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LESSONS LEARNED FROM STUDENT MANAGED PORTFOLIOS*

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We study asset management decisions of three competing student managed funds in Vienna, Austria for a ten-year period. This real-world experience allows us to precisely test the tournament effect of fund management, the disposition effect, and managerial team size. We find support for risk taking by the trailing funds in an annual tournament, and risk reductions by leading funds. The disposition effect usually observed in the case of retail investors is reversed. Finally, we find that smaller management teams outperform larger ones. Using a partly controlled setting, we relate the results to practice in the areas of institutional client evaluation of managers and the social and organizational structure of asset management companies.

1 Introduction

In the last 30 years, the field of behavioral finance has largely focused on the decisions made by individual investors. During the same period institutional ownership percentages in equities and the magnitude of assets under management have soared. It is therefore important to understand how behavioral finance relates to asset managers, e.g., money managers, investment advisers, consultants, etc. Nevertheless, it is often difficult to obtain direct evidence about the inner workings of such organizations because of proprietary and strategic reasons. In this paper, we use a partially controlled setting with student investors making real-world investment decisions to focus on three important patterns observed in practice: the tournament effect of risk-taking incentives in fund management, the disposition effect of selling decisions in portfolios, and the implications of team size with respect to fund management decisions.

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In doing so, we utilize a unique data set of actual portfolio decisions made by teams of student-run portfolios for a ten-year period. Our study provides important evidence on team decision-making, and results are significant despite the relatively small sample used in this case study. Even though the advantage of using experiments to study behavioral finance has been documented previously (Raghubir and Das, 1999), the vast majority of experimental studies are oriented more at individuals rather than money managers. Through the precise design of the Vienna Portfolio Management Program (PMP), we can address some of these behavioral theories in a setting with substantial monetary rewards and with a program design that is more like the actual asset management industry. Our findings allow us to draw implications for fund management practices in two principal dimensions: (1) institutional client perspectives on the choice of asset managers in a competitive environment, and (2) the social and organizational form of fund management companies, themselves.

Our empirical analysis is based on the portfolio management decisions of three PMP funds over the first ten years (2004–2014) of their existence. We are able to do this because the PMP data set contains actual decisions with real monetary consequences. The first test we conduct is related to the theory of tournaments. According to this theory funds that are trailing at an intermediate date have incentives to take on more risk than those that are in the lead. We are able to focus on this effect 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, and only ten annual tournaments, it is remarkable that we still find statistically reliable support for not only the main tournament hypothesis, but also for 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 key implication for industry practice is that with such a form of managerial competition, institutional clients must be aware of the implicit incentives to stray too far from benchmarks when they are behind or to converge to excessively passive strategies when they are ahead.

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. Most existing work, e.g., Barber and Odean (1999), looks at retail investors. Because of our specific data and the records of asset sales and purchases, we are able to test this within a multi-manager and multi-fund context. Interestingly, 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 these results may derive from a form of "window dressing" incentive due to disclosure of portfolio holdings. The main implication for industry practice in this regard is that newly recruited fund managers may engage in forms of window dressing that can confound performance evaluation. Moreover, our results highlight that reverse disposition is even stronger with more frequent managerial rotation.

We finish with an analysis of the size of the managerial teams. There is exogenous variation in the size of each managerial group due to attrition before the second year. We find that team size matters and smaller groups have higher absolute (non-risk-adjusted) performance while taking more idiosyncratic risk. This extends a recent literature that has exclusively focused on mutual funds. Moreover since the mutual fund results are net of expenses, our data are interesting since fees are not incorporated.

Behavioral finance theories and the academic evidence are summarized, for example, in Barberis and Thaler (2003). 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 *et al.* (1996). We employ some tests that are similar to Brown *et al.* (1996) although we have more frequent data which enables us to extend their tests to other more refined aspects of strategic tournament play such as those identified in the model of Chen *et al.* (2018). The disposition effect was first discussed in the finance context by Shefrin and Statman (1985). An 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 *et al.* (2009) use this same data set to analyze the experiential behavior of individual investors. Other relevant papers are those of Ben-David and Hirshleifer (2012), who conduct a probit test of the disposition effect, Dhar and Zhu (2006) and Jin and Scherbina (2010), who find a reverse disposition effect as we do but with respect to mutual funds with managerial turnover and Hartzmark (2014), who not only considers the disposition effect but also a "rank effect". The disposition effect is also discussed in Chang *et al.* (2016). Effects on group size in the context of mutual funds have been found also by Bär *et al.* (2011). Patel and Sarkissian (2017) and Goldman *et al.* (2016) also make important contributions to the debate on this for mutual funds.

The literature on student-run investment portfolios is quite meager. 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. 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. Drawing upon the experiences of the student funds at Brigham Young University Sudweeks *et al.* (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 *et al.* (2011) posit a technical trading rule, backtest 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 is addressed to students who are currently engaged in a portfolio management program.

We begin with a short introduction to the funds performance in Section 2. The tournament effect is discussed in Section 3, the disposition effect in Section 4 and the team size effect in Section 5. Section 6 concludes the paper. Some technical details about the performance analysis are presented in the Appendix.

2 Portfolio performance

2.1 Background

This study comprises ten years of portfolio data from three student-run funds in the Vienna *Portfolio Management Program* (PMP). The PMP is a privately sponsored program organized at the WU Vienna University of Economics and Business with students from that university as well as two others nearby.

Three portfolios 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 have governed their investment strategy to this day. The *ZZ* fund is managed in an *"entrepreneurial"* fashion with a focus on cash flow yield.[1] 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 *YY* fund and the *XX* fund are both modeled after two prominent US university endowments. Both funds have a mandate consisting of the strategic asset allocation weights that are derived from the annual reports of these US endowments. The emphasis of the *YY* fund is on active management. This is usually accomplished by actively picking stocks, using active funds or making up a basket of positions using fundamental analysis. The goal of the *XX* fund, on the other hand, is to invest using passive investment instruments such as exchange-traded funds (ETFs). The only explicit constraint of the *XX* fund is that only up to 70% are allowed to be allocated to passively managed assets. None of the funds are given explicit benchmarks.

The format of the program involves overlapping generations. The PMP program is typically two years in length for all students. The first year involves serving as an "analyst". Those students who are admitted to the program are randomly assigned into the three 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.

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.[2] The program is also listed as a formal course at the 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 (Sharpe ratio) performance of their own portfolio, as well as how they do in their presentations and exercises at the weekly sessions.

Table 1 contains some descriptive statistics from the program which will be used in later sections. We provide both the average and median values for a number of variables. There are about one-third female students. The managerial team size averages about four in number, and has ranged from a minimum of two to a maximum of six. Originally six students are selected for each fund in the analyst year, however, there is attrition by the time the managerial year rolls around. Based on the experience of the instructors, attrition is not

Table 1

	Characteristics					Portfolio	Sales
	Female	Teamsize	TU students	NO degree	Age	Positions	Total Number
XX							
Mean	0.28	4.1	0.08	0.72	24.72	27.10	51
Median	0.22	4.0	0.00	0.71	23.97	27.00	
YY							
Mean	0.38	3.8	0.16	0.73	24.42	20.80	51
Median	0.37	4.0	0.20	0.75	24.37	23.00	
ZZ							
Mean	0.14	4.5	0.14	0.75	24.23	24.48	66
Median	0.00	4.5	0.18	0.80	24.27	19.00	

This table shows the mean and the median of the demographic variables and the number of positions held in the portfolio. Additionally, the total number of sales over the last seven years for each of the three funds is displayed in the last column. The column Female indicates the fraction of the manager team that are female, the column teamsize is the number of students, the column TU students is the fraction of the team who studied at the TU University, the column NO degree is the fraction of the students who entered the program without first having a degree, and Age is the age at the time of entry into the program.

due to fund underperformance, rather it is a matter of personal circumstances, e.g., some students decide to take advantage of a study abroad year in which case they must leave the program, others get a job in another location or decide to transfer to a degree program elsewhere. As a result of this there is a random effect on the number of managers in the second year, which we exploit in the analysis in Section 5. A small fraction of the students come from a mathematical finance program (TU students); the others are enrolled in a more general program. The majority of students did not have a degree at the time of entry (they were bachelor students in a five-year program). Their age was about 24 years. The portfolios consisted of roughly 20 different positions at any point in time and the total number of sales equaled around 50–60 during the last seven years of the study.

We should also emphasize that there are three main features that feature importantly in identifying the strategic behavior in our study: (1) there are three separately managed portfolios that are competing with one another; (2) the students are given a very large investment universe to analyze and explore, without any explicit benchmarks; and (3) the program has a definitive terminal date after which management responsibilities are transferred and the students graduate.

2.2 Data

In addition to fund characteristics, we also use a data set consisting 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.[3] In addition, we have collected the asset purchase and sales dates along with the associated asset prices from Bloomberg, which are later used in the analysis of the disposition effect.

2.3 Performance and benchmarks

We illustrate the total return performance of the three funds in comparison to a commonly used

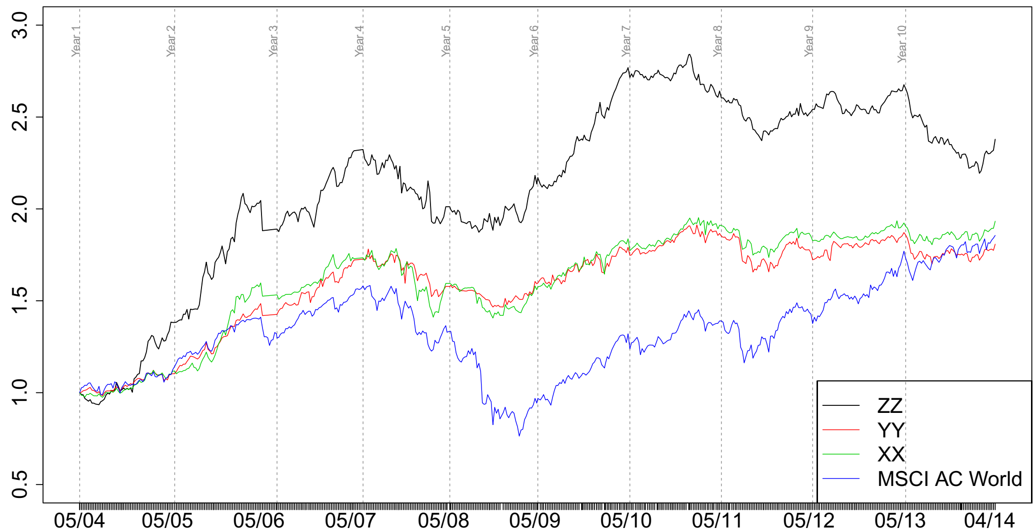

Figure 1 The chart presents the total return performance of the three PMP funds (ZZ, YY, XX) in comparison to the MSCI AC World index. Discrete weekly returns are used over a ten-year period starting in May 2004.

index of both developed and emerging market international equities, the MSCI All Country World Index. 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 funds 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% while the other two student-run funds were up by about 75%. Compared to the MSCI AC World index, the ZZ fund experienced strong outperformance over the ten-year period, while XX and YY had better cumulative performance over the first nine years, falling back into conformity by May 2014.

2.4 *Risk-adjusted performance*

Since the three funds do not have an explicit benchmark and their strategies vary widely across

Table 2

	Ticker	Name	Asset Class
Benchmarks			
1	STOXX	STOXX 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

The table shows the Bloomberg Ticker and the name of the benchmarks used in the style analysis. The last column refers to the asset class that is attributed to the different benchmarks in the style analysis.

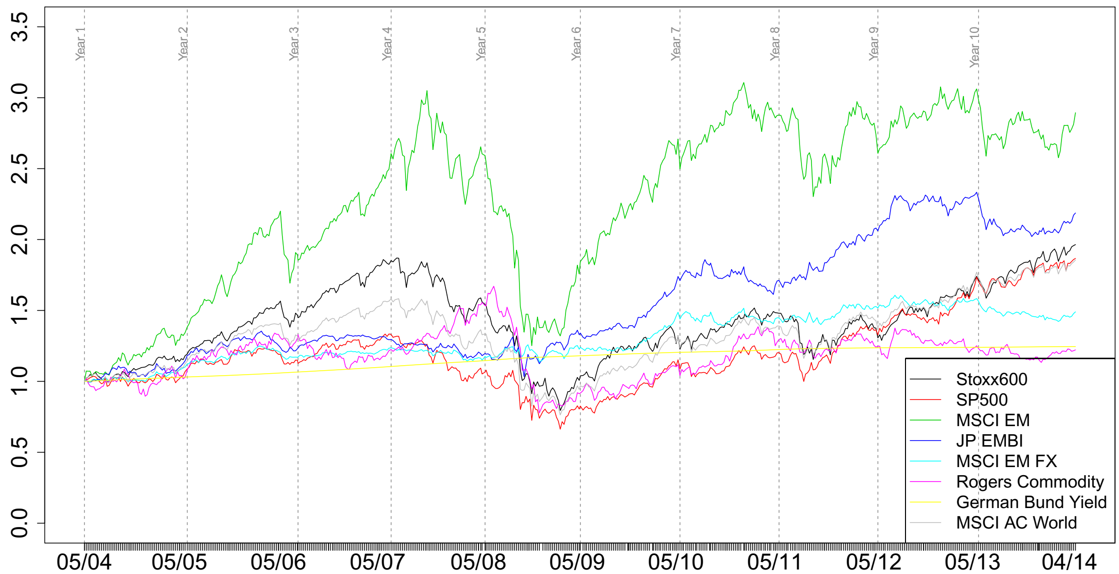

Figure 2 The chart presents the total returns performance of various benchmarks used in the style analysis over a time period of ten-years starting in May 2004. Discrete weekly returns are used.

markets, asset classes, and over time, we follow Sharpe style analysis to identify yearly custom benchmarks. We selected an additional seven indexes for the style analysis. These indexes are listed in Table 2. 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.

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

Table 3

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Total
Sharpe Ratios											
Market	0.74	1.70	2.22	—	—	1.74	0.86	—	2.29	0.66	0.25
ZZ	2.32	1.91	2.25	—	0.43	2.80	—	—	0.79	—	0.60
YY	0.92	2.89	2.13	—	—	0.69	0.63	—	1.07	—	0.42
XX	1.15	2.62	1.52	—	—	0.96	0.73	—	0.91	0.15	0.48
Alphas											
ZZ	0.23	−0.02	0.17	−0.20	0.14	0.13	−0.07	−0.06	0.02	−0.09	0.06
YY	−0.01	0.05	0.07	−0.16	0.06	−0.02	0.00	−0.03	0.01	−0.03	0.04
XX	0.04	0.06	0.03	−0.07	0.07	−0.03	0.00	−0.01	0.03	0.00	0.04

The table presents the annualized Sharpe ratios of the three PMP funds (ZZ, YY, XX) in comparison with the Sharpe ratio of the market index (MSCI AC World) for each of the ten-years as well as the total ten-year period. In the table the entry "–" indicates a period where the *ex post* value is negative. The lower panel ("Alphas") shows the alpha values of the three PMP funds when regressed on their style portfolio as documented in Appendix A.

strongest overall performance while commodities were weakest.

We compute Sharpe ratios using the volatility of the weekly returns, σ_i. Excess returns are computed on a weekly basis by deducting the risk-free rate, $r_{f,t}$, from the fund returns, $r_{i,t}$.[4] The explicit formula for the Sharpe ratio can be written as:

$$SR_i = \frac{r_i^{EX}}{\sigma_i},$$

with $r_i^{EX} = \Sigma_{t=1}^{n} r_{i,t} - r_{f,t}$, where n is the number of time periods over which the Sharpe ratio is computed (e.g., weeks during a year).

We also compute the risk-adjusted performance as alphas relative to each funds custom benchmark from the Sharpe style analysis. We employ a multiple constrained linear regression analysis as discussed in Appendix A to identify the style weights. The annual details are also described in this Appendix.

Table 3 serves as an overview of the Sharpe ratios and the annualized alphas for each of the ten manager years and the whole ten-year period. There is considerable variation among the funds on a year-by-year basis. Nevertheless there is clearly very good overall performance and relative performance compared to a custom benchmark based on the six risky indexes.

3 Tournaments

One of the unique aspects of the Portfolio Management Program in Vienna is that there have been three student-run funds, XX, YY, and ZZ, competing with each other since inception. Each of these funds is managed by a disjoint group of students for a well-defined period of time, where the start and end dates at which the portfolio is turned over to the next generation are exogenously given. This setting is ideal for testing the tournament effect whereby trailing funds take more risk to try and surpass winning funds by the end of the management year. In order to test this hypothesis we look at contingency tables as in Brown *et al.* (1996) and attempt to reject the null hypothesis of independence between changes in risk taking in the fourth quarter and the ranking at the end of the third quarter. We also take advantage of the strategic lock-in effect of Chen *et al.* (2018) in a linear regression framework in order to investigate the interactive effect of the size of the lead with the top ranked fund.

3.1 Rewards

We first want to establish that there are significantly greater overall rewards from finishing first in terms of total return at the end of the year. There are three major forms of compensation received by the students: (1) monetary prizes given to the top performing fund; (2) higher grades in the course for finishing first; and (3) better employment opportunities. The first is clear. We also provide support for the second and third categories.

As mentioned previously an important component in the grade is the ranking of the fund at the end of the year. We have examined the records for eight of the ten-years.[5] Based on these grades we provide the following contingency table showing the probability of receiving each grade 1 through 5, where grade 1 is the equivalent of an "A" in the American system and grade 5 is equivalent to failing the course. Table 4 shows the probability of receiving each grade based on the respective ranks.

The vast majority of students either received a grade of 1 or 2. As can be seen from Table 4 it was far more likely that students who finished first received the highest grade than those finishing either second or third. On the other hand, with a lower grade of 2, it was more likely that they finished either second or third compared to finishing first. This supports the claim that a tournament

Table 4

	Rank at the end		
	1	2	3
Grades			
1	0.56	0.32	0.12
2	0.28	0.34	0.37
3	0.50	0.33	0.17
4	0.33	0.33	0.33
5	0.25	0.25	0.50

The table shows a contingency table that relates the ranking at the end to the grades received by each student. Grade 1 stands for "excellent", while grade 5 stands for "failed". The table can be interpreted as follows: of those who received a grade of 1, 56% finished first, 32% finished second, and only 12% finished third. Of those with a grade of 2, 28% finished first, 34% finished second, and 37% finished third.

over total returns is directly related to the grades received.

Most of the students graduated are now based in money management firms throughout Europe. Trying to measure the quality of the firms that recruited each graduate is fraught with difficulty and privacy regulations did not allow us to ascertain their starting salaries. Nevertheless we can provide some support that having a higher finishing rank led to receiving a prestigious position with the sponsoring money management firm. We have anecdotal evidence that the sponsoring firm paid well and that when graduates had competing offers they were more likely to accept one from the sponsoring institution. Table 5 shows a similar contingency table of probabilities that a student would either be employed at the sponsor firm or not, based on their funds ranking at the end of the year. We find that when a student received and accepted an offer of employment from the sponsor it was much more likely that their fund finished at the top. When the student did not accept an offer, there was very little difference in how their fund performed.

Table 5

	Rank at the end		
	1	2	3
Employment			
Yes	0.45	0.25	0.30
No	0.32	0.36	0.32

The table shows the contingent probability of the ranking at the end of the year to the likelihood of being employed at the sponsor. The table is based on the following formula $P(\text{ranking} \mid \text{employment})$ and can be interpreted as follows: 45% of the students, who were employed, where ranked first, whereas only 25% and 30% were ranked second and third.

Based on the evidence presented above we have found direct evidence that fund ranking led to higher course grades and a very good job opportunity upon graduation. All of these measures were based on total return ranking, unadjusted for risk.

3.2 Total risk

Table 6 shows the pattern of rankings at the end of each cohort year. The ZZ fund finished first the most times (five out of ten-years), while XX was next, with four top finishes. The YY fund only finished first in one year.

Table 6

	Rank		
	1	2	3
Funds			
ZZ	5	2	3
YY	1	5	4
XX	4	3	3

The table shows a contingency table that relates the final ranking (ranking after four quarters) to the three funds. The results can be interpreted as follows: The ZZ fund finished first five out of ten times, whereas the YY fund finished first only one out of ten times, etc.

Table 7

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

The table shows a contingency table that relates the ranking after three quarters (Rank Q3) to the final ranking (Rank at the end). The results can be interpreted as follows: In seven out of ten cases, the fund that was *ranked first* after three quarters also finished first after four quarters; in three out of ten cases, the *first ranked* fund after three quarters only finished second at the end; but it never finished third.

Table 8

	Rank (Q3)		
	1	2	3
VR in Q4			
High	1	3	6
Middle	5	3	2
Low	4	4	2

The table shows a contingency table that relates the ranking after three quarters (Rank Q3) to the risk taken in the fourth quarter, which is measured in terms of total volatility (VR in Q4). The results can be interpreted as follows: In six out of ten cases, the fund that was *ranked third* after three quarters took the highest risk in the fourth quarter; only in one out of ten cases the *first ranked* fund after Q3 took the highest risk in Q4. The χ^2 test statistic is equal to 6 with four degrees of freedom for a p-value of 0.199.

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

Following Brown *et al.* (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

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

As with the fund returns we rank funds based on their volatility ratios from the third to fourth quarters, and label them low, middle, and high.

Table 8 gives our first results for the tournament effect. This is a contingency table involving the three funds. The fund that is ranked highest in the third quarter only had the highest risk ratio in the fourth quarter in 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 toward 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. Based on a Chi-squared test of a null hypothesis that there is no relation between rankings and volatility ratios, we find that the test statistic for this contingency table is $\chi^2 = 6$ with a p-value equal to 0.199. Hence despite the qualitative support for the tournament hypothesis, we cannot reject independence of the variables at conventional significance levels.

The tournament hypothesis actually argues that the top ranked portfolio sometimes reduces risk in the last quarter relative to the second and third ranked funds, while there should not be a difference in risk taking between the second and third ranked funds. In order to test this, we consider the contingency sub-table comparing the behavior of the first with the third ranked funds, considering those observations where these two funds had either the highest or lowest volatility ratios. We find strong significance for this in the form of Table 9. Indeed the χ^2 test statistic is equal to 3.75 with one degree of freedom and an associated p-value equal to 0.053. Hence we are able to reject the hypothesis of independence of behavior between the first and third ranked funds at conventional significance levels.

We have also performed 2×2 contingency analysis of the other pairs, e.g., rank 1 against 2 and 2 against 3. In unreported results we find no difference in behavior between the second and third ranked funds, as theory would predict; but also no difference between funds ranked first and second, which can be due to the fact that the first ranked fund only is predicted to reduce risk with a large enough lead.

Table 9

	Rank (Q3)	
	1	3
VR in Q4		
High	1	6
Low	4	2

The table shows a 2×2 contingency table that relates the ranking after three quarters (Rank Q3) to the risk taken in the fourth quarter, which is measured in terms of total volatility (VR in Q4). In this case, only the first and third ranked funds are considered contingent on taking the highest or the lowest risk (second ranked funds and funds taking middle risks are excluded). The results can be interpreted as follows: In six out of ten cases, the fund that was *ranked third* after three quarters took the highest risk in the fourth quarter; only in one out of ten cases the *first ranked* fund after Q3 took the highest risk in Q4. The χ^2 test statistic is equal to 3.75 with one degree of freedom and a p-value equal to 0.053.

3.3 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. In other words, risk shifting should take place using non-systematic strategies. To test for this, we assume that the MSCI AC World proxies for systematic risk. We therefore run the following regressions of fund returns on market portfolio returns (MSCI AC World) for two different time periods, namely the first three quarters and the fourth quarter separately:

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

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

We then compute the residual risks from these regressions, $\sigma_{i,\epsilon_{Q1-Q3}}$ and $\sigma_{i,\epsilon_{Q4}}$ and the normalized idiosyncratic volatility ratio by:

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

Table 10 shows a contingency table that relates the ranks at the end of the third quarter to the idiosyncratic risk ratio. We see that these results mirror what was already seen in terms of total risk. The funds ranked highest have the lowest risk ratio almost all the time and the frequency of the highest risk ratio is associated with the lowest ranked funds. Using this 3×3 contingency analysis using the idiosyncratic risk ratio gives results which are stronger against the independence hypothesis than with total risk. However the results are not significant at conventional levels, namely we obtain χ^2 equal to 6.6, with four

Table 10

	Rank (Q3)		
	1	2	3
IVR in Q4			
High	1	3	6
Middle	4	3	3
Low	5	4	1

The table shows a contingency table that relates the ranking after three quarters (Rank Q3) to the risk taken in the fourth quarter, which is measured in terms of idiosyncratic volatility (Risk in Q4). The results can be interpreted as follows: In six out of ten cases, the fund that was *ranked third* after three quarters took the highest idiosyncratic risk in the fourth quarter; only in one out of ten cases the *first ranked* group after Q3 took the highest idiosyncratic risk in Q4. The χ^2 test statistic is equal to 6.6, with four degrees of freedom and a p-value equal to 0.159.

degrees of freedom and an associated p-value of 0.159.

We also compute the 2×2 contingency table of idiosyncratic risk changes between the first and third ranked funds. Here we obtain our strongest results supporting the tournament hypothesis, as indicated in Table 11. For this table independence of the first and third ranked idiosyncratic risks is rejected with a χ^2 value equal to 6.19 with one degree of freedom and a p-value of 0.013, almost at the 1% level.

The results involving return rankings and volatility ratios are illustrated in Figure 3. These are boxplots 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 first ranked fund in terms of total risk, while there is increasing risk for both the second and third ranked funds (i.e., positive median). The right panel shows a similar rank and risk pattern for idiosyncratic

Table 11

	Rank (Q3)	
	1	3
IVR in Q4		
High	1	6
Low	5	1

The table shows a 2×2 contingency table that relates the ranking after three quarters (Rank Q3) to the risk taken in the fourth quarter, which is measured in terms of idiosyncratic volatility (IVR in Q4). In this case, only the first and third ranked funds are considered contingent on taking the highest or the lowest risk (second ranked funds and funds taking middle risks are excluded). The results can be interpreted as follows: In six out of ten cases, the fund that was *ranked third* after three quarters took the highest risk in the fourth quarter; only in one out of ten cases the *first ranked* fund after Q3 took the highest risk in Q4. The χ^2 test statistic is equal to 6.19, with one degree of freedom and a p-value of 0.013.

volatility, with the exception that the first ranked fund is actually *reducing* its risks in the last quarter (i.e., negative median), while the second and third ranked funds tend to keep their idiosyncratic risks unchanged.

In Chen *et al.* (2018) a refinement of the strategic tournament analysis was considered in a competition which shows that whether or not the top fund reduces risk relative to the others depends on the size of the lead. With three funds they demonstrate the existence of a lock-in effect whereby the reduction in risk occurs if and only if the lead is sufficiently large. To test for this refinement we add an interactive term in a regression framework, by defining the lead ratio as

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

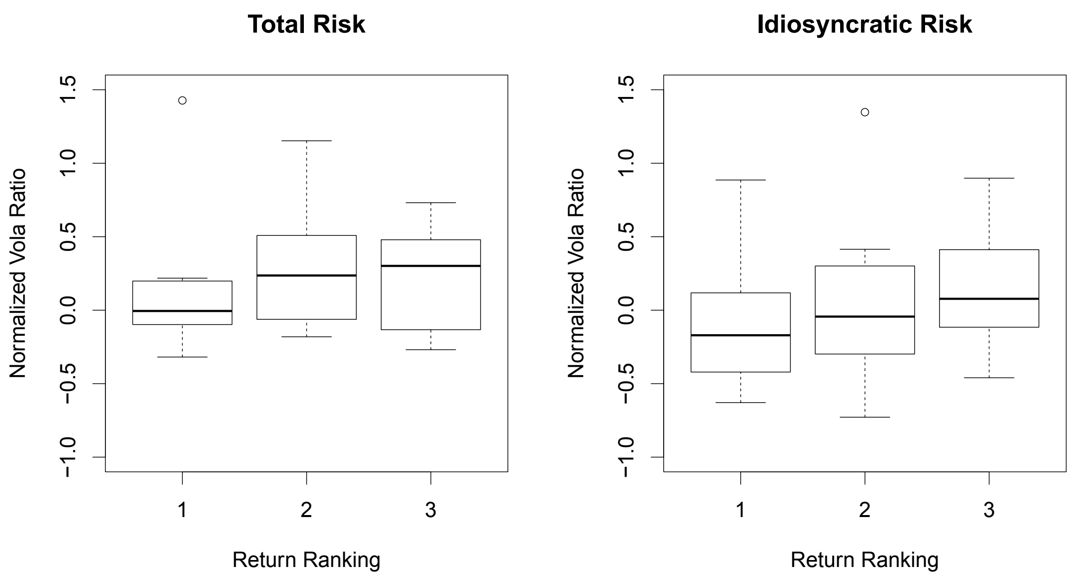

Figure 3 The chart presents boxplots that graphically display the volatility ratios (y-axis) contingent on the ranking after three quarters (x-axis). While the left panel shows the volatility ratio of the total risk, the right panel refers to the volatility ratios of the idiosyncratic risk. The black bold line of a boxplot refers to the median (of the ten independent tournaments), while the box displays all observations that lie between the 25% quantile, and the 75% quantile; additionally, the minimum, the maximum, and outliers are displayed. While a volatility ratio of close to zero indicates that the risk taken in the first three quarters is the same as the risk taken in the fourth quarter, a ratio above zero refers to an increase, and a ratio below zero refers to a decrease.

where $r_{1,Q1-Q3}$, $r_{2,Q1-Q3}$, and $r_{3,Q1-Q3}$ are the respective returns of the first, second, and third ranked funds over the first three quarters. The lead ratio thus shows the relative difference between the first and the second fund in relation to the difference between the first and the third fund. By definition the lead ratio is the highest when the first ranked fund leads the second and the third by almost the same amount. We then derive an indicator variable, the *lead ratio dummy* (LRD) which equals one if and only if the lead ratio is greater than the median value of the lead ratio in our sample, 0.505.

We now perform the following regression relating the total volatility ratio to the ranks and the interactive term including the lead ratio dummy:

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

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

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

Table 12 shows the results of the regression with and without the lead ratio dummy variable. Without the interaction total risk was significantly increased by the third ranked fund (the intercept) in terms of total volatility. The first ranked fund decreases risk relative to the third ranked fund, although it is not significant. The increase of the third ranked fund is of lower magnitude when looking at idiosyncratic volatility, but now we find that the first ranked fund not only decreases idiosyncratic risks relative to the third ranked fund, but also on an overall basis. However, once again there is a lack of significance. When we add

Table 12

	Total risk		Idiosyncratic risk	
	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.246*	0.246*	0.137	0.137
	(0.135)	(0.131)	(0.153)	(0.146)
rank1dummy	−0.122	0.095	−0.240	0.037
	(0.191)	(0.226)	(0.216)	(0.252)
rank2dummy	0.051	0.051	−0.081	−0.081
	(0.191)	(0.185)	(0.216)	(0.206)
I(rank1dummy*LRD)		−0.433		−0.555*
		(0.261)		(0.291)
R^2	0.031	0.124	0.045	0.162
Adj. R^2	−0.041	0.023	−0.025	0.066
Num. obs.	30	30	30	30

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

The table presents the results of the OLS regression of the volatility ratios (LHS) on the ranking (RHS) at an intermediary point in time (after three quarters) and the lead ratio dummy: $Risk = \alpha + \beta_1 Rank1 + \beta_2 Rank2 + \beta_3 Rank1 * LRD + \epsilon$. The volatility ratio for the total risk is set up by $VR = \frac{\sigma_{Q4}}{\sigma_{Q1-Q3}} - 1$, whereas the volatility ratio for the idiosyncratic risk is computed by $IVR = \frac{\sigma_{\epsilon_{Q4}}}{\sigma_{\epsilon_{Q1-Q3}}} - 1$. A volatility ratio of zero indicates that the risk taken in the first three quarters is the same as the risk taken in the fourth quarter. The interactive term of the lead ratio dummy allows to measure the size of the risk reduction of the first ranked group dependent on the magnitude of the lead (e.g., a negative sign refers to less risk the bigger the lead). A positive sign of the intercept indicates an increase of risk in the fourth quarter by the third ranked group. The coefficients of Rank1 and Rank2 show the marginal effects of the first and second ranked groups compared to the third ranked group (intercept). The data contains ten unique tournaments with three groups which results in 30 observations. Standard Errors are in parentheses.

the interactive dummy, we find that the magnitude of the coefficient indicates that top ranked funds with a large lead decrease both their total risk and their idiosyncratic risks so that there is an overall reduction, as predicted by the refined theory. In the case of idiosyncratic risk, this reduction with a large lead is statistically significant. Further there is a large increase in the adjusted R^2 of the regression specification with the interactive term. All of these observations are in accord with strategic tournament theory.

To verify that our specification of a tournament based on absolute total returns (rather than risk-adjusted returns) is correct, we repeated the analysis above using risk-adjusted alphas from the style analysis. In unreported results we find that student managed funds *do not* behave as though there is a risk-adjusted tournament. This finding is natural, given that the student rewards are not based on risk-adjusted performance.

3.4 *Implications for industry practice*

Our results demonstrate that institutional investors need to be aware of incentives that asset managers have that cause them to deviate from their benchmarks. Institutional clients such as pension funds and endowments frequently set up explicit or implicit tournaments whereby managers are compared against each other for retention or dismissal. For instance Goyal and Wahal (2008) show that managers are usually hired after an abnormally high performance period and those that are fired come after an abnormally low performance period.

Using the tournament form of competition between fund managers has advantages in a way that it encourages productive effort expenditure and leads to the creation of new and innovative ideas. However, plan sponsors and their advisers must be aware of the dynamics of risk-taking incentives throughout the competitive process. Funds that are trailing might take too much idiosyncratic risk and stray from their mandates. One way of mitigating this adverse outcome would be to implement tracking error measures and modify these throughout the evaluation period. In doing so, one needs to take account of the current ranking of the fund manager. Lower ranked funds should be constrained more from a maximum tracking error perspective (upside), while higher ranked funds should be rewarded from a minimum tracking error perspective (downside). Cornell and Roll (2005) assume that delegated managers receive a penalty based on tracking error, and find that this affects their asset allocation decision and can show up as an additional factor in security returns. Our results imply that encouraging tracking error can, in certain cases, be desirable from the clients' perspective. Another way of mitigating such strict tournament behavior would be to attempt to introduce a greater "career concerns" perspective to fund managers. By allowing greater forbearance for managers who underperform over short periods, the management company is effectively providing downside sensitivity. This makes it more likely the manager will have a longer-term perspective in order to survive for another tournament next period. These considerations apply also when consultants are employed for evaluation purposes and are themselves involved in their own tournament.

Regarding the social and organizational implications of tournaments, there are a number of factors fund management companies should take account of. When fund management companies utilize either explicit or implicit tournaments between their respective fund managers for promotions and retention decisions the risk shifting motives need to be recognized. This can be viewed as a negative effect of using such tournament incentives. On the other hand, tournaments might mitigate the free rider problem that ensues when some part of managerial compensation is based on overall performance of the management company.

4 Disposition effects

Previously we have focused only on return data which are available for each student-run fund. Now we turn to the portfolio weights data and disaggregated pricing data for each asset in the funds. 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. Our analysis of the disposition effect considers years 2007–2014, since during the first three years the funds were liquidated annually.

4.1 Selling decisions

Figure 4 illustrates the number of assets held in all three funds over time. At its peak the ZZ fund held the largest number of assets of almost 60 in number. The turnover periods are indicated by the gray lines. As is evident, the number of assets drops around the turnover periods as the new managers restructure their portfolio to some extent. The greatest restructure was in June 2010 when the ZZ fund sold off about half of their assets. The total number of selling decision for each of the three funds was given in Table 1, and shows that the funds sold positions on 51–66 dates. This number is not large, but reflects the fact that many

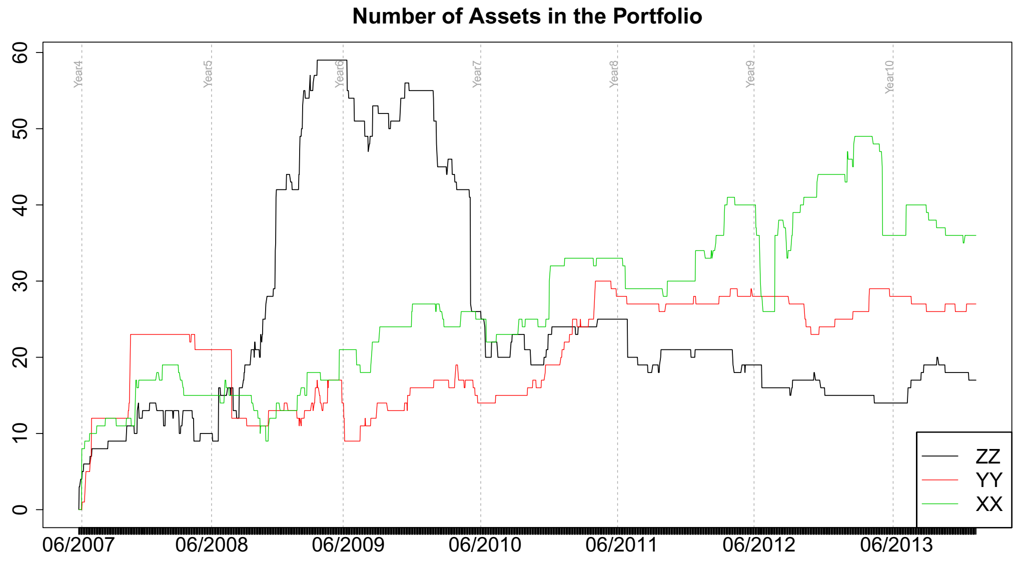

Figure 4 The chart presents the total number of assets held by each of the three funds, ZZ, YY, and XX, over a time period of seven years starting in June 2007. (Note: The full ten-year history cannot be used since the PMP program was structurally different in the first three years, were portfolios were not rolled over). The vertical gray lines show the time points when the portfolios are rolled over to the next manager generation.

positions had natural expiration times, such as in fixed income or futures which are not considered as discretionary selling activities. Students are not graded or told to minimize turnover or to reduce transaction costs; these are only reflected in overall returns which are net of such fees.

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. Price data retrieved from Bloomberg was used for each purchase and sales date.[6] 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 13 depicts the results for the last seven years of the program. 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 XX funds. The difference is insignificant for the YY fund. Overall across all three funds 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.

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

Table 13

	Total		Realized		Ratios		PGRminPLR			Count
	Gains	Losses	Gains	Losses	PGR	PLR	Delta	SE	t-stats	SalesDate
Individual										
ZZ	1065	480	74	52	0.069	0.108	−0.039	0.016	−2.400	66
YY	465	489	34	40	0.073	0.082	−0.009	0.017	−0.502	51
XX	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

The table compares the proportion of realized gains with the proportion of realized losses. The first two panels shows the absolute number of total gains and losses as well as the realized gains and losses. The third panel displays the proportion of realized gains (PGR) and the proportion of realized losses (PLR). The fourth panel shows the difference between PGR and PLR (e.g., $\Delta = PGR - PLR$), the standard errors (SE) and the t-statistics (t-stats). The last panel counts the days when assets were sold. Standard Errors are computed as follows: $SE = \sqrt{\frac{PGR(1-PGR)}{n_{Gain}} + \frac{PLR(1-PLR)}{n_{Loss}}}$.

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 (2014) finds results similar to Odean (1998) using retail investors but for a separate sample of mutual funds he finds also a reverse disposition effect. Dhar and Zhu (2006) find that greater literacy mitigates the normal disposition effect, while Chang *et al.* (2016) hypothesize that as a reverse disposition effect holds for individual investments in mutual funds investments, they unload their losers because fault cannot be attributed to themselves.

Other potential motives for a reverse disposition effect are tax realizations of capital gains. In our case, we can exclude this as taxes are charged against the funds on an accrual rather than at realization. Momentum trading is another motive. 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 Section 5. 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. Finally 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. The faculty instructors grade students based on their presentations at these weekly sessions and that is part of their final grade.

4.2 Distinguishing selling hypotheses

In an effort to distinguish among some of these hypotheses we consider a logit regression analysis. This features a large number of factors that can enter into a decision to sell, other than just whether there is a gain or loss. The approach followed here is similar to Ben-David and Hirshleifer (2012) and Hartzmark (2014). We define Sell as an indicator variable in the following specification:

$$\begin{aligned}
\text{Sell} = d_0 &+ d_1(\text{LossDummy}) \\
&+ d_2(\text{Return*GainDummy}) \\
&+ d_3(\text{abs(Return*LossDummy)}) \\
&+ d_4(\text{BestDummy}) + d_5(\text{WorstDummy}) \\
&+ d_6(\text{Return*GainDummy} \\
&* \text{sqrt(holdingTime)}) \\
&+ d_7(\text{Return*LossDummy} \\
&* \text{sqrt(holdingTime)}) \\
&+ d_8(\text{sd250*GainDummy}) \\
&+ d_9(\text{sd250*LossDummy}) \\
&+ d_{10}(\text{weight}) + d_{11}\text{sqrt(holdingTime)} \\
&+ d_{12}(\text{SoldBySameGroup}) \\
&+ d_{13}(\text{SoldByNextGroup}) \\
&+ d_{14}(\text{fund}) \\
&+ d_{15}(\text{mom25Dummy}) + \epsilon
\end{aligned}$$

Table 14 contains the definitions of the right-hand side variables for the logit model.

The actual logit estimation is performed on the following equation:

$$\begin{aligned}
y_{ijs} = a &+ d_1 z_{1,ijs} + \cdots + d_n z_{n,ijs} \\
&+ b_1 x_{1,ijs} + \cdots + b_n x_{n,ijs} + u_i + e_{ijs},
\end{aligned}$$

Table 14

Logit model

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 a positive return since purchase, 0 otherwise
LossDummy	1 if it has a 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 the asset is sold by the next manager group (analysts at purchase), 0 otherwise
fund	Categorical variable indicating the three investment philosophies of the funds: ZZ, YY, XX
mom25Dummy	1 if the return over the last 25 trading days is positive, −1 if the return is negative and 0 otherwise

The table presents the variables that are used in the logit regression and gives a short description of their definition. The first row shows the variable *Sell*, which is used on the left-hand side of the regression, whereas all the other variables serve as explanatory variables.

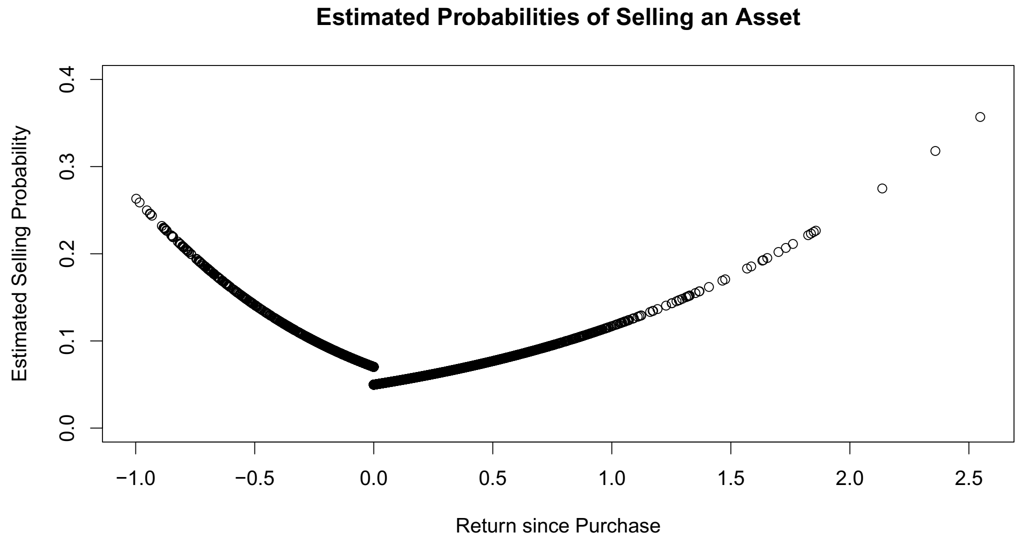

Figure 5 The chart presents the results of the following logit regression (Model 1): Sell $= d_0 + d_1$(LossDummy) $+ d_2$(Return*GainDummy) $+ d_3$(abs(Return*LossDummy)) $+ \epsilon$. The y-axis shows the estimated probabilities of selling an asset dependent on the return since purchase (x-axis). The chart shows an increase in the selling probability with higher absolute returns. This effect is even stronger for losers since the slope in absolute terms is steeper. A *reverse* disposition effect is indicated by the positive jump at zero, which means that independent of the return (x-axis) losers have a higher selling probability than winners.

where $i = \{$ZZ, YY, XX$\}$, $j = \{$stocks held at each sales date$\}$ and $s = \{$sales dates$\}$. $y_{ijs} = 1$ if a stock (j) is sold at sales date (s) from fund (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.

Five model specifications are tested: Model 1 only includes a loss dummy and the return interactions; Model 2 adds the ranking; Model 3 includes additional control variables; Model 4 introduces an additional fund specific dummy, while Model 5 adds a momentum dummy. We find importantly that the reverse disposition effect shows up for all five model specifications. The loss dummy variable is significantly positive. This implies that a losing asset is almost one and a half times as likely to be sold as a winner (for Model 1).[7] To deal with the possibility that selling decisions may not be independent over time for each fund, we cluster the standard errors by fund.

The results of Model 1 are illustrated in Figure 5. 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 5 shows an increase in the selling probability with higher absolute returns. This effect is even stronger for losers than for winners.

Table 15 shows the results of the logit regression. Five nested model specifications are included, which are in broad agreement. All of them show the much greater tendency to sell losers than to sell winners, with the propensity to sell increasing in the amount of the loss (an interactive effect). The only exception to this is at the top end where we also find that there is a tendency to sell the single best performing asset. 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. A very significant result is that assets are less likely to be sold by the same (current manager) group as well as by the very 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

Table 15

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	−2.948***	−2.930***	−3.126***	−3.269***	−3.288***
	(0.054)	(0.052)	(0.379)	(0.375)	(0.422)
LossDummy	0.365*	0.350*	0.644**	0.645**	0.627***
	(0.195)	(0.192)	(0.269)	(0.264)	(0.230)
I(Return * GainDummy)	0.926***	0.705***	1.250	1.395	1.433
	(0.011)	(0.110)	(0.911)	(1.108)	(1.044)
I(abs(Return * LossDummy))	1.557***	1.441*	3.858***	4.087***	3.981***
	(0.593)	(0.828)	(0.469)	(0.277)	(0.122)
BestDummy		0.528***	0.442***	0.404***	0.405***
		(0.201)	(0.081)	(0.079)	(0.074)
WorstDummy		0.150	0.026	−0.036	−0.028
		(0.344)	(0.323)	(0.313)	(0.302)
I(Return * GainDummy * sqrt(holdingTime))			−0.035	−0.038	−0.040
			(0.053)	(0.060)	(0.057)
I(abs(Return * LossDummy * sqrt(holdingTime)))			−0.143***	−0.145***	−0.141***
			(0.025)	(0.029)	(0.028)
I(sd250 * GainDummy)			17.163***	18.722***	18.910***
			(4.557)	(5.055)	(5.444)
I(sd250 * LossDummy)			2.794	3.263	3.515
			(2.353)	(2.784)	(2.398)
weight			4.010**	4.444**	4.443**
			(1.935)	(2.145)	(2.182)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
The table presents the results from the following logit regression: $y_{ijs} = a + d_1 z_{1,ijs} + \cdots + d_n z_{n,ijs} + b_1 x_{1,ijs} + \cdots + b_n x_{n,ijs} + u_i + e_{ijs}$. The dependent variable (LHS) is 1 if an asset was sold, and 0 otherwise. The data set contains the assets held in the portfolio (j) by each of the three funds (i)–ZZ, YY, XX–at each date an asset got sold (s). Transactions over a seven-year time period starting in June 2007 are considered.
Five models are displayed in the table: Model 1 presents the base model where a loss dummy and an interactive term of the absolute return and the gain/loss dummy are used. Positive coefficients indicate a higher likelihood of selling an asset, whereas negative coefficients refer to a lower probability. The coefficients of the logit model can be interpreted as the logarithm of an odds ratio. Using the β-coefficient of the loss dummy as an example, this implies that a losing asset is almost one and a half times as likely to be sold as a winner (e.g., odds ratio (OR): $OR = \exp^{\beta} = \exp^{0.365} \approx 1{,}44$).
Models 2–5 add additional control variables: Model 2 adds dummies for the best and the worst ranked assets, Model 3 adds additional control variables, Model 4 adds fund specific dummies and Model 5 adds a momentum dummy variable. Standard Errors are clustered on fund level and are shown in parentheses.

Table 15 (*Continued*)

	Model 1	Model 2	Model 3	Model 4	Model 5
sqrt(holdingTime)			0.005	0.004	0.005
			(0.020)	(0.019)	(0.021)
SoldBySameGroupDummy			−0.556***	−0.553***	−0.533***
			(0.096)	(0.107)	(0.156)
SoldByNextGroupDummy			−0.460**	−0.455**	−0.445**
			(0.184)	(0.200)	(0.226)
fundYY				−0.038	−0.037
				(0.116)	(0.114)
fundXX				0.274***	0.267***
				(0.088)	(0.099)
mom25Dummy					−0.044
					(0.090)
AIC	2079.204	2079.606	2058.464	2058.343	2059.926
BIC	2104.265	2117.198	2146.180	2158.589	2166.437
Num. obs.	3887	3887	3887	3887	3887

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 the last model adds a momentum variable, which does not show up significantly. Nonetheless, the negative sign indicates that assets are more likely to be sold if there is a short-term run up in price.

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.

4.3 Implications for industry practice

The tendency to sell losers earlier than winners is part of a strategy termed “window dressing”. In our setting such considerations arise because students have to make regular presentations, graded by faculty, in which they must defend their portfolio composition. Our findings indicate that institutional investors need to keep such considerations in mind as fund managers have incentives to liquidate losing positions prematurely and to chase positive past performance. These incentives arise whenever managers regularly report their portfolio compositions to their clients. When such reviews are too frequent they may be counterproductive and encourage short-run myopic decision making. When reporting does take place it is advisable to track a longer run past history of trades, and not to just focus on the latest snapshot of portfolio holdings. That is, a focus on the evolution of the overall portfolio composition is important. When benchmarks for managers are employed, the institutional investor may wish to use benchmark compositions from the beginning or the end of the evaluation period.

Our study indicates that reverse disposition effects are stronger at times of managerial turnover. Hence this implies that the investor can expect a greater reverse disposition effect with more frequent turnover decisions. On the other hand, when the investor has a reputation for allowing long-run managerial discretion, the regular disposition effect might be expected. If, on the other hand, funds have a tendency to hold onto losing positions too long, then our paper indicates that a policy of rotating managers might ameliorate the issue. The linkage between managerial turnover and the reverse disposition effect is one that our novel setting allows us to identify.

From the social and organizational perspective we expect to see similar effects. For instance when there are more frequent meetings between managers of different funds within the organization, the reverse disposition effect is more likely to be present. An advantage for holding regular meetings among fund managers is to capitalize on information exchange and coordinate expertise among peers. However, our results indicate that at such regular meetings, critical peer reviews can have possibly unintended consequences by motivating the early disposition of positions with losses.

5 Team size and performance

In this section we perform a cross-sectional analysis of the funds' performance attributes with respect to team sizes using demographic controls that were retained from the student records. These variables and their associated descriptive statistics appear in Table 1.

5.1 *Effect of team size on total return*

We perform a cross-sectional regression analysis of various performance metrics of the funds on fund characteristics. In a paper related to the "local bias" effect of individual investors, Seasholes and Zhu (2010) document that when the number of investors in the sample greatly exceeds the number of available assets returns can be significantly correlated, thereby creating a bias in favor of significance when there is none. They propose a calendar time returns methodology to address this concern involving holdings data and forming aggregate portfolios using buy and sell decisions. In our study we are using annual data with only three funds and the potential number of investments is virtually unlimited due to the magnitude of the investment universe. We also are not able to record the ex post returns of assets sold because those do not appear in our database. In order to address possible interdependence of calendar time returns at the fund level, we utilize clustering in computing the standard errors.

We utilize a linear regression framework to analyze how returns are related to fund characteristics.

$$\begin{aligned} r_{t,i} = a_i &+ b_1(teamsize)_{t,i} + b_2(female)_{t,i} \\ &+ b_3(TUstudents)_{t,i} + b_4(NOdegree)_{t,i} \\ &+ e_{t,i}, \end{aligned}$$

where $i = \{\text{ZZ, YY, XX}\}$ and $t = \{1, 2, \ldots, 10\}$ years.

Table 16 presents the results of an analysis of all three funds for ten years. Team size is marginally significant using Model 1 specification; we lose a small amount of significance in Model 2, perhaps because of using both fund fixed effects as well as the fund clustering.

5.2 *Effect of team size on alpha*

We use the following regression model to analyze the effect of team sizes on the annualized alpha coefficients for the three funds over the ten-year

Table 16

	Model 1	Model 2
(Intercept)	0.275	0.269
	(0.191)	(0.195)
teamsize	−0.046*	−0.051
	(0.026)	(0.032)
female	−0.148	−0.114
	(0.119)	(0.195)
TUstudent	0.041	0.051
	(0.235)	(0.301)
NOdegree	0.009	0.019
	(0.081)	(0.104)
fundYY		−0.014
		(0.045)
fundZZ		0.032
		(0.026)
R^2	0.164	0.179
Adj. R^2	0.030	−0.035
Num. obs.	30	30

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
The table presents the results of the OLS regression of the absolute return of the three PMP funds (LHS) on team size and the control variables and the fund dummy (RHS): $r_{t,i} = a_i + b_1(teamsize)_{t,i} + b_2(female)_{t,i} + b_3(TUstudents)_{t,i} + b_4(NOdegree)_{t,i} + e_{t,i}$. A negative coefficient refers to a lower absolute performance. The data contains ten different manager years for all three funds (ZZ, YY, XX), which results in 30 observations. Standard Errors are clustered at fund level and shown in parentheses.

Table 17

	Model 1	Model 2
(Intercept)	0.001	−0.001
	(0.039)	(0.037)
teamsize	−0.019*	−0.022*
	(0.011)	(0.012)
female	−0.064	−0.033
	(0.045)	(0.055)
TUstudent	0.113	0.142
	(0.120)	(0.147)
NOdegree	0.120***	0.136***
	(0.040)	(0.039)
fundYY		−0.033**
		(0.015)
fundZZ		0.005
		(0.007)
R^2	0.190	0.218
Adj. R^2	0.060	0.014
Num. obs.	30	30

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
The table presents the results of the OLS regression of the annualized alphas of the three PMP funds based on a custom benchmark (LHS) on the characteristic variables and the fund dummy (RHS): $\alpha_{t,i} = a_i + b_1(teamsize)_{t,i} + b_2(female)_{t,i} + b_3(TUstudents)_{t,i} + b_4(NOdegree)_{t,i} + e_{t,i}$. A negative coefficient refers to a lower risk-adjusted performance (alpha). The data contains ten different manager years for all three funds (ZZ, YY, XX), which results in 30 observations. Standard Errors are clustered at fund level and shown in parentheses.

time horizon:

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

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

where $i = \{ZZ, YY, XX\}$ and $t = \{1, 2, \ldots, 10\}$ years. Note that the alphas are derived as before from the custom benchmark analysis.

The demographic control variable coefficients in Table 17 are similar to those in the total return performance depicted in Table 16. Team size has a negative effect on alpha and the lack of a degree a very significantly positive effect. The results are stronger than using raw returns, which can indicate less systematic exposure for these types of fund managers, i.e., larger teams are taking less actively managed approaches.

5.3 *Effect of team size on idiosyncratic volatility*

In a next step we want to find out whether the size of the team has an influence on the idiosyncratic risk taken by the funds. As before, we compute the residual from the style analysis:

$$\epsilon_{i,t} = r_{i,t} - \left[\alpha_i + \sum_j \beta_{ij} f_{j,t}\right].$$

We use the following regression model to analyze the effect of team sizes on the annualized demeaned idiosyncratic volatility:

$$\begin{aligned}\Delta\sigma(\epsilon_{weekly,i})_{t,i} * \sqrt{(}52) &= a_i + b_1(teamsize)_{t,i} + b_2(female)_{t,i} \\ &\quad + b_3(TUstudents)_{t,i} + b_4(NOdegree)_{t,i} \\ &\quad + e_{t,i}.\end{aligned}$$

Considering the impact of team size on the risk-taking behavior it is essential to control for the fund-specific investment philosophies. Model 2 of Table 18 thus shows that the ZZ fund takes significantly more idiosyncratic risk than the YY and XX funds. Additionally, the team size variable shows up significantly negative, i.e., the bigger the team the lower the unsystematic risk. Finally students in the quantitative TU program tend to take much less idiosyncratic risk.

In summary, we find that larger teams take less idiosyncratic risk. Both risk-adjusted and non-adjusted performance is stronger with a smaller number of managers. We do not find evidence of any gender effects on any of these return or risk measures associated with performance.

Table 18

	Model 1	Model 2
(Intercept)	0.041	0.036
	(0.037)	(0.023)
teamsize	-0.008^{*}	-0.011^{*}
	(0.005)	(0.006)
female	-0.027	-0.012
	(0.037)	(0.032)
TUstudent	-0.044^{**}	-0.051^{***}
	(0.019)	(0.008)
NOdegree	0.009	0.010
	(0.036)	(0.040)
fundYY		0.005
		(0.005)
fundZZ		0.028^{***}
		(0.004)
R^2	0.164	0.319
Adj. R^2	0.030	0.142
Num. obs.	30	30

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
The table presents the results of the OLS regression of the idiosyncratic volatility of the three PMP funds (LHS) on the variables and the fund dummy (RHS): $\Delta\sigma(\epsilon_{weekly,i})_{t,i} * \sqrt{(}52) = a_i + b_1(teamsize)_{t,i} + b_2(female)_{t,i} + b_3(TUstudents)_{t,i} + b_4(NOdegree)_{t,i} + e_{t,i}$. A negative coefficient refers to a lower idiosyncratic volatility, thus lower risk. The data contains ten different manager years for all three funds (ZZ, YY, XX), which results in 30 observations. Standard Errors are clustered at fund level and shown in parentheses.

5.4 Implications for industry practice

The most direct implication of our findings on team sizes concerns performance and risk-taking. We expect to see lower idiosyncratic risk taking and performance for team managed funds with more managers. The implications of team sizes for mutual funds have been actively studied recently. It should be noted that recent US data on mutual funds show that the number of mutual fund managers ranges from one at the fifth percentile to six at the 95th percentile. Hence the range in our study from two managers to six is a representative sample.[8] Bär *et al.* (2011) finds only weak evidence for lower performance of team managed mutual funds. Patel and Sarkissian (2017) report that team managed funds outperform single managed funds across various performance metrics. However Goldman *et al.* (2016) show that funds managed by a single manager tend to perform better and have more concentrated portfolios, which corresponds to greater idiosyncratic volatility in our study.

The recent evidence on mutual fund managerial sizes is also confounded by the issue of endogeneity in team size. For instance it has been argued that better managers prefer to manage alone rather than in a team. Our study features exogenous variation in team size since managers themselves have no influence over it. The attrition that results comes mostly from the analysts (first year) before they ever ascend to fund management. Our study therefore provides support for limiting team sizes to a relatively small number. From the clients' perspective our results imply that investing in funds managed by large teams may not be very different from indexing and therefore fees for such funds should be kept to a minimum.

6 Conclusions

This paper has used a specific data set coming from the actual investment decisions and results from three student-run portfolios in a ten-year period to test specific behavioral finance theories of the tournament effect, the disposition effect and to identify a managerial group-size effect. Our setting is a controlled one where rewards are clearly defined and managerial turnover occurs on a specific graduation date.

We find that funds which are trailing midway through the annual tournament take riskier strategies in order to increase the probability of catching up by the end. Funds that are ahead at the interim date reduce their risks on average compared to the ones that are behind. Furthermore risk taking by trailing funds tends to be idiosyncratic rather than systematic. Leading funds exhibit opposite behavior. We identify a *reverse* disposition effect whereby losing positions are more likely to be sold than winners. Within this overall pattern of behavior, it is noteworthy that the reverse disposition effect is stronger when the original position was established by earlier cohorts of student managers. Finally, we show that smaller student teams take on more risk and have a higher absolute performance.

We emphasize that the key to the importance of our clear cut results on the tournament and the disposition effects is that we have exogenous managerial turnover, in contrast to the endogeneity in the real world. In our environment the relevant competitors are clear, there is no question what the peer group is. While at first glance this might appear to make our results less relevant to practice, we believe that instead our controlled environment enables the tournament and disposition effect to be pinpointed more precisely. In our environment what constitutes winning is clear, the competitors are well-defined and the managerial team is identified and constant. If we had not been able to find support for behavioral hypotheses in our controlled setting, why would we expect it to be a consideration in practice?

In summary, the results of this study have practical implications in two areas of the fund management industry: (1) the design of fund manager evaluation by institutional clients, and (2) the social and organizational structure of asset management firms. We find that clients must account for implicit incentives that arise from competition between funds in addition to those that arise from explicit benchmarking. Fund management companies should address their peer review environment to ensure appropriate outcomes. Students from this program as well as many other such programs are now in important positions in the money management industry. We believe that behaviors identified from their student experience are likely to be relevant in their careers and therefore present in practice.

Appendix A

A. Style analysis

To begin with, we record the Sharpe ratios of the three PMP portfolios, the six risky benchmarks and the MSCI AC World equity index.

We display Sharpe ratios for each of the ten years and for the total period in Table A1. 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 XX fund 0.48, and the YY fund 0.42. The overall equity market had a Sharpe ratio of 0.25. Out of the indexes the JP EMBI was best with a Sharpe ratio of 0.54.

Now we apply a style analysis similar to (Sharpe, 1992) to the portfolio returns using the six risky factor portfolios described previously. 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 A2 shows the results of a constrained regression for the ZZ portfolio. First notice that there

Table A1

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Total
PMP											
ZZ	2.32	1.91	2.25	—	0.43	2.80	—	—	0.79	—	0.60
YY	0.92	2.89	2.13	—	—	0.69	0.63	—	1.07	—	0.42
XX	1.15	2.62	1.52	—	—	0.96	0.73	—	0.91	0.15	0.48
Benchmarks											
Stoxx600	1.36	2.52	2.64	—	—	0.85	1.44	—	2.48	1.19	0.27
SP500	0.27	0.34	1.59	—	—	1.90	0.64	0.50	2.22	0.86	0.23
MSCI EM	1.80	2.86	2.69	—	—	1.78	0.97	—	1.10	—	0.42
JP EMBI	1.10	0.02	0.82	—	0.44	2.91	—	1.92	1.14	—	0.54
MSCI EM FX	1.01	0.30	0.25	—	0.22	1.71	—	0.42	0.38	—	0.23
Rogers Commodity	—	1.16	—	1.53	—	0.61	1.39	—	—	—	—
Market											
MSCI AC	0.74	1.70	2.22	—	—	1.74	0.86	—	2.29	0.66	0.25

The table presents the annualized Sharpe ratios of the three PMP funds in comparison with six risky benchmarks that are used in the style analysis and the MSCI AC World. The Sharpe ratios are shown for each of the ten years as well as the total period. In the table the entry "-" indicates a period where the *ex post* value was negative.

Table A2

ZZ fund	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	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
***R*2**											
*R*2	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

The table shows the results of the style analysis of the ZZ fund for each of the ten years and the total period. In the panel "Intercept" the alpha values and the Standard Errors in parentheses are displayed. The panel "Benchmark" shows the weights attributed to the six risky benchmarks, while the panel "Cash" accounts for the remainder up to 1 (e.g., $Cash = 1 - \sum \beta_{ij}$). The panel "$R2$" refers to the explanatory power of the styles, whereas $1 - R2$ refers to the asset selection.

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 line with the mandate of these portfolio managers. The remaining alpha is never statistically significant in any of the years. The uniqueness

Table A3

YY fund	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	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
***R*2**											
*R*2	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

The table shows the results of the style analysis of the YY fund for each of the ten years and the total period. In the panel "Intercept" the alpha values and the Standard Errors in parentheses are displayed. The panel "Benchmark" shows the weights attributed to the six risky benchmarks, while the panel "Cash" accounts for the remainder up to 1 (e.g., $Cash = 1 - \sum \beta_{ij}$). The panel "$R2$" refers to the explanatory power of the styles, whereas $1 - R2$ refers to the asset selection.

Table A4

XX fund	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	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
***R*2**											
$R2$	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

The table shows the results of the style analysis of the XX fund for each of the ten years and the total period. In the panel "Intercept" the alpha values and the Standard Errors in parentheses are displayed. The panel "Benchmark" shows the weights attributed to the six risky benchmarks, while the panel "Cash" accounts for the remainder up to 1 (e.g., $Cash = 1 - \sum \beta_{ij}$). The panel "$R2$" refers to the explanatory power of the styles, whereas $1 - R2$ refers to the asset selection.

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.

Table A3 now indicates the same figures for the YY portfolio. It is apparent that the YY fund 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.

Finally Table A4 shows that the XX 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.

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 styles along with the returns to a cash account in Euros. Emerging market investment is an important component in explaining returns for all of the portfolios, but especially for the ZZ portfolio.

Notes

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

2 We document some career outcomes in Section 3.

3 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 deducted from 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 YY and XX group with a statutory tax rate of 25%. The method of tax adjustment does not affect our findings as in an earlier version of this paper we made no adjustments and achieved the same empirical results.

4 We use the short-term German Bund yields as a risk-free rate (Bloomberg Ticker: GRGYSHRT).

5 Unfortunately the course grades for years two and three are missing.

6 A value-weighted average price was used for assets with several buy dates.

7 This interpretation is based on the odds ratio taken from the logit regression: $exp^{0.365} = 1.44$, i.e., a losing asset is approximately 1.44 times as likely to be sold than a winning asset (intercept).

8 We thank Youchang Wu for providing these data from 2,372 mutual funds reporting from 1999 to 2012.

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