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ARE STUDENT-MANAGED FUNDS CLOSET INDEXERS?

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ABSTRACT

Many business schools offer finance students the opportunity to run student-managed funds, which are meant to give participants experience running real money in real time. The usefulness of such an experience, however, depends on the structure of the fund: is it grounded in economic principles; does it mitigate or exacerbate behavioral investment biases; does it focus on stock picking, or emphasize portfolio management; does it promote true active management, or encourage benchmark-mimicking closet indexing? In this paper, we present a description of our university's fund, highlighting critical industry measures of active management to assess its performance. Some of our main generalizable findings are that funds' benchmarks must be consistent with the actual investment approach employed, that performance metrics must be clearly and explicitly determined in advance, and that the fund's investment policy statement must be reflective of empirical market realities.

JEL: G11, G21

KEYWORDS: Student-Managed Investment Fund, Active Share, Closet Indexing

INTRODUCTION

These days, if a university has a business program, it probably has a student-managed fund (SMF, sometimes called a student managed investment fund, SMIF). These funds offer participants the "ultimate" experiential learning opportunity to run real money in real time (D'Souza and Johnson, 2019), and—as they become ubiquitous—they are playing "an increasingly significant role in business college curriculums" (Phillips, *et al.*, 2020). Charlton, *et al.* (2015) note that SMFs develop not only students' ability to work with money but also with people, as students undertake group leadership roles and responsibilities; these authors assert that the high levels of student involvement encourage knowledge retention and the development of life-long skills. Clinebell and Murphy (2016) show that SMF alumni demonstrate superior communication skills and a deeper understanding of investments even eight years into their careers. Students seem to like these funds, and to gain relevant financial knowledge from running them (Hysmith, 2017). However, do they really gain useful money management experience from buying stocks with a university's money? Even if we stipulate that actively managing an equity portfolio of a few hundred thousand dollars can be a good idea, do the student managers actually manage actively? Or do they succumb to the plague of real-world active managers: closet indexing?

Petajisto (2013) defines closet indexing as "the practice of staying close to the benchmark index while claiming to be an active manager." This obviously undermines the portfolio goals of the client. It is also a "heinous" example of moral hazard (Taylor, 2004), since managers of closet index funds charge as if they were truly active, getting paid for something they do not do. Only the manager's active positions can contribute alpha, but she charges her fees on all of her stocks, even the index-replicators. Student fund managers do not impose this fee burden on their clients, but if their mandate is active management, they should not be trained to hug a benchmark. In this paper, we examine our own university's student managed fund, the PTA fund, for evidence of closet indexing. We use Cremers and Petajisto's (2009) active share measure, as well as tracking error, attribution, and traditional portfolio metrics, to assess how actively our students are actually managing the money entrusted to them. We find that while they are not closet indexers—which is consistent with the *spirit* of the fund—their active management actually violates the *letter* of their investment policy statement, whose quantitative objectives almost compel closet indexing. We offer our example as a case study in the necessity of ensuring consistency across the initial design and ongoing monitoring of a university student-managed fund. The paper proceeds as follows. In the next section, we briefly review the burgeoning literature on student-managed funds, then describe the active share measure and other relevant industry metrics. We then characterize our university's SMF using many of these standard approaches, as well as more unusual techniques such as polynomial goal programming. We discuss these results next, paying particular attention to the relationship between the fund's actual performance and its policy mandate. We conclude with a few suggestions for other SMF participants.

LITERATURE REVIEW

Our paper draws on several strains of research. Since we wish to identify any discrepancies between the promise and reality of student portfolio management, we begin by reviewing some of the prior literature on student-managed funds. We then describe work on relevant industry metrics of active management, including those specifically employed to identify closet indexers.

Student-Managed Funds

Student-managed funds provide students the opportunity to manage real money in real time. Indeed, they "not only offer unique learning opportunities, but also are valuable for resume enhancement, school promotion, alumni networking, and involvement of practitioners with finance programs" (Gradisher, *et al.*, 2016). The number of funds has grown quickly: in his early 1990 sample, Lawrence (1990) identified 22 extant SMFs, but by 2014, Bruce and Greene (2014) had cataloged 338. This growth is a testament to the experiential learning potential afforded by SMFs. However, as D'Souza and Johnson (2019) note, the specific structure of the fund is critical to all aspects of its success. The literature has identified three salient aspects of this structure: where the fund's seed money comes from, how its investment decisions are made, and how it is integrated into its university's standard curriculum (Gradisher, *et al.*, 2016). We will consider each of these for our PTA fund, then consider one final element essential for a successful fund: the investment policy statement. For our PTA portfolio, the initial investment came from a donor, who gave it specifically to establish the fund, which therefore operates like a restricted endowment. Students make the investment decisions. Faculty advisors provide guidance, but do not choose investments; advisors do, however, have veto power. Block and French (1991) argue against such administrative power, asserting that it "undermines the premise for establishing the fund in the first place."

Nonetheless, while we certainly acknowledge advisors' need to avoid controlling and overriding the students' actions and for allowing mistakes as students are learning (see Charlton, *et al.*, 2015), we believe that having a veto is prudent and consistent with the university's fiduciary duty. The veto has never been used. While the donor created the fund as a learning tool, it is run as an extracurricular activity, with no academic credit. This is our most controversial choice. According to Gradisher, *et al.* (2016), it would be better to have fund management explicitly linked to a class (as are 71% of funds in Lawrence's 2008, sample). This would ensure that students are engaging in educational, rather than professional, management, and that professors are acting solely as educators; these are important considerations for complying with the Uniform Prudential Management of Institutional Funds Act (UPMIFA). Links to specific courses would also ensure a baseline level of financial knowledge for the students; for example, Block and French (1991) suggest that fund managers should take corporate finance and investments (and preferably portfolio theory and derivatives as well).

On the other hand, Bergquist, *et al.* (2020) advocate for an extracurricular approach to SMF management. For them, "[i]mplementing a student investment group as a club as opposed to a course can provide an inclusive, non-restrictive, interdisciplinary environment for learning which closely resembles work environments in which most students will enter upon graduation." Since these authors nonetheless believe that some background is required, they train their incoming students using six peer-led "modules." This sort of fund-specific training seems to be becoming more common. It is also often preceded by stringent application requirements. For example, D'Souza and Johnson's (2019) school's fund requires aspiring student managers to submit an application, demonstrate substantial relevant academic and practical experience, and have an interview. At Ammermann, *et al.*'s (2020) university, interested students must compete for SMF management slots through an innovative request-for-proposal process.

Our fund neither requires explicit coursework nor SMF-specific training. Instead, making two presentations to the members, along with approval from the faculty advisor, is sufficient for admission to the investment board. This allows students from non-business disciplines to participate, but it prohibits the assumption of a common baseline of knowledge. Our lack of a rigorous screening mechanism may be a weakness to our fund's structure, since high demands encourage similarly high levels of student engagement and commitment (Tashjian, 2020). Regardless of funding source or curriculum integration, all studies of successful funds agree that an SMF should have a governing document. Indeed, Boughton and Jackson (2020) consider an investment policy statement (IPS) so fundamental to the SMF experience that they conclude that as long as the fund has such a governing policy, there is no other requisite common structural feature for an effective fund. Most SMFs do appear to have a policy statement. In Neely and Cooley's (2004) 61-fund sample, 49 funds had a traditional IPS, three others used their university's endowment's, and only three funds had no policy at all. Our PTA fund is both discussed in our university endowment's IPS and has its own fund-specific version (although the latter devotes a large proportion of its length to descriptions of internal fund affairs and officer descriptions, topics which might be better relegated to bylaws.) Involving students in the writing or editing of their fund's IPS can be extremely educational (Neely and Cooley, 2004; see Horstmeyer, 2020, for a discussion on how to write an IPS for a student-managed fund). Active involvement affords student-managers the opportunity to become familiar with their own fund's constraints and risk objectives—such as the adherence to Catholic values, capitalization and portfolio weight guidelines, and sector ranges that Daugherty and Vang's (2015) students handle in their annual rewrite. It also can help them learn broader lessons; for example, Gradisher, *et al.* (2016) stress that incorporating IPS guidelines like those of the CFA Institute introduces students to the standards of prudence and fiduciary care mandated by UPMIFA. Given the potential benefits, Phillips, *et al.* (2020) suggest that students write the IPS from scratch every year. We do not do this for our fund; while we have all students in our portfolio management class write a *de novo* IPS for the PTA fund as an exercise, writing an actual IPS each year would require far too much administrative staff time to be practical.

Despite the centrality of the IPS to the fund's management—and of return and risk objectives to the IPS—we did not find in the literature any specific references to other schools' relative or absolute return targets. Every fund has some sort of benchmark, but at most the associated IPS sets an objective to "exceed" it (for example, see Horstmeyer, 2020). Many funds just seek to match their benchmarks (see, for example, Ghosh, *et al.*, 2020, and Betker and Doellman, 2020; see also Haddad, *et al.*, 2020, for the objectives set for the Tennessee Valley Authority's program, which is associated with the funds of 25 universities). In contrast, our PTA fund has both a relative return target (100 bp above the Russell 3000) and a tracking error target (200 bp). These targets are an important consideration in our empirical work, as we will discuss below. Next, however, we consider the relevant literature on closet indexing.

<u>Closet Indexing and Industry Metrics</u>

Closet indexers pretend they actively manage their portfolios, but they really hug an index. Taylor (2004) tests a strategy of shorting suspected closet indexers while buying true index funds, which—if the shorts are really indexing—should allow the trader to benefit from the difference in the longs' (low) and shorts' (higher) fees. However, he finds that the strategy's Sharpe ratio is almost the same as the market's, leading him to conclude that "widespread closet-indexing does not exist in the mutual fund industry." In contrast, Petajisto (2013) finds that closet indexing has been increasing since 2007, accounting for about one-third of mutual fund assets at the time of his study. He uses several metrics to identify such behavior, as will we. We begin with the most novel: active share. Cremers and Petajisto (2009) note that a truly active equity fund can be viewed as an index fund core with a long-short portfolio satellite appended to it. Thus, they and Petajisto (2013) investigate the prevalence and ramifications of closet indexing using active share, which they define as the proportion of the fund that differs from its index, given the weighting differences of index stocks. For example, consider a concentrated fund that chooses to plunge into a single stock, out of a universe of three stocks. Compared to an equally weighted index of the universe, the concentrated fund has an active share of $(0.5)*[|(1 - 0.333)| + |(0 - 0.333)| + |(0 - 0.333)|] = 67\%$. (The absolute values abstract from the direction of the difference; the multiplication of the sum by 0.5 keeps the active share of non-shorting portfolios between 0% and 100%.) Such a fund's manager "fishes" only in the top third of his universe. In contrast, a fund that only slightly changed the index weights—say to (.40, .20, .40)—would have an active share of $(0.5)*[|(0.40 - 0.333)| + |(0.20 - 0.333)| + |(0.40 - 0.333)|] = 13\%$. This latter fund would be a closet indexer. In general, Petajisto (2013) categorizes a fund with less than 50% active share as a combination of an actively managed fund and an index fund. Assuming that half of all funds perform better than the index and the other half perform worse, holding less than 50% active share means some of a manager's positions "cannot exist because the manager expects them to outperform the index; they exist only because he wants to reduce his risk relative to the index, even when that means including negative-alpha stocks in the portfolio." 50% is the "theoretical minimum" active share than a pure active manager can have. However, not every fund with low active share is a closet indexer. Instead, Petajisto (2013) categorizes funds into four types—described below—using both active share and a more traditional comparison metric: tracking error. He defines tracking error as the standard deviation of the difference between the fund's return and the index's (not adjusting for beta exposure), since he asserts that the simple difference is the more common performance measure for active managers. He then associates tracking error with exposure to systematic factors (e.g., picking sectors, choosing styles, holding cash), and active share to stock selection—the only two possible ways an active manager can add value.

Given these two dimensions of active management, he creates his fund categories. Active stock pickers will have high active share. If they diversify those bets, they will also have low tracking error, making them "stock pickers"; in contrast, more concentrated stock bets mean more tracking error for the "concentrated" group. "Factor bets" have low active share but high tracking error, which comes from their high exposure to systematic factor risk. Finally, closet indexers have both low active share and low tracking error—they stick close to their benchmarks, hoping that their mediocrity will be inoffensive. In his sample, the factor-bet/high tracking error funds "destroyed value." In contrast, funds with high active share—concentrated funds and diversified stock pickers—outperform. Only stock pickers, however, add value after fees. These active stock pickers can do especially well when the cross-sectional dispersion in index returns is high. This "cross-vol" measure is based on the weighted differences in the individual stocks' returns relative to the index. High idiosyncratic risk may drive high cross-sectional volatility, providing active stock pickers with target-rich environments: their active returns will be high if the firm-specific mispricings resolve themselves over the managers' holding period. Indeed, Petajisto (2013) finds that high cross-sectional volatility is positively related to stock pickers' future returns.

However, Petajisto (2013) does not link cross-sectional volatility with the performance or prevalence of closet indexing. Brown and Davies (2015a, 2015b), on the other hand, put volatility—albeit the volatility of the individual funds, rather than that of the index stocks in general—at the heart of their theoretical model. They conclude that closet indexers strategically increase the volatility of their funds to help themselves masquerade as truly active funds. In so doing, they limit the efficacy of Petajisto's (2013) active share metric as an identifier of closet indexing behavior. In the Brown and Davies (2015a, 2015b) model, highly skilled managers—those with more than a threshold level of skill—will invest the resources necessary to run a truly active fund. Less-skilled managers will become closet indexers. These "charlatans" hope their clients mistake them for true active managers; otherwise, the high fees will stop. If the true active managers' returns are more variable, it becomes harder for investors to determine whether a fund did poorly because its manager failed or because she did not try—to distinguish a true active manager from a closet indexer. Performance becomes a noisier signal of value. This not only encourages more closet indexing, but also induces the charlatans to inject more variability into their own returns, by "signal jamming." They do this by making uninformed changes to their funds' weights of index stocks, just so their portfolios will differ from the index. (Similarly, Cremers and Petajisto, 2009, suggest closet indexers may also "mask" their essentially passive funds with excess turnover.) If the managers do not play this game, they risk outing themselves as closet indexers. Thus, in this model, every charlatan plays: "[n]oise injection and closet indexing are complements; as the moral hazard problem becomes more severe, closet indexers inject more noise, attenuating investors' abilities to identify skilled managers." Since this strategic behavior may make tracking error and active share less effective indicators of true active management, Cremers and Petajisto (2009) suggest that investors should use both measures when choosing active managers, as well as the prior year's returns (to take advantage of empirically demonstrated performance persistence in the most active funds). That is the framework that we will use in this paper. We now turn to characterizing our fund using these metrics, as well as both some more traditional and some more novel ones.

DATA AND METHODOLOGY

In this section, we first provide some background on the structure our school's PTA fund and on the characteristics of our past student managers. We then describe the performance data we will use to characterize our fund. Our fund is run by undergraduate students who study business within a general liberal arts curriculum. Since its inception in late 2016, the fund has had five executive teams, typically consisting of a president, vice president, treasurer, market research chair, outreach chair, and secretary. Executive positions are typically spread across class cohorts, with the presidency held by a junior or senior, and students may hold executive roles multiple years in a row. Approximately 85% of all executive positions have been held by male students. This includes all five presidents, as well as every market research chair and secretary. No women were on the executive team until spring of 2019; half of the female participation we have had has been in the role of outreach chair. As noted in the literature review section, no formal coursework is required for participation in the club that runs the fund, and all trading decisions (subject to an as-yet never used administrative veto) are made by the students. Having described the structure of the fund and the types of students who run it, we turn now to the data we will use to evaluate its performance. Our sample period runs from the date of the fund's inception, 8/29/16, through 4/15/21. Our SMF started investing in individual stocks on 3/10/17, having held its assets only in an index "parking place" for the first six months. We chose our annual analysis periods to conform roughly to the active parts of our university's school years, therefore defining our year-end to be around April 15th (specifically, 4/13/17, 4/13/18, 4/15/19, 4/15/20, and 4/14/21). We ascribe the initial 24 trading-day period from 3/10/17 through 4/13/17 to our "incubation period," focusing our analysis on the last four years (see Cremers and Petajisto, 2009; we are following their very loose interpretation of the incubation period from Evans, 2004). Data for all but two of the portfolio's stocks, as well as for all indexes, comes from Yahoo! Finance. The remaining two portfolio stocks, The Michael's Companies (MIK) and Instructure (INST), went private during our sample period; we obtained date for these stocks from Quandl. For MIK, which was bought out in April of 2021, just after our sample period, we have data for the full period; for INST, however, we have data only through 3/23/20. We therefore measure all covariances with INST using the subperiod 8/29/16-3/32/20.

RESULTS

In this section, we summarize the results of our investigations into the performance of our student-managed fund. The various approaches we use will help us determine whether our fund is being run as a truly active fund. We begin with returns- and holdings-based analyses, turnover, and tracking error, then turn to metrics and techniques that may be more novel for SMFs: active share, attribution, and polynomial goal programming.

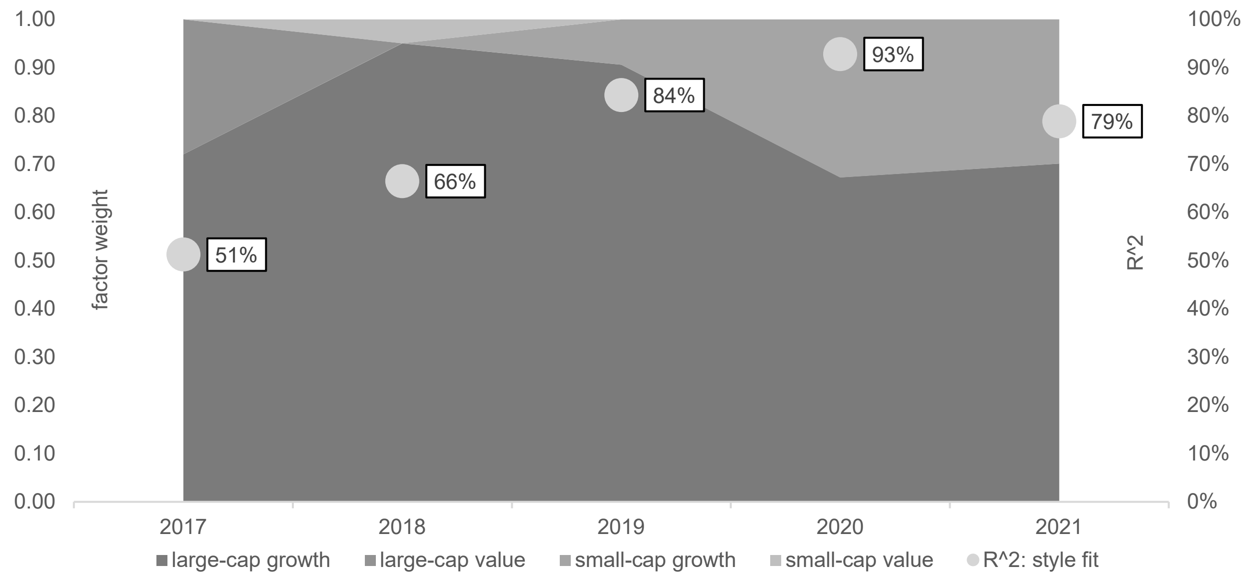
Returns- and Holdings-Based Analysis, Turnover, and Tracking Error

We performed both holdings-based and returns-based analysis, which allow us to identify any style biases in the portfolio (see Gastineau, *et. al.*, 2007; see Taylor, 2004 for a recommendation that holdings-based analysis be used to identify closet indexing). We will first discuss the latter. For each annual subperiod and for the full period, we regressed the returns of the PTA portfolio on four ETFs spanning the U.S. domestic equity market: VTWV (small-cap value), VTWG (small-cap growth), VONV (large-cap value), and VONG (large-cap growth) (see Gastineau, *et al.*, 2007). We constrained the coefficients to be nonnegative and required them to add to 1, so that we can interpret them as factor weights. The resulting rolling style chart is shown in Figure 1. The fund is clearly being run as a growth fund, despite having a broad Russell 3000 mandate. The white dots in the graph identify the constrained regressions' R^2 values, which can be interpreted here as the style fit (the complement, [$1-R^2$], measures the security selection component). These factor tilts—84% since inception—explain the vast majority of the fund's performance, overwhelming any contribution from active stock picking. Taylor (2004) notes that a high R^2 from a comparison of fund and index returns is a necessary indicator of closet indexing, and identifies his "suspect" closet indexers from among funds with R^2 values of at least 97%. However, R^2 is not sufficient, since it may not persist. Thus, the PTA fund may not be a closet indexer, but it is clearly not a balanced fund.

We confirmed the fund's style bias with holdings-based analysis. Using market value, trailing twelve-month earnings per share, year-over-year quarterly revenue growth, trailing price/earnings, price/book, dividend yield, and sector, we characterized the PTA fund's stocks by size and style (see Gastineau, *et al.*, 2007). Large-cap growth stocks always represented a majority of the portfolio. During the "incubation period" from August 2016 through April 2017, the PTA fund held only growth stocks, two-thirds of them large-cap. From April, 2017 to April, 2018 it had its highest weight on value, at one-third, evenly split between small- and large-cap; two years later, it was at its most evenly balanced, with a since-inception minimum of 58.8% in large-cap growth (plus 11.8% small-cap growth, 23.5% large-cap value, and 5.9% small-cap value). Most recently, from April, 2020 through 2021, large-cap growth stocks have hit their since-inception maximum: 75%; only 18.8% of all securities are in value, with 6.3% small-cap value and 12.5% large-cap value. Overall, it is evident that the PTA is heavily overweight in large-cap growth stocks, which is inconsistent with their benchmark of the Russell 3000.

Later in this section, we consider this tilt's impact on the fund's tracking error. First, however, we examine the PTA fund's turnover. Turnover is our initial measure of the PTA fund's active management. In general, we expect less turnover from less active funds (Cremers and Petajisto, 2009); for example, the Center for Research in Security Prices (2021) notes that some "funds that have a passive management style may… show very low or zero turnover." However, there are at least two caveats. First, we do not really expect *no* turnover from a true indexer, since even these funds must accommodate investor flows and adjust to events such as the annual Russell reconstitution. Thus, in Frino, *et al.* (2004), index funds average 6.47% annual turnover, while enhanced indexers average 12.26%; in Cremers and Petajisto (2009), the most passive category of funds has turnover of 18.1% per year.

Figure 1: Rolling Style Chart for PTA Fund



The figure shows the proportional effective exposure of the PTA fund to four mutually exclusive and exhaustive factor tilts. The shaded areas represent the weights of the four market-spanning equity-market indicators representing those factors, which were used as independent variables in a regression of the PTA fund's returns. The labeled white dots are the regressions' R^2 values, which here measure the style fit. The large area accounted for by the large-cap growth indicator, and the high R^2 values, indicate that the fund is being run as a growth fund, rather than as the blend that its benchmark would suggest.

Second, as we noted earlier, higher trading activity might just be a way to make a manager look busy and mask their closet indexing—the tactic Cremers and Petajisto (2009) call "signal-jamming." Unless trading enhances good active bets, it will not create value. To assess the PTA's fund's level of trading activity, we used Frino, *et al.*'s (2004) definition of turnover: the minimum of annual dollar sales or purchases, divided by the daily average portfolio size. We find turnover of 7% and 16%, in 2019 and 2020, respectively; for all other years, the managers made no sales, so that the numerator of the turnover ratio—the minimum of purchases and sales—was zero. Thus, while these low levels of measured turnover land solidly in Cremer and Petajisto's (2009) indexing category (and between Frino, *et al.*'s, 2004, indexing and enhanced indexing strategies), we suspect that the turnover this early in the fund's life is an artifact of its "incubation," rather than a reflection of its active management style. The donor released his funds in tranches, and the members' early priority was on investing those funds, not on optimizing the portfolio as a whole. Members still do not have a codified sell discipline; indeed, two of the five sales events were from stocks being taken private, not from club decisions. Even for years that do have sales, the magnitude of the purchases was at least four times higher (and at least twice as large as the average purchase proportion reported in Frino, *et al.*, 2004), indicating the members' focus on buys. Thus, while turnover may be an important metric to watch going forward, we do not believe it sheds much light on the past behavior of our student-managers. Of course, we could be observing some behavioral biases in the turnover numbers. Members may be reluctant to sell assets bequeathed to them by prior groups (endowment bias). From anecdotal evidence, we suspect that this may be a factor, especially since the fund is still not fully invested. On the other hand, Block and French (1991) suggest that incoming managers may deem their predecessors' choices "unwise," choosing to sell them immediately to get the fund back "on… track." They attribute their own SMF's high turnover to such inclinations (although they do not quantify how "high" their turnover actually is). We plan to explore these sorts of attitudes in a future survey of current and former PTA fund members. However, for now, we turn to the first of two active-management measures used by Cremers and Petajisto (2009): tracking error. For each school year, as well as for the full since-inception period, we calculated tracking error (TE) using both the beta-adjusted and the common simple-difference definitions.

The former uses the volatility of the error term from a regression on the benchmark, for which we use the following:

$$R_{PTA,t} = intercept + beta * \left(R_{benchmark,t}\right) error_t \quad (1)$$

(The relatively small variability of the Treasury series over this period implies that using the excess return form of this regression would have an immaterial effect on our estimated betas and errors; for example, betas using the two different regression forms for the normal benchmark regression are identical out to the fifth decimal place. We do verify these betas using excess returns in the discussion section of the paper, below.) The simple-difference version (dubbed "common" in both Petajisto, 2013, and Cremers and Petajisto, 2009) is simply the standard deviation of the difference between the fund's return and the benchmark's; this assumes that the beta from equation (1) is one. For our benchmarks, we used the PTA fund's actual Russell 3000 benchmark (proxied by the ETF VTHR), a large-cap growth benchmark (the ETF VONG), and a normal benchmark composed of 70% VONG and 30% VTWG, our small-cap growth ETF. In all cases, the betas from equation (1) were close enough to one so that the two tracking-error measures differed by only a few basis points, so we will focus our discussion on the common measure. We report our results in Table 1.

Table 1: PTA Fund Summary Statistics and Tracking Error Data

	2017	2018	2019	2020	2021	Since Inception
arithmetic mean	-0.00153	0.00027	0.00080	0.00050	0.00201	0.00084
variance	0.00004	0.00011	0.00016	0.00040	0.00023	0.00022
standard deviation	0.00593	0.01048	0.01284	0.01991	0.01506	0.01484
holding period return (chain-linked)	-43.2%	5.7%	19.9%	7.9%	61.0%	112.1%
annualized standard deviation	9.4%	16.6%	20.3%	31.5%	23.8%	23.5%
RUSSELL 3000						
beta	0.90	1.06	1.19	1.01	0.98	1.03
intercept	-0.0010	-0.0004	0.0003	0.0005	0.0002	0.0001
simple difference tracking error	0.00424	0.00677	0.00692	0.00715	0.00926	0.00753
beta-adjusted tracking error	0.00422	0.00676	0.00671	0.00714	0.00925	0.00752
annualized TE: simple difference	6.71%	10.71%	10.95%	11.30%	14.64%	11.90%
LARGE-CAP GROWTH						
beta	1.19	1.05	1.02	0.97	0.92	0.97
intercept	-0.0011	-0.0006	0.0002	0.0001	0.0002	-0.0001
simple difference tracking error	0.00401	0.00605	0.00512	0.00601	0.00776	0.00626
beta-adjusted tracking error	0.00395	0.00604	0.00511	0.00597	0.00768	0.00625
annualized TE: simple difference	6.34%	9.57%	8.09%	9.50%	12.26%	9.90%
NORMAL						
beta	0.83	1.04	1.02	0.96	0.95	0.97
intercept	-0.0012	-0.0006	0.0003	0.0003	0.0000	0.0000
simple difference tracking error	0.00452	0.00622	0.00522	0.00534	0.00692	0.00594
beta-adjusted tracking error	0.00445	0.00621	0.00522	0.00527	0.00689	0.00625
annualized TE: simple difference	7.14%	9.83%	8.26%	8.44%	10.94%	9.39%

This table provides summary statistics and tracking error (TE) values for the PTA fund. In the top panel, we provide periodic and annualized risk and return metrics for the fund. To put the holding period returns in perspective, we note that the 2021 values for the Russell 3000, the large-cap growth ETF, and the custom benchmark were 56.1%, 55.6%, and 63%, respectively; since-inception values were 88.8%, 137.4%, and 96.2%. The remaining three panels provide tracking error data for the three benchmarks, using both the simple-difference method and the beta-adjusted method. In all cases, for years after the "incubation" year of 2017, these tracking error values put the PTA fund in the top 20% of the tracking-error sample in Cremers and Petajisto (2009).

The top panel of Table 1 gives the summary statistics for the PTA fund over all subperiods. The other three panels present inputs and results for the tracking error measurements, using our three benchmarks. Across all five years and all benchmarks, the maximum TE is 14.64%, and the minimum is 6.34%. Ignoring the "incubation" year of 2017, the minimum rises to 8.09%. These ranges place the PTA fund beyond Petajisto's (2013) characterization of closet indexers, which in his sample of 1,124 funds have a mean TE of 3.5% with a standard deviation of 0.9%. If we create a range of (mean ± 1 standard deviation), using Petajisto's (2013) summary statistics and his classifications of fund types (stock pickers, concentrated, factor bets, moderately active, and closet indexers), we find that 93.3% of the PTA's 15 index-year combinations fall within the range defined for factor bets (characterized as high TE/low active share), while none do for the closet indexer range (low on both dimensions). (The others are stock pickers: 53.3%; concentrated: 13.3% and moderately active: 20% [all in incubation year]). This result is consistent with the strong loading of the PTA fund's returns on the two growth ETFs, and strongly suggests that the fund is not a closet indexer.

Having considered the more standard measures of portfolio performance, we turn now to the more novel.

Active Share, Attribution, and Polynomial Goal Programming

The second dimension that Cremers and Petajisto (2009) use to categorize funds—along with tracking error—is active share. As noted earlier, active share is half the absolute difference in asset weights between the fund and its benchmark. (See also Frino, *et al.*, 2004, for a similar measure they call the "absolute deviation.") For long-only funds like the PTA fund, this measure will fall between 0% and 100%, with higher values indicating a higher level of active management. Since the PTA fund has between three and sixteen stocks during our analysis period, its active share versus the benchmark Russell 3000 is obviously extremely high: over 90% for each year (as were 21% of Cremer and Petajisto's, 2009, sample). This would place the PTA fund firmly in the "concentrated" category of Cremers and Petajisto's (2009) taxonomy. The difference between concentrated and factor bets categories is the high active share. But is that active share measure really as meaningful a contributor to the PTA fund's results as is the tracking error? To explore further the implications of the fund's active share, we perform the following simple attribution:

$$\left(R_f - R_b\right) = \sum_{i=1}^{n}(R_i - bogey) * \left(wt_{i,f} - wt_{i,MV}\right) + \sum_{i=1}^{n}(R_i - bogey) * (wt_{i,MV} - wt_{i,b}), \quad (2)$$

where R_f is the return for the PTA fund for the period; R_b is the benchmark return; the wt_i terms are the weights of index stock i in the *f*und, *MV*-weighted, and *b*enchmark portfolios; the "bogey" is simply the return for our Russell 3000 benchmark, VTHR; and n is the number of stocks in that benchmark. (Measuring the stocks' returns relative to the bogey allows easy identification of over- and underperformers.) Since the PTA fund is a long-only domestic equity fund benchmarked to a market capitalization-weighted index of the broad market, the only way it can generate outperformance is to choose outperforming stocks (and omit underperformers) and/or to overweight the "good" stocks. Our simple attribution therefore has two parts. *Security selection* is measured using the difference between the performance of the stocks the fund chooses and that of the full set of stocks in the benchmark. The weights of the chosen stocks in this term are "naïve": they are simply the weights that would be used in a market cap-weighted index using only that subset of stocks. (Thus, if the fund chose only two stocks, both of which had the same market cap, then each of their $wt_{i,MV}$ terms would be 0.50, and the weight of all other benchmark stocks would be zero.) This is the second term in equation (2). Having used the naïve weights to measure security selection, we then use the fund's deviation from those weights as the measure of the *intensity* of the student managers' commitment to each of their selections. Thus, the first term in the attribution is based on the difference between a selected security's actual fund weight and its naïve weight. The "actual" weights are the average daily weight over the period, so there is asynchrony between them and the year-end values of the benchmark weights.

The PTA fund beat its benchmark in the last three of the five periods (four years, plus the 24-day 2016 "incubation" period). In all but the last year, stock selection was a positive contributor (contributing from 1.4% of outperformance in the incubation period to 27.5% in 2020), while intensity was negative (contributing from -3.5% in both the incubation period and 2019, to -11.2% in 2020). This pattern occurred in both good and bad market years. In 2021, when intensity determined 103% of the 193 bp excess return, the portfolio benefitted tremendously from its positions in Square (SQ), Axon Enterprise (AXON), and Etsy (ETSY): none of these stocks makes up more than 0.3% of the Russell 3000, but the PTA fund weighted them at 5%, 15%, and 3% (approximately 2, 8, and 5 times their naïve values, respectively). Our holdings-based analysis categorized these three stocks as growth stocks. Their impact on the portfolio may therefore have been more an artifact of a good period for growth than a reflection of superior active insights about these specific stocks. To continue our examination of the fund's stock weighting insights (intensity), we compared the actual weights chosen for the PTA fund at the end of our sample period (called $wt_{i,f}$ in the attribution above) to the optimal weights for that set of stocks. To determine these optimal weights, we used Excel's MMULT and Solver functions to identify the unconstrained and constrained (nonnegative) weight sets, respectively, that would give the lowest variance to a portfolio that had the same mean return as the PTA fund's 2021 portfolio. We used the sixteen included stocks' returns for our full data set, 8/30/16-4/14/21, to create the covariance matrix.

The differences were stark: Solver assigned a zero weight to fully half of the PTA fund's holdings; MMULT would short-sell six of them. The MMULT and Solver solutions share the same top five stocks, but the PTA fund has only two of those in its top five. MMULT's second most heavily weighted stock, Wal-Mart at 37%, is thirteenth for PTA (at 4%). (The Solver weight is 16%, the fourth highest.) In contrast, the PTA fund's top stock, Axon, is weighted almost twice as heavily as it is in either of the optimized portfolios (15% v. 8%). The PTA fund does better with its smaller holdings: four of its lowest-weighted five stocks are in Solver's "omit" category; three of these have negative weights in MMUL's unconstrained optimum. And all portfolios agree in putting ATT last in the rankings. To quantify these differences, we compared the PTA fund's weights to those of the optimized MMULT and Solver portfolios using the Spearman rank correlation coefficient. Higher values for this metric imply better correspondence between the PTA fund's choices and the optimized portfolios'. PTA and MMULT's result was 34%; PTA and Solver's—both of which prohibited short sales—was 41%. Although the PTA fund's weighting scheme differs markedly from the optima determined by MMULT and Solver, it may nonetheless confer benefits not considered in traditional mean-variance analysis. We therefore used polynomial goal programming (PGP) to incorporate skewness and kurtosis into the optimization objective function, so that we could compare the fund's weights to those optimized over four moments (see Lai, *et al.*, 2006, for an overview of the procedure, and Livingston, 2019, for an application to an SMF). To implement this approach, we minimized the following objective function:

$$Z = \left|\frac{d_1}{R*}\right|^{\lambda_1} + \left|\frac{d_2}{V*}\right|^{\lambda_2} + \left|\frac{d_3}{S*}\right|^{\lambda_3} + \left|\frac{d_4}{K*}\right|^{\lambda_4} \tag{3}$$

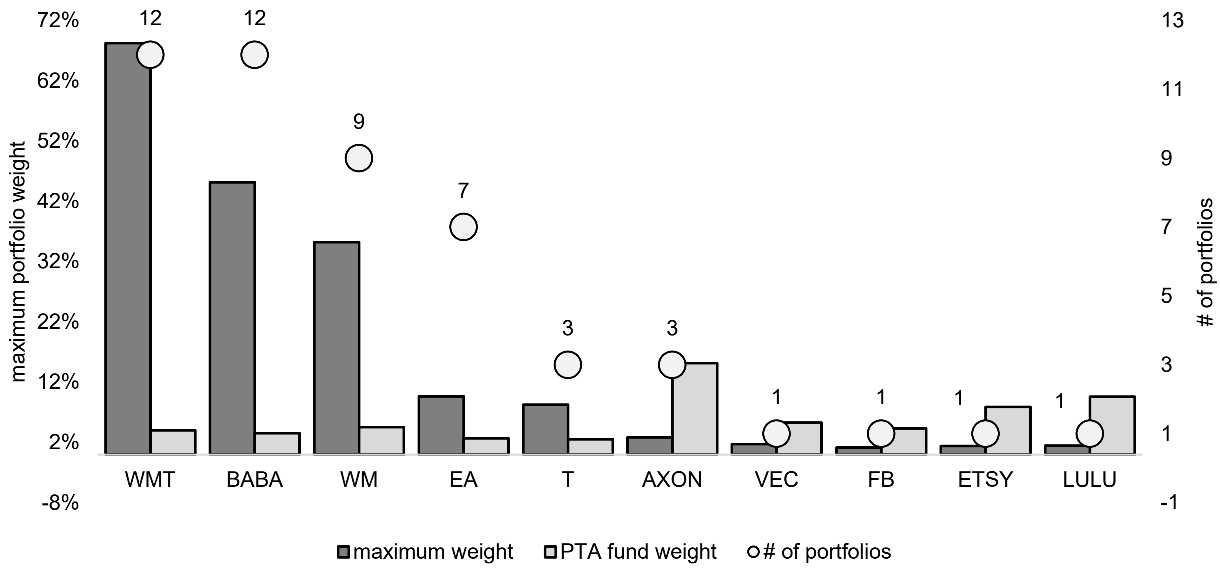
Here, R*, V*, S*, and K* are the "aspired" levels for mean, variance, skewness, and kurtosis, respectively; thus, V* and K* are the minimum possible values of variance and kurtosis, given our set of stocks, and S* and R* are the maximum possible skewness and mean return. (All of these aspired values are subject to our non-negativity constraint. As we will see, unless we also limit maximum weights, the max-return portfolio will plunge into the highest-mean asset, and R* will equal its mean.) Once the market opportunities are characterized, we add representations of the investor's preferences. These are the λ values: λ_1 reflects the investor's preference for the first moment, mean; λ_2 reflects variance; λ_3, skew; and λ_4, kurtosis. Preferences guiding portfolio creation are therefore described as (λ_1, λ_2, λ_3, λ_4) sets; for example, (1100) is the traditional mean-variance portfolio, while (1110) adds skewness as a equivalently valued criterion and (1111) adds both skewness and kurtosis. An investor with a stronger preference for a particular moment will tend to see more attractive values for that moment in her optimized portfolio (Davies *et al.*, 2004). We used the twelve λ_i preference sets used by Kemalbay, *et al.* (2011), including (1100), the mean-variance portfolio. (See caption of Figure 2 for full list.)

The PGP optimization proceeds by choosing the *d* terms to minimize the objective function. These *d* terms measure the distance between the portfolio's moment and the optimal level of that moment. Thus, d_1 represents the amount by which the portfolio's mean falls below M*: d_1 = (M* - portfolio mean), and d_3 measures the difference in skew: d_3 = (S* - portfolio skew). The d_2 and d_4 values measure portfolio distances from V* and K*, respectively, defined by subtracting the aspired values (which will be smaller) from the portfolio values. (Thus, *d* values are defined to be positive.) The absolute value functions correct for possible negative values of M* and S*. (For our optimizations, M* and S* are positive, so we can ignore the absolute values; we therefore optimize using Excel Solver's GRG Nonlinear/Multistart engine rather than its Evolutionary engine. See Winston, 2016.) Figure 2 summarizes our results. Five of the PTA fund's sixteen stocks were never used in any of the PGP optimized portfolios (Home Depot [HD], Microsoft [MSFT], Intuitive Surgical [ISRG], BlackRock [BLK], and TPI Composites Inc

[TPIC]). Another, Square (SQ), was used only once: in the mean-optimized "aspired" portfolio (given the constraint against nonnegative weights, this portfolio plunges into the highest-mean asset). Four stocks (Vectrus [VEC], Facebook [FB], Etsy [ETSY], and Lululemon [LULU]) have trivial impacts, appearing in only the mean-variance optimized portfolio, and all at less than a 2% weight. (ETSY does have an 8% weight in the aspired minimum-kurtosis portfolio, however.) AXON shows up in three portfolios emphasizing low variance, but again, its weights are negligible (less than 3%). AT&T (T) enters the same portfolios as AXON, but generally has higher weights; its strongest presence is in the aspired minimum-variance portfolio, where its weight is just over 16% (this weight is cut in half in the mean-variance optimized portfolio). Electronic Arts (EA) also is included in the variance-focused portfolios, but is most important in the kurtosis-focused portfolios: it makes up 32% of the aspired low-kurtosis benchmark, as well as almost 10% in the 1311 and the 1113 portfolios.

The most important stocks in the PGP-optimized portfolios are Walmart (WMT), Alibaba (BABA), and Waste Management (WM), in that order. All appear in the aspired minimum-variance portfolio. BABA also makes up 60% of the minimum-kurtosis portfolio; WMT is 100% of the maximum-skew portfolio. In the optimized portfolios, WM primarily contributes to those that are variance-focused (for example, it is weighted at 35% in the mean-variance portfolio 1100, and at 20% in 1110); otherwise, though, its only major appearance is its 21% weight in 3110. WMT and BABA, in contrast, each show up in 12 of the optimized portfolios; in fact, eight of these (all of which have a high-emphasis "3" in any moment position) are essentially two-asset portfolios of about 40% BABA and 60% WMT. However, as is clear from Figure 2, the PTA portfolio makes little use of the potential benefits of WMT and BABA. We therefore cannot conclude that the student-manager's intensity choices have made meaningful contributions to the portfolio's higher-moment characteristics. Thus, the polynomial goal programming results support the conclusion from the attribution: the PTA fund does not demonstrate particular insight in weighting *its own* stocks. Instead, it has derived value from having chosen growth stocks during a period when large-growth funds "trounced" and "smashed" large-value funds (Lynch, 2021). We are thus inclined to attribute the PTA fund's performance to its style tilt, and place it firmly in the "factor bets" category.

Figure 2: Summary of Polynomial Goal Programming Optimal Weights



This figure gives highlights from the PGP optimizations. The PTA fund's stocks are Walmart (WMT), Alibaba (BABA), Waste Management (WM), Electronic Arts (EA), ATT&T (T), Axon (AXON), Vectrus (VEC), Facebook (now Meta; FB), Etsy (ETSY), and Lululemon (LULU). There were 12 preference sets considered: (1100), (1110), (1111), (3110), (3121), (3123), (3131), (1311), (1313), (2331), (1113), and (1232). The dots, which are plotted on the right-hand axis, identify the number of those sets in which the given stock appears. Thus, Walmart and Alibaba are in all 12; each of Vectrus, Facebook, Etsy, and Lululemon is in only one. The dark grey bars (plotted on the left-hand axis) represent the maximum weight assigned to the stock by the PGP technique across these preference sets, while the lighter bars are the actual PTA fund weights. Given the disparity between the PGP weights and the actual weights, we can see that the PTA fund is not taking advantage of any possible skewness or kurtosis benefits from its chosen stocks. (The PTA fund does have a maximum weight of 10%, but nonetheless does not weight its stocks optimally relatively to each other.)

DISCUSSION

Given the tracking error, active share, and attribution results, it seems clear that the PTA fund has *not* been acting as a closet indexer. This conclusion would be edifying for the donor who endowed the fund: he wanted to provide students an opportunity to run real money in an actively managed fund. However, the fund's investment policy statement seems inconsistent both with his wish and with the fund managers' actual behavior. In this section, we consider further evidence that both the IPS's risk/reward objectives and its broad-based benchmark, the Russell 3000, are inconsistent with the intent and practice of the fund. As shown above, the PTA fund has demonstrated a "persistent and prominent" bias toward growth investing. Since its benchmark is supposed to incorporate its "salient investment features," including its "significant exposures to particular sources of systematic risk," the fund should be using a growth benchmark (Bailey, *et al.*, 2007). To underscore the conclusion that the current benchmark is inappropriate, we ran regressions of the PTA fund's excess returns on the excess returns of three possible benchmarks: the actual Russell 3000 benchmark (VTHR); the large-cap growth Russell benchmark (VONG); and the 70/30 custom benchmark which we created based on the rolling style results from our returns-based analysis (we call this benchmark "VMIX"). We used the 20-year constant maturity Treasury series as the risk-free rate, and ran the regressions over the since-inception period (3/13/17-4/14/21).

First, we note that the betas for all three of these excess-return regressions were the same as the raw-return regressions shown in Table 1. Of more interest here are the annualized alphas and the implied information ratios (IRs). The alpha for the custom VMIX benchmark was -0.9% per year, with an IR of -0.35, indicating both a good fit for the benchmark and index-like performance by the fund. In contrast, using the fund's actual Russell 3000 benchmark, the alpha was 4.6% with an IR of 2.25 (the VONG's values were -2.6% and -0.96). Clearly, the assessment of the fund's performance will vary wildly depending on the benchmark used, and the poorly matched Russell 3000 makes it difficult to "differentiate managers...who add value through investment insights from those who do not" (Bailey, *et al.*, 2007). We also see the benefit of the custom VMIX benchmark over the poorly specified VTHR using Bailey, *et al.*'s (2007) active/style breakdown, which describes a portfolio's return as the sum of the market, the style contribution, and the active management contribution. Defining the style contribution as the difference between the portfolio's benchmark and the market (for us, [VMIX – VTHR]) and the active component as the difference between the portfolio and its benchmark [PTA fund – VMIX]), the authors assert that a good benchmark leads to active and style components that are uncorrelated. Our correlation is 0.074 ($R^2 = 0.0055$). The correlation between style and "error" (for us, [PTA fund – VTHR]) should be significantly positive; ours is 0.62 ($R^2 = 0.38$). VMIX therefore functions well as a benchmark for the PTA fund.

In contrast, the Russell 3000 benchmark prescribed in the PTA fund's IPS does not reflect the fund's style. Similarly, the risk/reward objectives reflect neither that style nor the active mandate of the fund in general. The IPS for the PTA fund mandates active, long-only, domestic equity investing. Since as "an active fund, a target return above the agreed upon benchmark is appropriate," the IPS sets an objective of 100 bp above the Russell 3000. As noted earlier, many SMFs do not set excess return targets; for example, the University of Connecticut's fund "does not presume that students will be able to beat the market on a consistent basis," focusing instead "on delivering high-quality, practical education to students" (Ghosh, *et al.*, 2020). Nonetheless, our target is not inconsistent with Cremers and Petajisto's (2009) findings that the most successful active mutual funds—which the authors assert do exhibit active skill—outperform their benchmarks by 1.51% to 2.40%. In particular, they find that high active share/low tracking error active funds in their sample beat their benchmarks by about 134 bp/year.

However, our fund's tracking error is not low. Despite the IPS's specified maximum of 200 bp, we have already seen that its actual since-inception TE against its benchmark is almost 1,200 bp. The prescribed 200-bp maximum places our fund's objective completely within the lowest tracking error bracket in Cremers and Petajisto's (2009) classification (whose highest category is "14%+"). While low tracking error can be associated with active management, the authors assert that this requires "large but diversified" positions away from the index—a requirement neither the conception of (via the IPS) nor the history of the PTA fund supports. In Petajisto (2013), there is no such fund at active share above 50%, the "theoretical minimum a pure active manager could have," and, in Cremers and Petajisto (2009), active share above 60% (the upper cutoff for their "very low" levels of active share) is never associated with tracking error of less than 2%. In fact, Petajisto's (2013) most salient examples of closet indexers have tracking errors of 3.1% and 4.4%. Thus, the tracking error objective for the PTA fund seems wildly inconsistent with its active mandate. Horstmeyer (2020) reports objectives that are more realistic for a fund like ours: the George Mason University SMF is to "exceed" its S&P500 benchmark with a tracking error of less than 750 bp. Thus, both the TE and the alpha targets for this fund are more liberal than ours. They also suggest that our operating history and tracking error record are not unique, and that revising our objectives in light of that history would not put our fund out of the mainstream. In any case, our analysis forces us to conclude that while our PTA fund is not, in fact, a closet indexer, its IPS incongruously apparently wishes it were.

As a final investigation into the appropriateness of our risk/return objectives, we ran two simulations to assess the probability that both the fund's excess return and tracking error targets could be met simultaneously. For the first simulation, we used the actual sixteen stocks held by the fund at the end of our sample period, the fund's Russell 3000 benchmark, and return data for our full sample period (August, 2016 through April, 2021). We used the fund's portfolio weights as of the last day of our sample, and assumed daily rebalancing. For the second simulation, we used the fund's portfolio returns and our VMIX custom benchmark for the period from March, 2017 (when the fund started investing) to April, 2021. In both cases, we used Crystal Ball's batch fit feature to fit distributions and estimate correlations for the return series (see Charnes, 2012), and our outputs were annual "alpha" (PTA fund return – benchmark return), tracking error, and an indicator variable that equaled one when both return and risk targets were met simultaneously. We ran 10,000 trials in each simulation. In *none* of those 20,000 trials did both the tracking error and the incremental return meet the guidelines of the IPS. For the stock-level simulation, the tracking error's distribution was positively skewed, leptokurtic, and had a mean of 22.5%; the incremental return was negatively skewed, leptokurtic, and had a mean of 27.8%. Obviously, these simulated results—especially the returns—were dramatically affected by the extreme experience of 2021 (see Table 1); the mean for the portfolio-level incremental return trials is a very-different -60 bp. Average tracking error for those, though, is still high, at 32.3%. Overall, the simulations underscore what has been clear throughout: the restrictions in the PTA fund's IPS are inconsistent with active management in general and with the fund's management in particular.

CONCLUDING COMMENTS

Student-managed funds are now expected elements of finance education, and while there are various ways to structure these funds, most seem to focus on active management through stock picking. Our university's fund, the PTA fund, has such an active mandate, but it also has a very restrictive tracking error objective. In this paper, we analyze the returns of our fund to determine whether our student managers are acting as true active managers or as effective closet indexers. We find that while they are running an active, highly concentrated fund, they are not—and cannot be—meeting the risk constraints of the fund's investment policy statement, since the IPS effectively mandates closet indexing. To evaluate our fund's performance, we used both traditional professional portfolio assessment techniques, such as returns- and holdings-based analysis, as well as more unconventional methods such as polynomial goal programming. We structured our approach using Cremers and Petajisto's (2009) taxonomy, which is based on tracking error and on their novel metric, active share. We found that—with over 90% active share—the fund is definitely active, in accordance with the initial donor's wishes. However, it is being run as a large-cap growth portfolio, which is inconsistent with its Russell 3000 benchmark. More seriously, its tracking error has been between three and seven times larger than the constraint imposed in the investment policy statement—a constraint that effectively requires the fund to be a closet indexer. Our simulations demonstrate that it is not possible for the fund to simultaneously meet all of the constraints in its governing documents.

Given our results, we offer the following three suggestions to advisors of student-managed funds. First, confirm that the fund's benchmark is consistent with the actual investment approach employed. Second, clearly and explicitly identify the relevant performance metrics in advance. Third, ensure that the fund's investment policy statement reflects empirical market realities. The first two of these are standard procedure for professional funds (see, for example, Maginn, *et al.*, 2007). However, while many prior papers have stressed the need for students to be conversant with their fund's policy statement (see, for example, Phillips, *et al.*, 2020, and Daugherty and Vang, 2015), we know of none that has highlighted the even more basic requirement that the statement be appropriate in the first place. If the purpose of the fund is to have students make active bets—as it is for our fund—then they must have the risk budget to accommodate that mandate.

There are several limitations of our analysis. First, for the last two years, students have been unable to work with each other and with their faculty mentors as envisaged, given that our residential campus has been frequently closed because of the covid pandemic. The resulting disruptions to our academic routine have been profound, and their ramifications for the fund—and for the complete curriculum—are as yet unknowable. We suspect, however, that fewer meetings have meant fewer stock pitches and less turnover than we would otherwise have seen. A more easily appreciated limitation is our (necessary) focus on a young fund. Our sample period starts from the fund's inception, and therefore encompasses its incubation period. Indeed, the fund still does not have a rigorous formal sell discipline, standardized stock-pitch structure, or comprehensive report template. The inconsistencies between the investment policy statement's mandates and the fund's actual investment approach undoubtedly stem partly from the steep initial learning curve for a new fund. Our research is one part of that ongoing development process.

Our next research steps involve characterizing the behavioral biases that are both possible and extant in our fund's management team. For example, are our younger students—who can join the club given our lack of coursework and experience requirements—more averse to active risk, as in Chevalier and Ellison (1999; described in Taylor, 2004)? Are their more experienced counterparts better at picking stocks, as in Daugherty and Vang (2015), or are they more liable to "gravitate toward 'closet indexing,' structuring portfolios with only modest deviations from the market, ensuring both mediocrity and survival" (Swensen, 2009)? Perhaps most importantly, is the make-up of our executive teams—dominated by male students—causing us to accept too much risk and reap too little reward, as in Barber and Odean (2001)? Better understanding who makes our portfolio decisions and how they do it will help us position the fund for improved performance in the future.

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