$$VR = \alpha + \beta_1 \text{rank1} + \beta_2 \text{rank2} + \beta_3 \text{rank1*LeadRatio} + \epsilon$$

where rank1 and rank2 are indicator variables. We also do the same for the idiosyncratic volatility ratio:

$$IVR = \alpha + \beta_1 \text{rank1} + \beta_2 \text{rank2} + \beta_3 \text{rank1*LeadRatio} + \epsilon.$$

Table 19 shows that total risk was significantly increased by the third ranked fund in terms of total volatility. The increase is of lower magnitude when looking at idiosyncratic volatility. The interactive term has a negative sign, which indicates that indeed risk is reduced when the top fund has a larger lead ratio, in conformity with the theory.

	Total 1	Total 2	Total 3	Idiosyn 1	Idiosyn 2	Idiosyn 3
Intercept	0.246^{+}	0.246^{+}	0.293^{**}	0.136	0.136	0.112
	(0.135)	(0.132)	(0.087)	(0.152)	(0.151)	(0.099)
Rank1	-0.121	0.262		-0.240	0.135	
	(0.190)	(0.321)		(0.215)	(0.367)	
Rank2	0.051	0.051		-0.081	-0.081	
	(0.190)	(0.187)		(0.215)	(0.213)	
I(Rank1*LeadRatio)		-0.790	-0.438		-0.773	-0.511
		(0.538)	(0.276)		(0.614)	(0.314)
R^2	0.031	0.105	0.082	0.045	0.100	0.086
Adj. R^2	-0.041	0.002	0.050	-0.025	-0.004	0.054
Num. obs.	30	30	30	30	30	30

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 19: This table shows the results of the regression of the volatility ratios (LHS) on the ranking and the lead ratio (RHS). The lower number in parenthesis shows the standard error.

4.3 Systematic Risk

We finish this section by considering the impact of systematic risk chasing. Since tournaments theory predicts that the lagging funds should try and take increased risks that are not easily mimicked, they take increased idiosyncratic as opposed to systematic risk. If there are also risk constraints on the overall amount of risks that can be taken, this then implies that the level of systematic risk should *decrease* over the last quarter. From equations (1) and (2) we take the slope coefficients and compute a normalized beta ratio similar to our volatility ratios:

$$BR = \frac{\beta_{i,Q4}}{\beta_{i,Q1-Q3}} - 1.$$

Table 20 considers a linear regression between the ranks and the beta ratios. For robustness, we also consider what happens when we add the interactive term for the leading ratio as defined above. Note that the intercept is statistically significant, indicating that the first fund increases systematic risk in the first model specification relating the changes in betas to ranks. We also find significance for the indicator variable for the third fund, indicating that it decreases systematic risk relative to the first fund. Finally the interactive term shows that when the lead is larger for the leading fund, it tends to increase systematic risk. These findings are completely consistent with tournament theory.

	Model 1	Model 2
Intercept	0.991^{**}	0.452
	(0.322)	(0.719)
Rank2	-0.579	-0.039
	(0.456)	(0.788)
Rank3	-0.852^{+}	-0.313
	(0.456)	(0.788)
I(Rank1*LeadRatio)		1.111
		(1.321)
R^2	0.119	0.142
Adj. R^2	0.054	0.043
Num. obs.	30	30

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 20: This table shows the results of the regression of the beta ratios (LHS) on the ranking and the lead ratio (RHS). The lower number in parenthesis shows the standard error.

These results are illustrated in the form of a box plot in Figure 5.

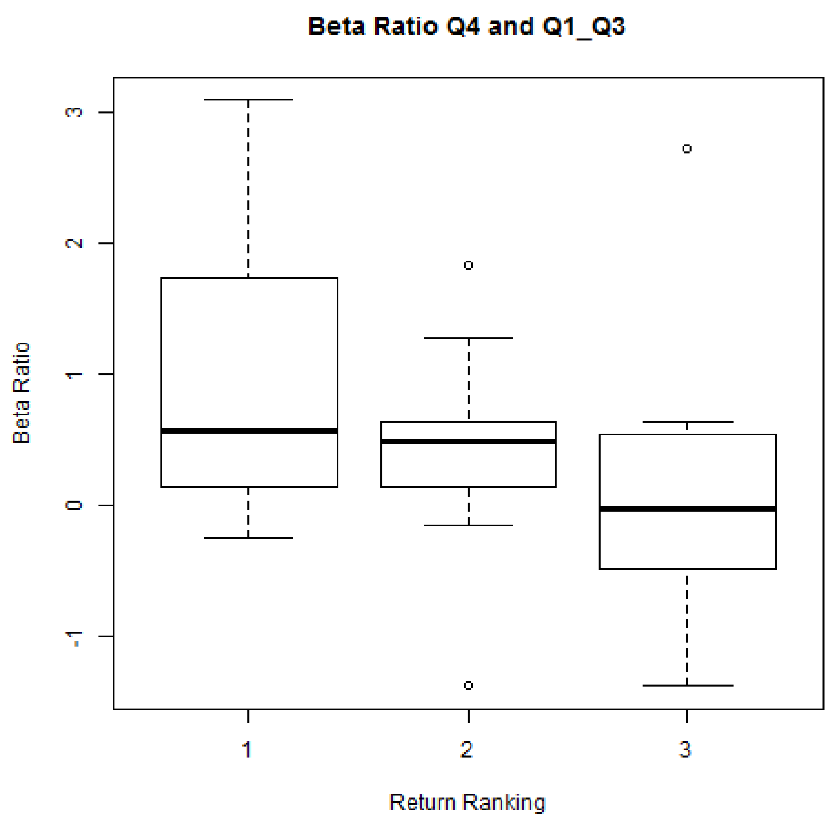

Figure 5: Boxplot of the beta ratios explained by ranking

Note that we looked for differences in risk profiles during the fourth quarter of the managerial term, i.e., at the end. As a robustness check, we re-ran all of our tests using the mid-year risk ratios. We found no relation between these risk ratios and rankings at the mid-year period.[7] Hence, we find support that the tournament effect takes place at the end of the year, as it should in theory.

In summary, we have found strong support for a number of related hypotheses concerning fund tournaments. First, leading funds decrease risk relative to trailing funds and they do so in particular by decreasing absolute levels of idiosyncratic risk. Perhaps because of risk controls, they increase their systematic risk exposures since this is the type of risk that is mimicked by the trailing funds. Further there is a lock in effect whereby the idiosyncratic risk reduction of the leader is greater with a larger lead. The trailing funds increase their risks, with the magnitude being largest for the funds ranked last at the end of the first three quarters.

5 Disposition Effects

Previously we have focused only on returns data which is available for each student-run portfolio. Now we turn to the portfolio weights data and disaggregated pricing data for each asset in the portfolio. We utilize these data to study whether there are any systematic biases in decisions to sell, i.e., to study whether there are disposition effects.

There were some differing procedures involving the management of the portfolios for the first three years, 2004-2007, compared to the remaining seven years. In those earlier years, the entire portfolio was sold off at the end of the year, converted to cash and then the new managers started fresh with new portfolio composition. Beginning in 2007, the portfolio was rolled over in its entirety from year to year and the new managers inherited assets from the old managers. However since they were working as analysts for the same fund, there were elements of continuity during the transition periods. For this reason our study of the disposition effects focuses only on the time period 2007-2014, the last seven years of the portfolio operations.

5.1 Selling Decisions

Figure 6 illustrates the number of assets held in all three portfolios over time. At its peak the ZZ portfolio held the largest number of assets, almost 60 in number. The turnover periods are indicated by the gray lines. As is evident, the number of assets drops significantly around the turnover period as the new managers restructure their portfolio to some extent. The greatest such time period was in June 2010 when the ZZ portfolio sold off about half of their assets.

[7] Numerical results are available from the authors

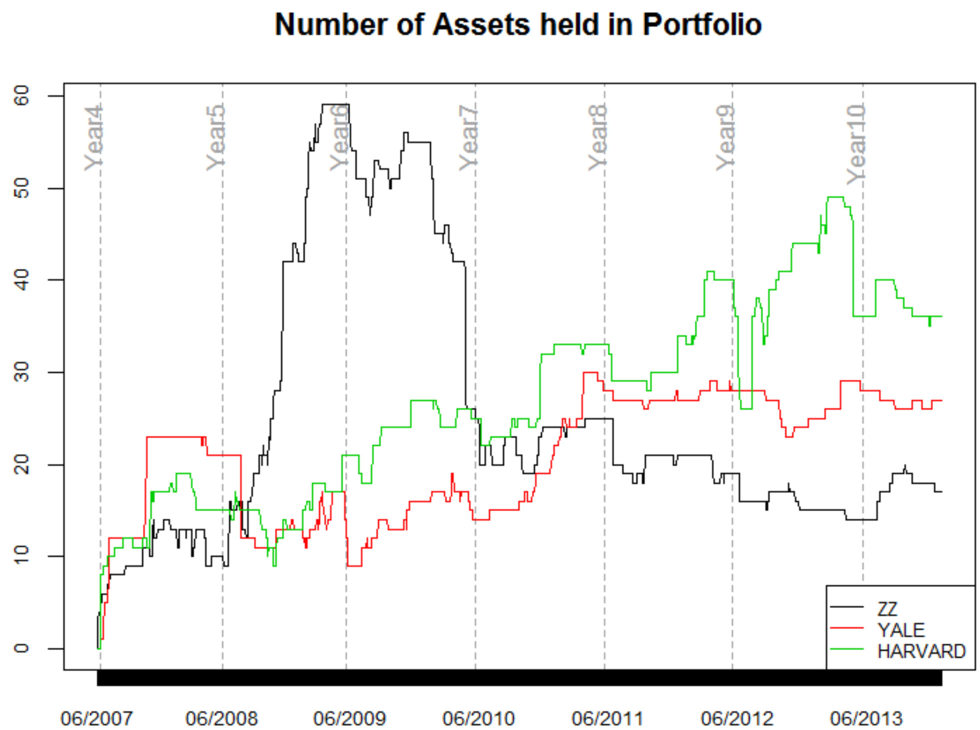

Figure 6: Total number of assets held in the portfolio over time

To test the disposition effect we follow Odean (1998) by measuring the proportion of gains realized compared to the proportion of losses realized. This involves looking at each sales date and computing for each asset in the portfolio the realized gain or loss. Bloomberg prices were used both for each purchase and sale date.[8] The percentage capital gain is computed as $R_{it} = \text{Price}_{it}/\text{Purchase Price}_i - 1$. When $R_{it} \geq 0$, this becomes an asset with a gain, and otherwise a loss. The percentage of gains realized is then the number of gainers sold as a fraction of total gains in the portfolio, $PGR = \text{Realized Gain}/\text{Total Gains}$. Likewise the percentage of losses realized is defined as $PLR = \text{Realized Losses}/\text{Total Losses}$.

Table 21 depicts the results for the last seven years of the program. There were 66 sales dates for the ZZ portfolio, and 51 each for the Yale and Harvard portfolios. This table gives the total gains/losses and realized gains/losses. As can be seen, the PGR is always smaller than the PLR for each of the funds. This indicates that there is a greater propensity to sell losers than there is for gainers. The difference between these two ratios is always negative, $\Delta = PGR - PLR$, and with the computed standard error, is significant at the 5% significance level for both the ZZ and Harvard groups. The difference is insignificant for the Yale group. Overall across all three groups the difference is statistically significant at the 1% level. We have therefore found results opposite to those of Odean (1998), whose sample consisted of small individual retail investors. This is a reverse disposition effect.

[8]A value-weighted average price was used for assets with several buy dates

	Total		Realized		Ratios		PGRminPLR			Count
	Gains	Losses	Gains	Losses	PGR	PLR	Delta	SE	Tstats	SalesDate
Individual										
ZZ	1065	480	74	52	0.069	0.108	−0.039	0.016	−2.400	66
YALE	465	489	34	40	0.073	0.082	−0.009	0.017	−0.502	51
HARVARD	793	519	47	52	0.059	0.100	−0.041	0.016	−2.620	51
Total										
TOTAL	2323	1488	155	144	0.067	0.097	−0.030	0.009	−3.249	166

Table 21: This table shows the proportion of realized gains or losses. The standard errors and the t-statistics are displayed for the the difference between PGR and PLR. We use the following formula to compute the standard errors: $SE = \sqrt{\frac{PGR(1-PGR)}{n_{Gain}} + \frac{PLR(1-PLR)}{n_{Loss}}}$

There are a number of potential explanations why we find a reverse disposition effect. One is that it is simply a different data set, one with a considerably smaller number of decision makers. A more interesting hypothesis is that these are managers with a different "memory". Because managers leave at the end of each year and new managers come in, they are less constrained by past decisions and are therefore more able to sell their losing positions. In many cases these losing positions were established by other managers of a previous generation. Indeed Jin and Scherbina (2010) find a reverse disposition effect for mutual funds where new managers take over, as compared to those where old managers continue to run the fund. In a recent paper, Hartzmark (2013) finds results similar to Odean using retail investors but for a separate sample of mutual funds he finds also a reverse disposition effect. Another possible reason for the reverse disposition effect is that managers operate as a group and not as individuals. This points to the possibility that group decision making is different from individual decision making, which we have found some support for in our section on demographics. Of course another possibility is that the managers, being students at business schools who study finance intensively and are advised by academic faculty are aware of some of the behavioral biases and in fact seek consciously to avoid them. Indeed at the weekly sessions at which decisions are discussed and defended, students in the program are compelled to explicitly address the failure of a position, which might lead them to eliminate it.

We also implemented the test of Hartzmark (2013), which involves looking at the propensity to sell the assets in the tails of the capital gains distribution. That is we define the percentage of best, worst and middle sold by:

$$PBS = \text{Best Sold}/(\text{Best Sold + Best Not Sold}),$$

$$PWS = \text{Worst Sold}/(\text{Worst Sold + Worst Not Sold}),$$

$$PMS = \text{Middle Sold}/(\text{Middle Sold + Middle Not Sold}).$$

The middle assets are all assets for which a Bloomberg price was available and which are neither the best nor the worst asset.

Table 22 shows the results for these extreme assets. Of course the sample of best assets that are sold (or not sold) and the set of worst assets sold (or not sold) is very small. We find interestingly, that there is a tendency to sell more of the tails of the capital gains distribution than assets in the middle.

	Best		Worst		Middle		Ratios		
	Sold	NotSold	Sold	NotSold	Sold	NotSold	PBS	PWS	PMS
Individual									
ZZ	10	56	12	54	106	1342	0.152	0.182	0.073
YALE	8	43	8	43	58	807	0.157	0.157	0.067
HARVARD	5	46	7	44	87	1151	0.098	0.137	0.070
Total									
TOTAL	23	145	27	141	251	3300	0.137	0.161	0.071

Table 22: This table shows the absolute and the relative proportion of the best, middle and worst assets sold. Additionally, the standard errors and the t-statistics are computed.

We also look at the difference between these ratios and test for significance. Table 23 shows that the difference between best and worst is not significant, but that the difference between selling the best compared to the middle is marginally significant for the ZZ and Yale groups. The highest significance is obtained by the ZZ group in selling the worst assets compared to the middle range.[9]

	Best-Worst			Best-Middle			Worst-Middle		
	Delta	SE	Tstats	Delta	SE	Tstats	Delta	SE	Tstats
Individual									
ZZ	−0.030	0.065	−0.467	0.078	0.045	1.753	0.109	0.048	2.264
YALE	0.000	0.072	0.000	0.090	0.052	1.740	0.090	0.052	1.740
HARVARD	−0.039	0.064	−0.616	0.028	0.042	0.657	0.067	0.049	1.375
Total									
TOTAL	−0.024	0.039	−0.613	0.066	0.027	2.465	0.090	0.029	3.141

Table 23: This table shows the difference of the relative proportions of the best, middle and worst assets sold. Additionally, the standard errors and the t-statistics for the difference tests are computed.

5.2 Logit Analysis

Obviously there are a large number of factors that can enter into a decision to sell, other than just whether there is a gain or loss, and to the extent that we have data, we have implemented a logit regression to identify other factors influencing sales. The approach followed here is similar to Ben-David and Hirshleifer (2012) and Hartzmark (2013). We define Sell as an indicator variable in the following specification:

$$\begin{aligned}\text{Sell} = {} & d_1(\text{LossDummy}) + d_2(\text{Return*GainDummy}) + d_3(\text{abs(Return*LossDummy)})\\ & + d_4(\text{BestDummy}) + d_5(\text{WorstDummy}) + d_6(\text{Return*GainDummy*sqrt(holdingTime)})\\ & + d_7(\text{Return*LossDummy*sqrt(holdingTime)}) + d_8(\text{sd250*GainDummy})\\ & + d_9(\text{sd250*LossDummy}) + d_{10}(\text{weight}) + d_{11}\text{sqrt(holdingTime)}\\ & + d_{12}(\text{SoldBySameGroup}) + d_{13}(\text{SoldByNextGroup}) + d_{14}(\text{style})\end{aligned}$$

9 We also run tests for the top five and top 3 assets in a manner similar to this and found analogous results.

Table 24 contains the definitions of the right hand side variables for the logit estimation.

Logit Regression	
Variable	**Description**
Sell (LHS)	dependent Variable: 1 if asset was sold on sell date (t), 0 if it was not sold
GainDummy	1 if it has positive return (since purchase), 0 otherwise
LossDummy	1 if it has negative return(since purchase), 0 otherwise
BestDummy	1 if it is the Best ranked asset with highest return since purchase, 0 otherwise (Middle, Worst)
WorstDummy	1 if it is the Worst ranked asset with the lowest return since purchase, 0 otherwise (Middle, Best)
Return	Return since purchase date (price at sales date (s) divided by the value weighted purchase price)
sd250	Standard deviation of daily price returns from 250 days prior to selling date
weight	Relative portfolio weight of each asset (all weights sum up to 1 for each selling date)
holdingTime	Time in days since purchase date
SoldBySameGroup	1 if the manager group at purchase and sell date are the same, 0 otherwise
SoldByNextGroup	1 if assets is sold by succeeding (next) manager group (analysts at purchase), 0 otherwise
style	categorical variable indicating the 3 investment philosohies: ZZ, YALE, HARVARD

Table 24: This table shows the variables used in the logit regression

The actual logit estimation is performed on the following equation:

$$y_{ijs} = a + d_1 z_{1,ijs} + \dots + d_n z_{n,ijs} + b_1 x_{1,ijs} + \dots + b_n x_{n,ijs} + u_i + e_{ijs},$$

where $i = \{\text{ZZ, YALE, HARVARD}\}$, $j = \{\text{various stocks held at each sales date}\}$ and $s = \{\text{sales dates}\}$. $y_{ijs} = 1$ if a stock (j) is sold at sales date (s) from group (i) and 0 otherwise. The variables z_n and d_n stand for categorical indicator variables and their coefficients, x_n and b_n represent continuous variables and their coefficients.

Table 25 shows the results of the logit regression. Four model specifications are tested: (1) only includes a loss dummy and the return interactions; (2) includes the ranking; (3) includes additional control variables; (4) introduces style dummies. We find importantly that the reverse disposition effect shows up here also. The loss dummy variable is significantly positive. We find that this implies that a losing asset is almost one and a half times as likely to be sold as a winner (for Model 1). The asset ranking (best, middle, worst), however, does not show up significant when control variables are added. This contradicts a possible rank effect. Also there is a strong tendency to sell a loser when it has a more extreme capital loss (the interactive effect), which is not true for gainers. Assets with capital gains are more likely to be sold when there is high past volatility. The same is not true for losers however. Additionally, larger positions with a higher weight of the total portfolio are significantly more likely to be sold than smaller positions. Interestingly, the holding time of an asset does not show up significantly when we control for specific groups that sold an asset. Assets are less likely to be sold by the same (current manager) group as well as by the next (current analyst) group. These findings suggest that the holding time of an asset itself is *not* crucial whether it gets sold or not, but rather whether the groups (managers and analysts) were involved in the original purchase and initiated it under their watch. Hence, succeeding groups that were not directly involved in the initial buying process are more likely to sell an asset. Finally our findings do not depend on the 3 investment styles since those control indicators have insignificant coefficients.

	Model 1	Model 2	Model 3	Model 4
(Intercept)	-2.948^{***}	-2.930^{***}	-3.126^{***}	-3.269^{***}
	(0.114)	(0.114)	(0.483)	(0.497)
LossDummy	0.365^{*}	0.350^{*}	0.644^{**}	0.645^{***}
	(0.169)	(0.170)	(0.196)	(0.196)
I(Return * GainDummy)	0.926^{***}	0.705^{**}	1.250^{+}	1.395^{*}
	(0.218)	(0.252)	(0.647)	(0.660)
I(abs(Return * LossDummy))	1.557^{***}	1.441^{***}	3.858^{**}	4.087^{**}
	(0.344)	(0.413)	(1.267)	(1.278)
BestDummy		0.528^{+}	0.442	0.404
		(0.281)	(0.287)	(0.293)
WorstDummy		0.150	0.026	-0.036
		(0.281)	(0.295)	(0.299)
I(Return * GainDummy * sqrt(holdingTime))			-0.035	-0.038
			(0.034)	(0.034)
I(abs(Return * LossDummy * sqrt(holdingTime)))			-0.143^{*}	-0.145^{*}
			(0.063)	(0.063)
I(sd250 * GainDummy)			17.163^{***}	18.722^{***}
			(3.913)	(4.104)
I(sd250 * LossDummy)			2.794	3.263
			(3.255)	(3.428)
weight			4.010^{*}	4.444^{*}
			(1.712)	(1.752)
sqrt(holdingTime)			0.005	0.004
			(0.019)	(0.020)
SoldBySameGroupDummy			-0.556^{+}	-0.553^{+}
			(0.322)	(0.322)
SoldByNextGroupDummy			-0.460^{+}	-0.455^{+}
			(0.238)	(0.238)
styleYALE				-0.038
				(0.179)
styleHARVARD				0.274
				(0.167)
AIC	2079.204	2079.606	2058.464	2058.343
BIC	2104.265	2117.198	2146.180	2158.589
Log Likelihood	-1035.602	-1033.803	-1015.232	-1013.171
Deviance	2071.204	2067.606	2030.464	2026.343
Num. obs.	3887	3887	3887	3887

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 25: Logit regression with dependent variable being 1 if asset got sold and 0 otherwise.
4 models are displayed: Model 1 only includes a loss dummy and the return, Model 2 adds dummies for the best and the worst ranked assets, Model 3 adds additional control variables, Model 4 adds style dummies. The lower number in parenthesis shows the standard error.

Our logit analysis is also notable for what is not picked up. Asset rankings only have a minor explanatory power. There does not seem to be a tendency that new managers, after positions are rolled over, completely reverse the strategy of their predecessors and sell off old positions.

The results from the simplest logit model (1) are illustrated in Figure 7. The left panel shows the sample as well as the fitted values; the right panel just the fitted values. The difference at zero gains/loss picks up the intercept in the logit regression and the slopes represent the magnitude of the return since purchase. Figure 7 shows an increase in the selling probability with higher absolute returns. This effect is even stronger for losers than for winners.

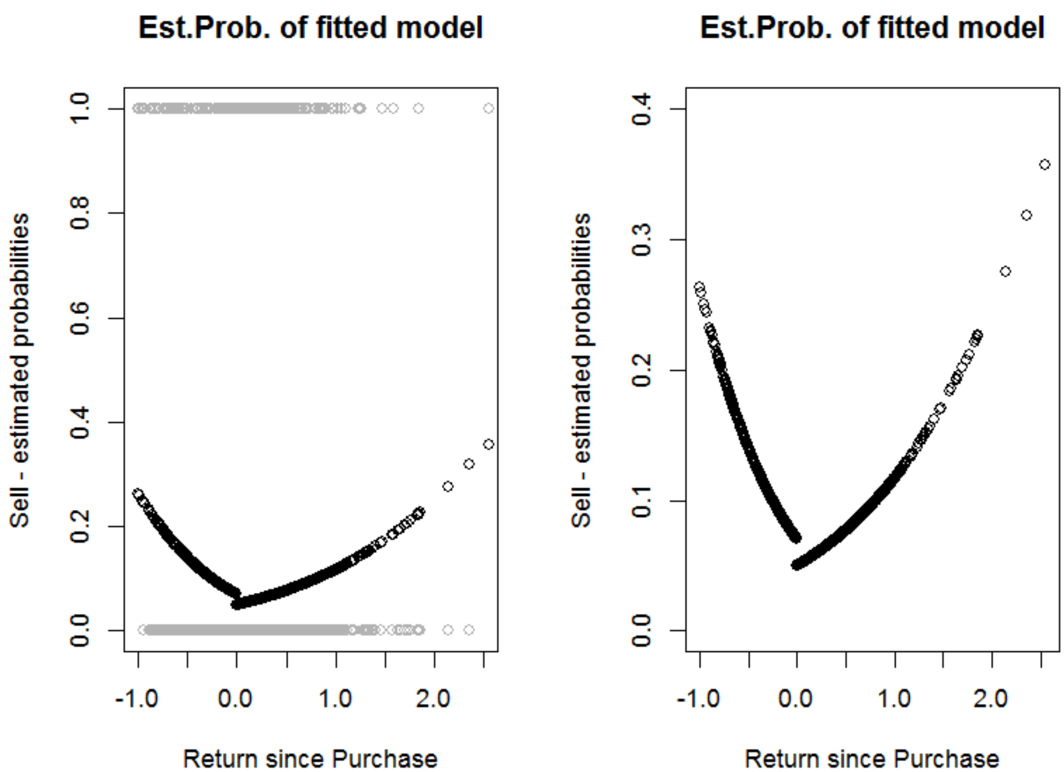

Figure 7: Left: Shows the actual realisation (grey) and the estimated probabilities (black). Right: Is the same as the left one but zoomed in. The slope for negative returns is higher than for positive ones. Additionally, there is a positive intercept for losers increasing the probability of selling.

In conclusion we have documented a significant reverse disposition effect and shown that this persists with a large number of controls. Despite the major differences in group composition and mandates, there is a similarity in the ingredients of asset sales across all of the groups. One possibility is that these groups are all educated in the theory of modern finance to a consistent manner and present their management strategies to a common audience. They are supervised by professors and tutors with common research backgrounds as well.

6 Conclusions

Although the magnitude of money invested is relatively small, the presence of student-run investment funds has been very influential not only for the thousands of students who have gained considerable experience and gone on to stellar careers, but also for the faculty who have served in advisory and tutorial capacities. We believe that the experiences over the first ten years of the PMP program in Vienna Austria can be beneficial in highlighting two important facets of asset management: the tournament effect and the disposition effect. Similar to a laboratory experiment, the program–like others around the world–is designed by academic researchers with specific features such as the amount of money under investment, the scope of investment opportunities, the composition of group decision-making, the interface to university coursework, the involvement of practicing professionals and, of course, the design of the reward system. Unlike a laboratory experiment however, the investment decisions take place in the real world, with actual prices, information asymmetries, trading costs, and group dynamics that cannot be precisely controlled by the academic researchers.

We have argued in this paper this kind of "natural experiment" is not only useful for the obvious development of the students, but also to deepen the understanding about the role that academic education plays in investment behaviors that have been observed in larger samples of individuals and financial institutions. Specifically if faculty are influential, the form of investment decisions ought to be different from those outside the university setting. We find some qualified support for this idea, which may be due to the well-defined limited tenure of the student managers. In the student-run setting there are limits to fund flow effects. Yet, we find that merely the motivation of winning an internal competition between funds can lead to the tournament effects of risk-chasing, mimicking and attempting to lock in a lead. Of course these are rational responses given the aspects of the tournament reward system. While we do not intend to extrapolate from our three fund experience, these incentives have not in general hampered overall performance over a ten year period. The reversal of the disposition effect, which we believe is strongly related to the two year tenure of students within each fund (first year as analysts and second as managers) can have positive benefits for the fund if it leads to more robust assessments of investment opportunities. This, may be a consequence of the lack of fund flows as well, since to free up funds to invest in new opportunities, some assets must be sold.

It might be tempting to conclude that one implication of our study is that there are benefits to shortening the managerial tenure of fund management. We would prefer not to make this interpretation since this is not a broad based study involving enough fund managers to establish reliable inference for this hypothesis. Instead, we believe the natural experiment affords a better test of the pervasiveness of these two investment management effects. We hope that this paper will encourage other such studies and further research on other behavioral finance theories.

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