Journal of
Risk and Financial Management

MDPI

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Which Should Be Your Top Pick, Separately Managed Accounts or ETFs?

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Abstract: This paper examined a large sample of equity SMAs (separately managed accounts, hereafter) from 1999 to 2023. This paper found that separate accounts have much higher expenses than ETFs and may outperform or underperform ETFs in terms of gross return and net return depending on their investment styles. However, this paper found that separate accounts consistently outperform ETFs in terms of risk-adjusted gross and net return alphas across different investment styles using the Fama and French Three Factor Model. Additionally, this paper found no significant evidence that tax is proactively managed within separate accounts. Lastly, this paper found that on average SMAs' risk-adjusted alphas do not persist over time.

Keywords: SMAs; performance; persistence; expenses; tax customization

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Citation: Zhang, Xianwu, Tao Guo, Yuanshan Cheng, and Haiyan Wang. 2024. Which Should Be Your Top Pick, Separately Managed Accounts or ETFs? *Journal of Risk and Financial Management* 17: 190. https://doi.org/10.3390/jrfm17050190

Academic Editors: Thanasis Stengos and Khaled Hussainey

Received: 29 February 2024
Revised: 24 April 2024
Accepted: 26 April 2024
Published: 5 May 2024

1. Introduction

Separately managed accounts (SMAs) are increasingly popular among institutional investors and households with high wealth levels. The separate accounts market asset under management has reached USD 1.8 trillion by 2021. The Office of Financial Research reported that the total assets under management in separate accounts managed more than twice the amount of assets managed in mutual funds since 2013.

Like traditional collective investments such as mutual funds and ETFs, separate accounts offer various investment strategies to their investors. But they are often marketed to offer additional benefits such as portfolio customization, transparency, and tax efficiency through the direct ownership of individual investments. Separate account investors are able to invest in a portfolio that deviates from the investment company's model portfolio based on their own preferences and unique holding situation. Instead of purchasing a share of a mutual fund or an ETF, separate account investors directly own the underlying individual investments, which makes it possible for customized tax treatments and the avoidance of the forced realization of capital gains/losses. These additional benefits may not come cheaply. They are usually accompanied by higher minimum investment requirements and/or higher fund expenses.

Therefore, it is beneficial to study whether these separate accounts could be an efficient investment vehicle to institutional investors and individual investors with high wealth. Will the additional costs justify the additional benefits these separate accounts provide? Furthermore, SEC started to regulate SMAs by asking investment advisors to report on their SMAs since 2016, but they are not required to disclose their risk and return tradeoff and cost information as currently required to mutual funds and ETFs. This makes it even more important to understand this investment vehicle that is seemingly attractive in terms of customization benefits but opaque in terms of returns and expenses.

2. Literature Review

There is a large body of literature focusing on analyzing investments products offered by institutional investment companies. Faugère et al. (2004) used the PSN data and analyze the sell decision of institutional money managers in identifying the value of fundamental and quantitative approaches. Knittel et al. (2007) took a plan sponsor's lens and analyze the relationship between asset flow and the performance of institutionally managed equity products using the PSN Investment Manager Database. They found that asset and fund flows are only partially explained by their performance and attributes. Gregory-Allen et al. (2009) used the same PSN data to examine stock selection skills of institutional money management using fundamental and quantitative approaches. The work of Busse et al. (2010) is one of the first studies that look at equity investments managed by institutional asset management firms from 1979 to 2008 using the data from Informa Investment Solutions (IIS). They find considerable heterogeneity in the performance but modest evidence of persistence in multiple factor models. Cremers et al. (2022b) introduced a holding-based procedure to create a best-fit benchmark for a mutual fund. When a mutual fund's best fit benchmark is different from its prospectus benchmark, authors find that those funds tend to be riskier and outperform their prospectus benchmark but underperform the best fit benchmark.

There is a growing line of studies focusing on separate accounts. Donaldson (2007) was one of the first that aimed at SMA and suggests investors pay a high premium for these additional features in the form of higher expenses and under-diversification. Peterson et al. (2011) use the PSN database and find that manager skill persisted in those separately managed accounts over the period of 1991 to 2009. They documented that active fund managers have better returns and a larger cash inflow and that a high number of accounts and larger assets under management are associated with lower future performances. Elton et al. (2014) used the Morningstar Direct database and provided evidence that the performance of separate accounts is similar to that of index funds. Chen et al. (2017) compared SMAs and mutual funds and found that when managers concurrently manage both mutual funds and their SMA counterparts, they tend to favor SMA performance over their mutual fund performance. Cremers et al. (2022a) found that separate accounts with high active shares show outperformance persistence. Evans et al. (2023) examined the diseconomies of scale for quantitative separate accounts (SA) and fundamental separate accounts and found that fundamental SAs show greater diseconomies of scale than quantitative SAs. Rohleder et al. (2023) examined the portfolio difference between separate accounts and mutual funds twins from the same fund companies and found evidence of performance differences and they argued that the findings may result from the limited attention of the managers. Additionally, investors' influence on managers' investment decisions may also play a role in their findings.

The contribution of our paper to the research into separate managed accounts is unique. As the minimum required investment of SMAs decreases, more investors may face the choice between high-cost SMAs and low-cost ETFs. A natural question to ask is whether SMAs are worth their costs. Our paper takes an investor perspective and is dedicated to examining SMAs' efficiency as an investment option. Specifically, we investigate whether SMAs can be an efficient alternative to ETFs regarding costs and performance by using comprehensive Morningstar data from 1999 to 2023.

Consistent with findings by Elton et al. (2014), our paper finds that on average, SMAs as a whole do perform similarly with ETFs based on both annual gross returns and annual net returns. However, our paper finds that SMAs may outperform ETFs depending on their investment styles. For example, based on annual gross returns, SMAs significantly (significant at 1% level) outperform their ETFS counterparts if their investment styles are Mid-Blend, Mid-Growth, Mid-Value, Small Blend, Small Growth, and Small Value[1]. However, based on annual net returns, SMAs' outperformance disappears in those investment styles above. Additionally, SMAs significantly (significant at the 10% level with respect to gross returns and at the 1% level with respect to net returns) underperform when compared to their ETFs counterparts if their investment styles are Large Blend, Large Growth, and Large Value, based on both annual gross returns and annual net returns.

On the other hand, SMAs significantly (significant at 1% level) outperform when compared to their ETFs counterparts based on the risk-adjusted gross alpha (if gross returns are used in the alpha calculations) across all the investment styles except the Large Blend. Again, the outperformance disappears based on the risk-adjusted net alpha (if net returns are used in the alpha calculations).

In addition to the return performance, our paper also examines the customization benefits offered by SMAs, specifically the customization benefits related to tax. On average, of the samples used in our paper, only 18% of SMAs (14% and 12% accordingly) proactively applied harvest tax losses strategies (the use of a long-term capital gain strategy and the use of tax optimization software). A total of 46% of SMAs (57% and 69% accordingly) do not offer harvest tax loss strategies (the use of a long-term capital gain strategy and the use of tax optimization software). A total of 36% of SMAs (29% and 19% accordingly) offer harvest tax loss strategies at clients' request (the use of a long-term capital gain strategy and the use of tax optimization software).

3. Data and Methodology

Our analysis uses a survivor-free database of separately managed accounts between January 1999 and December 2023. This Morningstar database of separate accounts is part of their Funds/Managed Products database, and it covers 10,660 funds on a survivor-free basis, including all categories at the time of the study. Those data are self-reported by investment companies using a data input template provided by Morningstar. Each investment company may offer various investment strategies. Then, investors can choose to establish an account under each specific investment strategy. The data provided by Morningstar are of separate managed accounts at the aggregate strategy level, not at the accounts level. The dataset for this study is the same as that of Elton et al. (2014) but our data covers years from 1999 to 2023.

Our paper focuses on SMAs that invest in US equity; so, for our analysis, we only include SMAs that were categorized as US equity by Morningstar. In total there are 6374 SMAs in US equity. We used the difference between annual gross return and annual net return to proxy annual expense, given the lack of self-reported expense information. Morningstar data are provided on both an annual and monthly basis. Our ETF dataset is also from Morningstar and includes 4788 funds at the time of the study. A total of 460 ETFs focusing on US equity are included in our analysis. It is worth pointing out that the figures and tables below are based on the annual data but our paper also runs an analysis based on the monthly data, and some of those analyses are included in the Appendix A.

When comparing SMAs and ETFs, performance and expense should be among the most important considerations of investors. The performance comparison focuses on both gross and net returns and risk-adjusted alphas. Following the literature, Fama–French Three Factor Model is used in measuring investment performances. The general model setting (Fama and French 1993) is

$$r_{i,t} = \alpha_i + \beta_1\left(r_{m,t} - r_{f,t}\right) + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_{i,t} \quad (1)$$

where $r_{i,t}$ is the annual excess return of account i in year t over risk-free T-bill rate, $r_{m,t} - r_{f,t}$ is the market excess return over risk-free T-bill rate in year t, SMB_t (small minus big) is the return in year t of the size factor-based long-and-short strategy, and HML_t (high minus low) is the return in year t of the value factor-based long-and-short strategy. The factor loadings β_1 β_2 β_3 indicate how much risk exposure each factor has. We use α_i to evaluate managers' skills for separate accounts.

We first conduct a comparison of the overall US equity SMAs and US equity ETFs. We then conducted the comparison on the different styles of SMAs and ETFs.

Figure 1 shows the number of newly created SMAs across years. Separate accounts emerged in the 1980s and have experienced significant growth since early 2000. So, Figure 1 shows the number of SMAs created starting in 1980. There are three types of SMA accounts depending on who those SMAs are open to. Based on Figure 1, most separate accounts were designed to open to both retail and institutional investors. Figure 2 includes only surviving separate accounts by calendar year. The number of separate accounts has increased over time but at a decreasing rate. Figure 3 shows the average minimum investment requirements of newly created separate accounts each year. The obvious trend is that these newly created separate accounts have lower investment requirements compared to existing ones. It is not a surprise that the SMAs that are only open to retail investors have the lowest minimum required investment on average. By contrast, SMAs that are only open to institutional investors require the highest minimum investments. Additionally, the average annual expense of those newly created SMAs that are open to both and those that are only open to institutions stays similar across years as shown in Figure 4. However, the average annual expense of those SMAs only open to retail investors has decreased over time, but those accounts charged the highest expense on average when compared to the other two types.

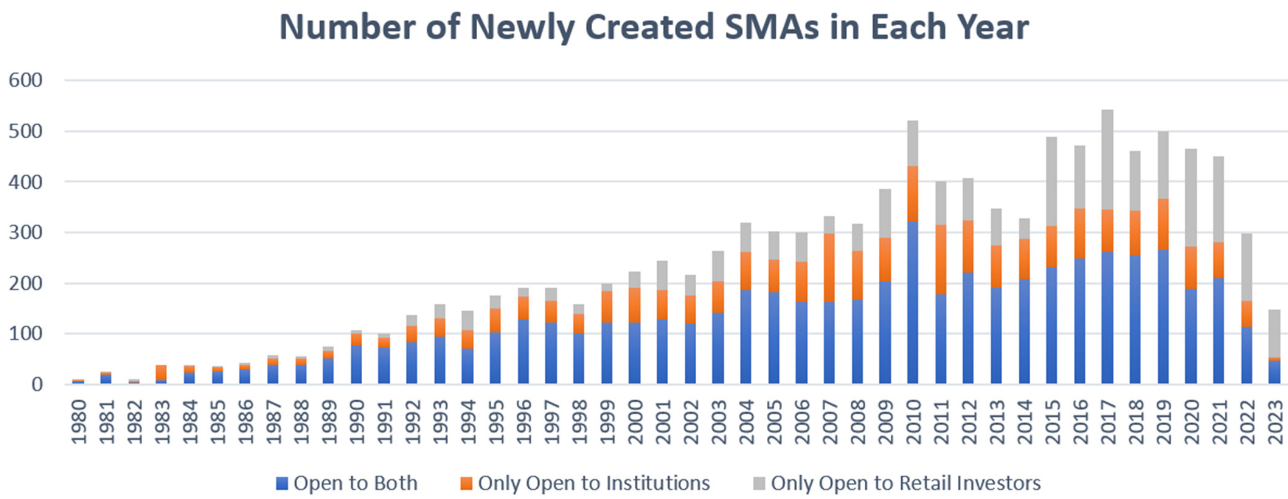


Figure 1. Number of newly created SMAs each year.

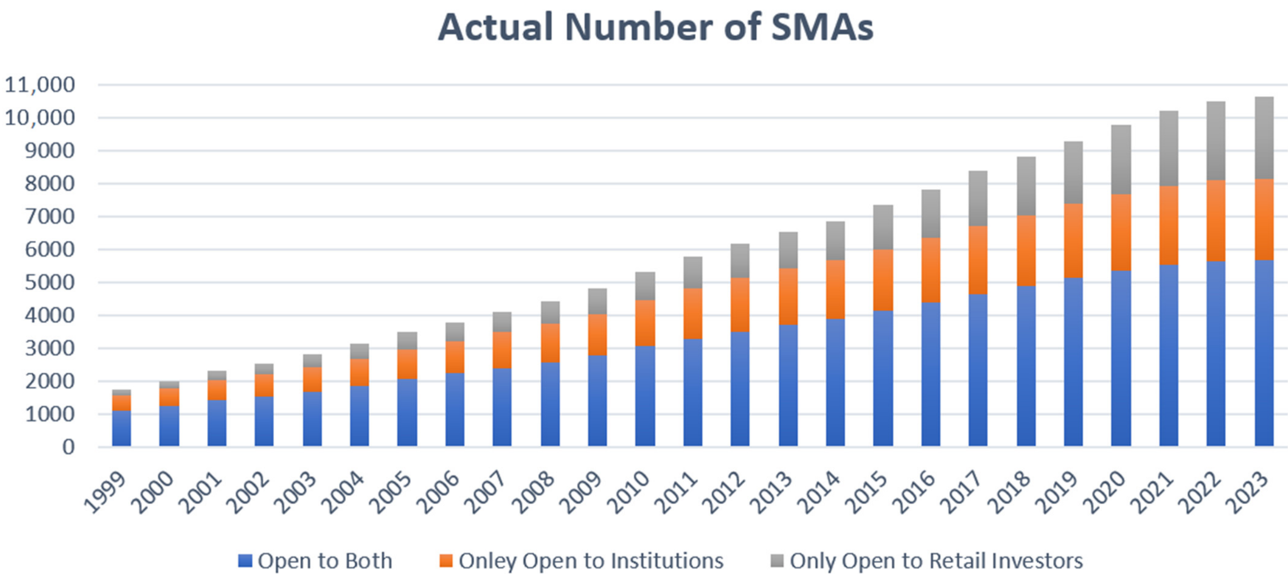


Figure 2. Actual number of SMAs by year.

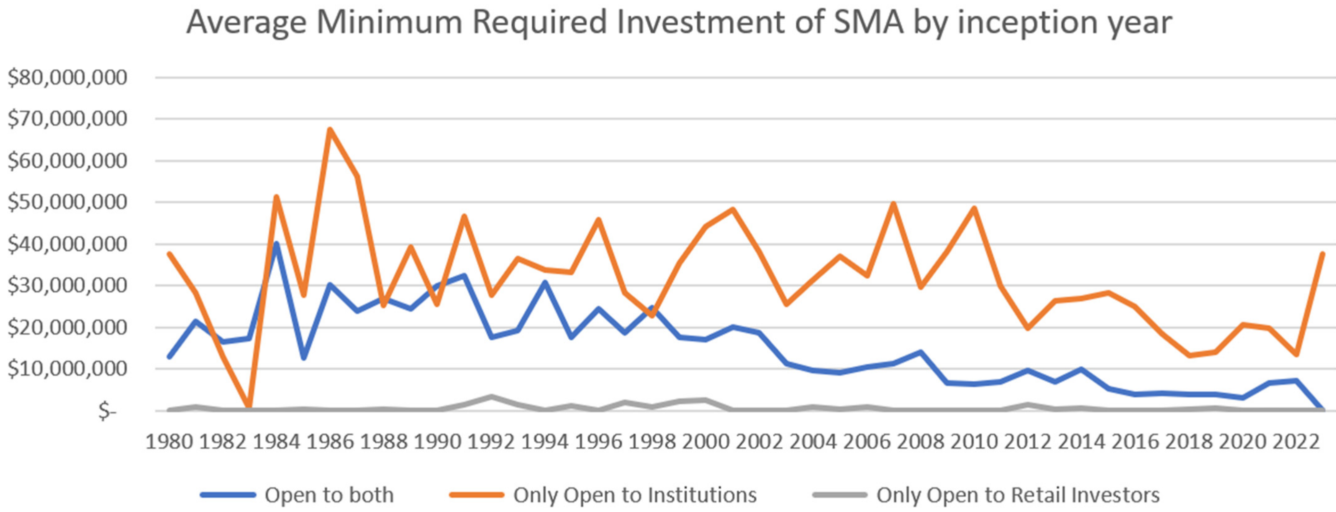


Figure 3. Average minimum investment requirement of newly created SMAs each year.

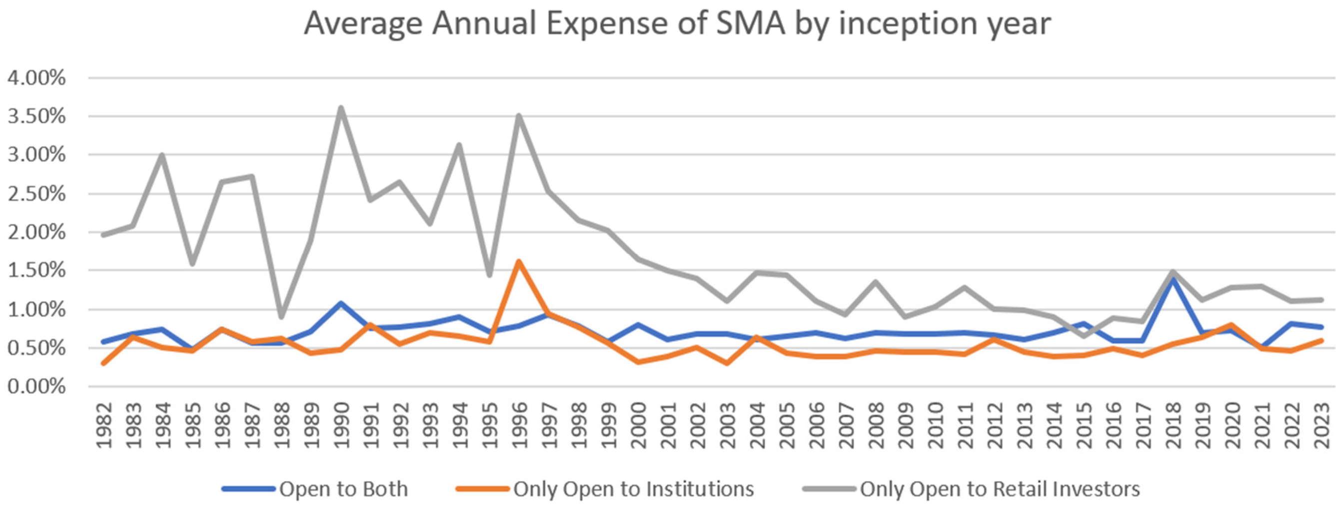


Figure 4. Average annual expense of newly created SMAs each year.

Figure 5 shows that separate accounts have higher annual expenses compared with ETFs across all percentiles. Specifically, on the more expensive side (high percentile side), SMAs are much more expensive than ETFs. But the expense gap between SMAs and ETFs is much smaller for the less expensive side (low percentile side). As shown in Figure 6, separate accounts have similar (maybe slightly better) gross returns compared to ETFs across all percentiles. After considering fees, as shown in Figure 7, ETFs are better than SMAs across the percentiles, except for when SMAs in the low percentiles show higher net returns compared with their ETF counterparts. This suggests that SMAs managers are able to control the tail risk as a group while ETFs are more passive. Alternatively, this could also be due to the existence of leverage ETFs in the sample. However, Figure 8a,b show that after adjusting for risk using the Fama–French Three Factor Model, SMAs overall show more skills than their ETFs counterparts, especially when we look at those two sides of the tails.

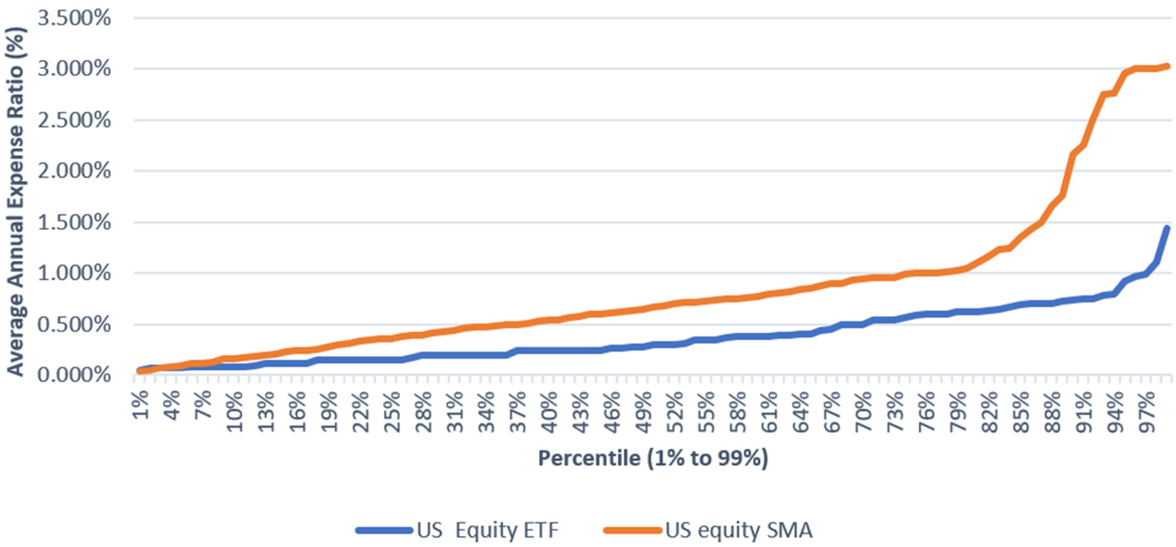


Figure 5. Average annual expense comparison.

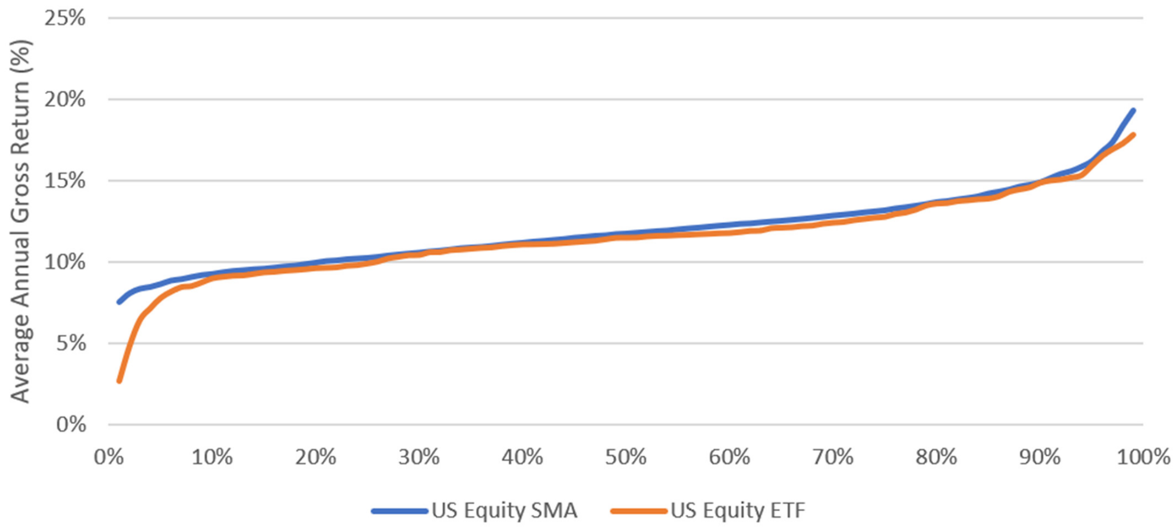


Figure 6. Average annual gross return comparison.

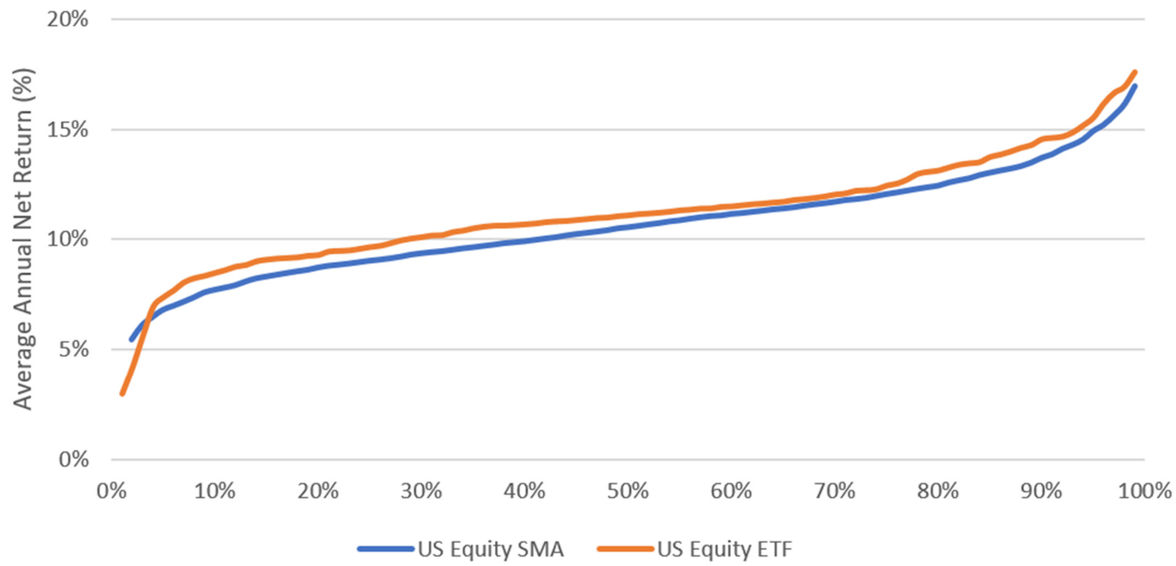
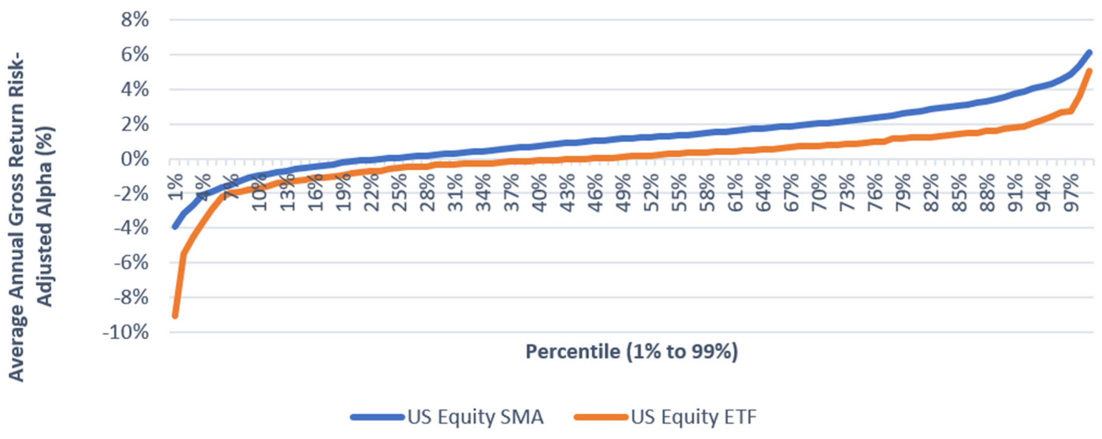
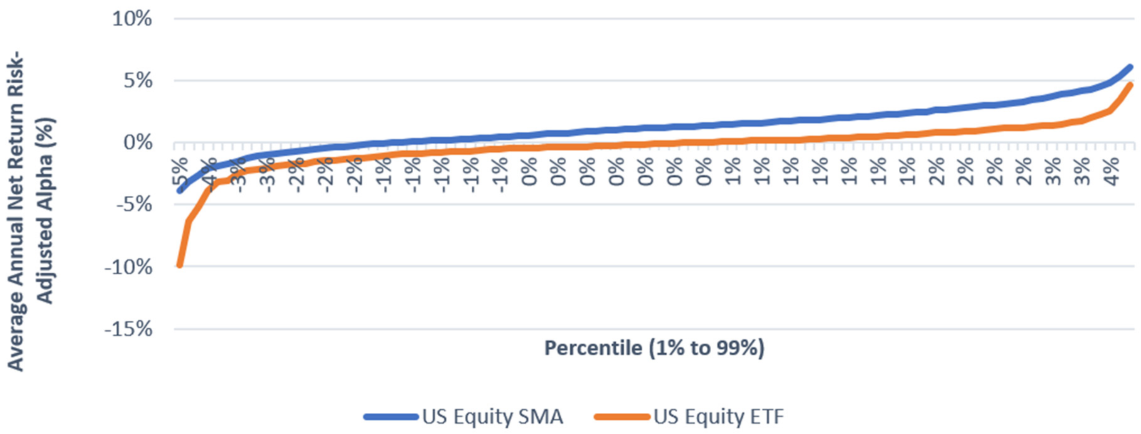


Figure 7. Average annual net return comparison.



(**a**)



(**b**)

Figure 8. (**a**) Average annual risk-adjusted alpha comparison based on gross returns. (**b**) Average annual risk-adjusted alpha comparison based on net returns.

4. Empirical Results

We start by comparing the expenses and gross returns of separate accounts and their ETF counterparts. Table 1 shows the average annual expense percentiles of US equity separate accounts according to equity style. Overall, we do see an increase in expenses across all the lower percentiles when equity styles change from Large to Small. Interestingly, for the higher percentiles like 75th percentile or 90th percentile, expenses are much higher for the Large cap equity style compared to the Small cap equity style. For example, Large Blend separate accounts are cheaper by 36 bps when compared with Small Value accounts in the lowest 10th percentile. This could be possibly explained by the argument that SMAs that focus on investing using the Small Value style may require more active management compared to SMAs that focus on the Large Cap style. Table 2 shows the annual expense percentiles of ETF investments. Similarly to separate accounts that Large Cap ETFs are cheaper overall than Small Cap ETFs, with a lowest cost of only 8 bps annual for Large Blend ETFs. Separate accounts consistently charge higher expenses across all the percentiles and all equity styles.

Table 1. Average annual expense percentiles of US equity SMAs by style. Our SMA samples cover 1999 to 2023 and comprise 6374 US equity SMAs after correcting survivorship bias. For SMAs, the expense ratio is not directly available in Morningstar. Consistent with other papers' methodologies, we used the difference between annual gross return and annual net return as a proxy for the annual expense ratio. For each SMA, we then calculated the average annual expense based on the annual expense ratio time series from 1999 to 2023. Percentiles were calculated by equity style.

Equity Style	The 10th Percentile	The 25th Percentile	The 50th Percentile	The 75th Percentile	The 90th Percentile
Large Blend	0.29	0.47	0.69	1.02	2.89
Large Growth	0.49	0.61	0.79	1.44	2.96
Large Value	0.44	0.56	0.71	1.04	2.96
Mid-Blend	0.41	0.61	0.85	1.21	2.58
Mid-Growth	0.57	0.72	0.89	1.06	2.94
Mid-Value	0.49	0.64	0.75	1.00	2.48
Small Blend	0.60	0.70	0.88	0.99	1.29
Small Growth	0.57	0.76	0.90	0.99	1.38
Small Value	0.65	0.76	0.90	1.00	1.69
Overall	0.50	0.65	0.82	1.08	2.35

Table 2. Average annual expense percentiles of US equity ETFs by style. Our ETF samples range from 1999 to 2023 and comprise 460 US equity ETFs after correcting survivorship bias. The annual net expense ratio is available in Morningstar. We used this variable to obtain the annual expense ratio for each ETF. Percentiles were calculated by equity style.

Equity Style	The 10th Percentile	The 25th Percentile	The 50th Percentile	The 75th Percentile	The 90th Percentile
Large Blend	0.08	0.15	0.27	0.50	0.93
Large Growth	0.10	0.20	0.41	0.64	1.19
Large Value	0.12	0.20	0.38	0.56	0.75
Mid-Blend	0.14	0.20	0.54	0.74	1.07
Mid-Growth	0.15	0.25	0.62	0.75	0.81
Mid-Value	0.20	0.25	0.55	0.89	1.19
Small Blend	0.12	0.15	0.38	0.64	0.91
Small Growth	0.09	0.20	0.30	0.67	0.90
Small Value	0.20	0.30	0.44	0.70	1.00
Overall	0.13	0.21	0.43	0.68	0.97

Tables 3 and 4 show the characteristics of separate accounts by annual gross and net return quintile. In both tables, risk-adjusted alphas using three factor models is positively associated with the quintile sort based on average annual returns. Before expenses, the top four quintiles have positive alphas. After considering fees, only the top three quintiles have positive alphas. Both the annual gross and net return quintiles are also positively associated with the size factor loadings and negatively associated the value factor loading, which means that SMAs invest in more Smaller Cap stocks compared to larger cap stocks and invest in more growth stocks compared to value stocks. Interestingly, fewer years of tenure of the management team are associated with the better returns on both a gross and net basis. Additionally, as shown in Table 4, lower net return quintiles charge higher expenses compared to higher net return quintiles by 82 bps per year. It is likely that some SMAs with large gross returns are included in the lower quintile because those SMAs happen to have a high expense ratio.

Table 3. Characteristics of US equity SMAs by annual gross return quintile. Our SMAs samples range from 1999 to 2023 and comprise 6374 US equity SMAs after correcting survivorship bias. We divided US equity SMAs into five quintiles based on average annual gross return and calculated the risk-adjusted alphas using the Fama–French Three Factor Model. We also included characteristics for each quintile.

Quintile Sorted by Average Annual Gross Return	Alphas and Three Factor Regression Loadings						Quintile Characteristics		
	Average Annual Gross Return	Alpha	MKT	SMB	HML	R-Squared	Manager Tenure Average	Average Annual Actual Return	Average Annual Expense Ratio
1	8.92	−0.05	7.49	7.70	−6.79	0.90	16.09	7.83	1.10
2	10.57	0.89	7.31	7.89	−8.17	0.90	16.17	9.37	1.20
3	11.75	1.32	9.47	8.66	−6.77	0.89	15.01	10.55	1.20
4	12.89	1.69	9.80	8.15	−6.48	0.88	14.73	11.62	1.26
5	15.65	2.18	15.16	8.31	−8.59	0.87	14.11	14.44	1.21

Table 4. Characteristics of US equity SMAs by annual actual net return quintile. Our SMAs samples ranged from 1999 to 2023 and comprised 6374 US equity SMAs after correcting survivorship bias. We divided US equity SMAs into five quintiles based on average net return and calculated the risk-adjusted alphas using the Fama–French Three Factor Model. We also included characteristics for each quintile.

Quintile Sorted by Average Annual Net Return	Alphas and Three Factor Regression Loading						Quintile Characteristics		
	Average Annual Net Return	Alpha	MKT	SMB	HML	R-Squared	Manager Tenure Average	Average Annual Gross Return	Average Annual Expense Ratio
1	7.46	−1.46	7.17	7.11	−4.75	0.89	15.43	9.28	1.82
2	9.40	−0.29	9.00	9.27	−8.99	0.91	16.07	10.53	1.12
3	10.61	0.28	8.00	8.25	−7.53	0.90	15.88	11.63	1.02
4	11.79	0.68	10.63	7.77	−7.10	0.88	14.43	12.79	1.00
5	14.54	1.33	14.44	8.32	−8.44	0.87	14.28	15.55	1.00

Tables 5 and 6 provide parallel results using ETFs with both annual gross returns and net returns. When comparing alphas before fees, we observe that separate accounts did a much better job than ETFs overall. In the first quintile, the worst separate accounts provide an alpha of −5 bps annually compared with −145 bps from ETFs. The top quintile in separate accounts has a gross alpha of 218 bps annually compared with 57 bps in ETFs. Similar trends can be observed using net return. The losing separate accounts quintile has an alpha of −146 bps annually compared with −185 bps in ETFs. The best performing quintile from separate accounts generates a net alpha of 133 bps annually compared with 30 bps annually from ETFs. In summary, the performance of separate accounts overall is better than that of ETFs based on risk-adjusted alphas on both a gross and net basis. Additionally, the performance of separate accounts is much better than ETF in the lowest quintile. This suggests that separate accounts could offer significant benefits compared to ETFs, especially when managing tails risk.

Table 5. Characteristics of US equity ETFs by annual gross return quintile. Our ETF samples range from 1999 to 2023 and comprise 460 US equity ETFs after correcting survivorship bias. We divided US equity EFTs into five quintiles based on average gross return and obtained the risk-adjusted alphas using the Fama–French Three Factor Model. We also included characteristics for each quintile.

Quintile Sorted by Average Annual Gross Return	Alphas and Three Factor Regression Loadings						Quintile Characteristics		
	Average Annual Gross Return	Alpha	MKT	SMB	HML	R-Squared	Manager Tenure Average	Average Annual Actual Return	Average Annual Expense Ratio
1	8.00	−1.45	4.07	−0.13	−1.95	0.87	4.40	7.57	0.46
2	10.38	0.31	1.59	3.20	4.60	0.93	4.57	10.05	0.31
3	11.45	0.15	2.01	0.78	4.69	0.93	4.66	11.12	0.35
4	12.50	0.40	3.98	0.05	2.12	0.94	3.87	12.11	0.41
5	15.16	0.57	15.88	0.81	−1.90	0.97	2.42	14.77	0.38

Table 6. Characteristics of US equity ETFs by annual actual return quintile. Our ETF samples range from 1999 to 2023 and comprise 460 US equity ETFs after correcting survivorship bias. We divided US equity EFTs into five quintiles based on average actual return and obtained the risk-adjusted alphas using the Fama–French Three Factor Model. We also included characteristics for each quintile.

Quintile Sorted by Average Annual Net Return	Alphas and Three Factor Regression Loading						Quintile Characteristics		
	Average Annual Net Return	Alpha	MKT	SMB	HML	R-Squared	Manager Tenure Average	Average Annual Gross Return	Average Annual Expense Ratio
1	7.56	−1.85	4.84	−0.17	−1.87	0.87	4.22	8.01	0.49
2	10.05	−0.26	2.52	2.29	3.30	0.93	4.47	10.40	0.32
3	11.10	−0.03	−2.21	1.73	4.06	0.94	4.87	11.45	0.37
4	12.13	0.12	6.34	0.00	4.17	0.94	4.00	12.49	0.37
5	14.79	0.30	16.05	0.85	−2.11	0.97	2.36	15.15	0.35

Table 7 summarizes the performance difference between separate accounts and ETFs. Based on annual gross returns, SMAs significantly (significant at the 1% level) outperform their ETFS counterparts if their investment styles are Mid-Blend, Mid-Growth, Mid-Value, Small Blend, Small Growth, and Small Value[2]. However, based on annual net returns, SMAs' outperformance disappears in those investment styles mentioned above. Additionally, SMAs significantly (significant at the 10% level with respect to gross returns and at the 1% level with respect to net returns) underperform compared to their ETFs counterparts if their investment styles are Large Blend, Large Growth, and Large Value, based on both annual gross returns and annual net returns.

On the other hand, SMAs significantly (significant at the 1% level) outperform their ETFs counterparts based on the risk-adjusted gross alpha (if gross returns are used in the alpha calculations) across all investment styles except Large Blend. Again, the outperformance disappears based on the risk-adjusted net alpha (if net returns are used in the alpha calculations).

Separate accounts not only provide a method of collective investment but they also offer portfolio customization and tax efficiency. In the market, separate account providers use these customization features as their selling points. In this next analysis, we investigate whether and how these customization features are associated with performance. Table 8 aims to explore the customization benefits that are uniquely provided by separate accounts. The providers of separate accounts self-reported to Morningstar whether and how they offer customized tax treatments.

Table 7. Percentile difference of US equity SMAs and US equity ETF by style. We use the difference of each percentile of SMAs and ETFs for distribution comparison. The p-value is also included in the last column of the table.

	Return Difference between Separate Accounts, and ETFs					
	10th	**25th**	**50th**	**75th**	**90th**	**$p(T \leq t)$ One-Tail**
Annual Gross Return						
Large Blend	−0.23	−1.19	−1.03	−1.52	−0.02	0.02 **
Large Growth	0.36	−1.5	−1.63	−1.54	−0.08	0.05 *
Large Value	−0.39	−0.48	−0.73	−0.31	0.27	0.06 *
Mid-Blend	0.93	0.13	0.61	1.55	3.23	0.04 **
Mid-Growth	0.26	0.7	1.21	1.38	1.93	0.01 ***
Mid-Value	0.88	1.07	0.98	0.99	0.95	0.00 ***
Small Blend	1.01	0.5	0.89	1.7	2.36	0.01 ***
Small Growth	1.33	0.73	1.14	0.3	1.33	0.00 ***
Small Value	6.09	0.76	1.07	1.5	2.1	0.04 **
Annual Net Return						
Large Blend	−1.52	−1.82	−1.85	−2.61	−0.91	0.00 ***
Large Growth	−1.27	−2.43	−2.9	−2.62	−1.14	0.00 ***
Large Value	−2.05	−1.4	−1.37	−1.2	−1.02	0.01 ***
Mid-Blend	−0.36	−0.57	−0.12	0.66	1.79	0.28
Mid-Growth	−1.06	−0.23	0.59	0.52	1.56	0.28
Mid-Value	0.11	−0.31	0.43	0.26	0.58	0.12
Small Blend	0.26	−0.15	0.1	0.79	1.84	0.09 *
Small Growth	0.31	0.09	0.52	−0.53	0.23	0.26
Small Value	5.26	−0.17	0.14	0.67	1.15	0.11
Annual Gross Alpha						
Large Blend	−0.65	−0.21	0.21	0.92	1.07	0.23
Large Growth	0.1	0.71	0.48	0.69	1.19	0.01 ***
Large Value	0.41	0.52	0.79	1.22	1.42	0.01 ***
Mid-Blend	0.38	0.75	0.96	1.38	1.78	0.01 ***
Mid-Growth	2.7	1.51	1.95	2.53	2.7	0.00 ***
Mid-Value	2.24	1.99	1.59	2.35	2.49	0.00 ***
Small Blend	0.5	0.6	1	1.49	2.02	0.01 ***
Small Growth	0.77	1.59	1.74	2.63	3.55	0.01 ***
Small Value	1	0.98	1.18	0.91	2.1	0.00 ***
Annual Net Alpha						
Large Blend	−2.12	−1.67	−0.37	0.05	0.61	0.00 ***
Large Growth	−1.48	−0.75	−0.35	−0.15	0.49	0.12
Large Value	−1.29	−0.36	−0.02	0.38	0.61	0.35
Mid-Blend	−1.25	−0.56	0.38	0.75	1.17	0.42
Mid-Growth	1.3	0.5	1.42	1.95	2.11	0.00 ***
Mid-Value	1.73	1.22	0.73	1.48	1.77	0.00 ***
Small Blend	−0.57	0	0.15	0.62	1.23	0.2
Small Growth	−0.13	0.79	1.07	1.85	2.43	0.03 **
Small Value	−0.02	−0.05	0.26	0.18	0.99	0.11

Note: * indicates significant at 10% level, ** indicates significant at 5% level, and *** indicates significant at 1% level.

Panel A of Table 8 is sorted by gross return and Panel B is sorted by net returns. On average, of the sample used in our paper, only 18% of SMAs (14% and 12% accordingly) proactively apply harvest tax loss strategies (the use of a long-term capital gain strategy and the use of tax optimization software). A total of 46% of SMAs (57% and 69% accordingly) do not offer harvest tax losses strategies (the use of a long-term capital gain strategy and the use of tax optimization software). A total of 36% of SMAs (29% and 19% accordingly) offer harvest tax loss strategies at a client's request (the use of a long-term capital gain strategy and the use of tax optimization software). To sum up, we found that separate accounts do not proactively provide the customizations they have marketed, and additionally we did not observe that better-performing separate accounts provide better customizations.

Table 8. Customization characteristics by multiple quintiles.

	Harvest Tax Losses			LT Cap Gain Use			Product Focus			Tax Optimization Software		
	By Request (%)	No (%)	Proactive (%)	By Request (%)	No (%)	Proactive (%)	Open to Both (%)	Only Open to Institutional Investors (%)	Only Open to Retail Investors (%)	By Request (%)	No (%)	Proactive (%)
Panel A: Customization Characteristics of SMAs by Annual Gross Return Quintile												
Low	40.40	45.03	14.57	30.82	59.59	9.59	67.63	17.63	14.74	20.74	71.11	8.15
1	37.76	44.76	17.48	24.11	58.16	17.73	61.84	21.05	17.11	19.12	68.38	12.50
2	31.08	45.95	22.97	23.57	59.29	17.14	61.15	22.05	16.80	15.56	64.44	20.00
3	32.54	51.59	15.87	29.03	58.87	12.10	60.53	24.74	14.74	17.95	71.79	10.26
High	37.70	41.80	20.49	37.61	50.43	11.97	65.35	23.10	11.55	21.50	69.16	9.35
Panel B: Customization Characteristics of SMAs by Annual Net Return Quintile												
Low	43.67	34.18	22.15	30.92	51.97	17.11	56.32	10.53	33.16	19.15	68.79	12.06
1	37.40	50.38	12.21	31.30	57.25	11.45	60.53	20.53	18.95	25.00	65.32	9.68
2	30.50	49.65	19.86	20.00	63.70	16.30	63.25	24.15	12.60	13.53	69.17	17.29
3	32.85	50.36	16.79	30.30	60.61	9.09	70.26	25.79	3.95	18.03	72.95	9.02
High	34.15	46.34	19.51	31.36	54.24	14.41	66.14	27.56	6.30	19.09	68.18	12.73

5. Persistence of SMAs' Risk-Adjusted Alphas

This section aims to explore how persistent the superior risk-adjusted alphas are for separate accounts and whether separate accounts consistently outperform ETFs.

We explore the persistence pattern by following Carhart (1997). As mentioned previously, monthly return data were also reported from investment companies in the Morningstar database. The analysis here needed to use monthly data, as we run regressions on a rolling basis to obtain alphas. We reported both current alphas and projected alphas. We used the monthly net returns of the previous 24 months to carry out regressions on current monthly alphas. For the projected alphas, we used the previous 24 months' net return data and factor returns to calculate factor loadings and then used the calculated loading for the current month to calculate the projected alphas. Then, we aggregated both the current month alphas and monthly projected alphas into a current annual alpha and annual projected alphas for each fund for each year. Then, we ranked each fund's alphas each year and assigned a ranking from 1 to 5 to each fund for each year. We tracked the subsequent rankings for the funds in the initial ranking groups in order to explore the persistence pattern.

As shown in Figure 9, no persistence patterns can be observed. They converge quickly into the average regardless of the initial year of the alpha rankings. This remained robust and consistent when we used rolling periods of 12, 24, 36, or 48 months, which are not reported here. Even though the results are consistent, we can see that the range is larger for the projected alpha. This indicates that more SMAs are placed in significantly different ranking groups in a dramatic way, which implies that SMAs managers may change their risk exposures fairly actively. The results indicate that within those separate accounts, we see no evidence of persistence in managers' skills. In a scenario where an investor buys a separate account, in terms of risk-adjusted performance, they are essentially buying a random separate account from the current pool.

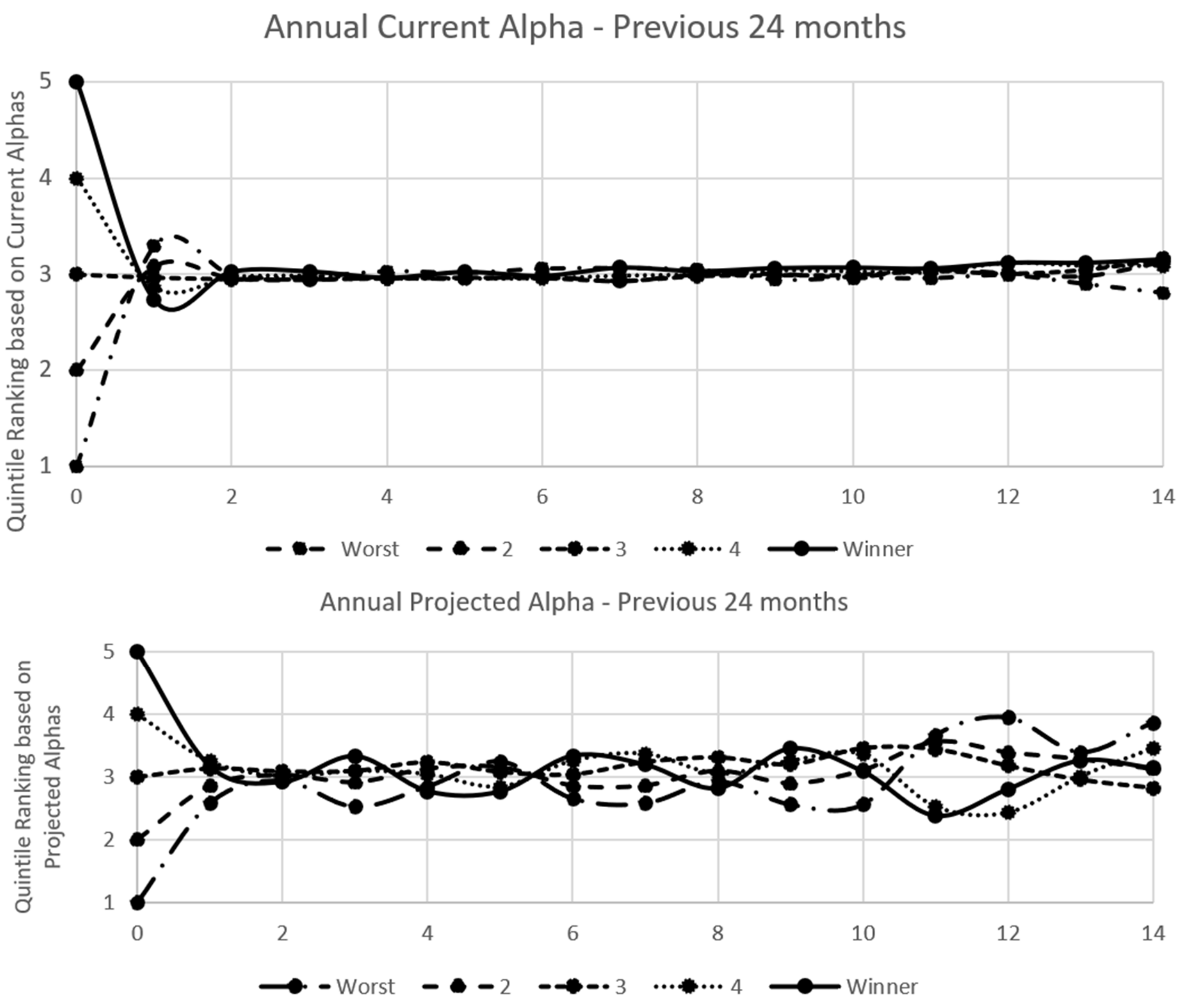


Figure 9. Persistence of separately managed accounts—years after initial ranking.

6. Conclusions

This study uses more recent data about separate accounts and provides a practical perspective when comparing both the fees and performances of separate accounts with ETFs, which have been widely used as an efficient investment tool. First, we found that separate accounts in general charge much higher expenses than their ETF counterparts. Second, separate accounts do not consistently outperform ETFs in terms of the gross return quintile and the net return quintile comparison. SMAs outperform ETFs in Mid- and Small Cap markets but underperform compared to ETFs in Large Cap markets. However, SMAs consistently outperform ETFs in terms of risk-adjusted return across the nine investing styles, except the Large Blend style. Third, by looking at self-reported tax strategies from investment companies, we found no significant evidence that tax is proactively managed within SMAs. Lastly, we also found that risk-adjusted performance does not persist within SMAs.

Author Contributions: We authors all collectively work on the paper. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data is from Morningstar Investment Management LLC.

Acknowledgments: Special thanks to Harold Evensky who helped in forming this research idea.

Conflicts of Interest: Author Tao Guo and Yuanshan Cheng were employed by the company Morningstar Investment Management LLC. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

1. We also conducted the analysis by using the monthly data from Jan 1999 to December 2023. Monthly results for Tables A1–A5 are included here.

Table A1. Characteristics of US equity SMAs by Monthly gross return quintile. Our SMAs samples range from 1999 to 2023 and comprise 6374 US equity SMAs after correcting survivorship bias. We divided US equity SMAs into five quintiles based on average monthly gross return and calculated the risk-adjusted alphas using the Fama–French Three Factor Model. We also included characteristics for each quintile.

Quintile Sorted on Average Gross Return	Alphas and Three-Factor Loadings for US Equity SMA						Quintile Characteristics		
	Average Gross Monthly return	Alpha	MKT	SMB	HML	R-Squared	Manager Tenure Average	Ave Monthly Net Return	Average Annual Expense Ratio
1	0.660	−0.003	1.299	0.786	−1.795	0.895	16.182	0.559	0.836
2	0.848	0.061	1.366	0.784	−1.428	0.896	16.113	0.749	0.930
3	0.949	0.082	0.944	0.582	−0.974	0.893	14.633	0.844	0.888
4	1.051	0.120	0.920	0.361	−1.125	0.889	14.692	0.944	0.846
5	1.321	0.169	1.204	0.240	−0.997	0.874	14.500	1.189	0.820

Table A2. Characteristics of US equity SMAs by Monthly net return quintile. Our SMAs samples range from 1999 to 2023 and comprise 6374 US equity SMAs after correcting survivorship bias. We divided US equity SMAs into five quintiles based on average monthly net return and calculated the risk-adjusted alphas using the Fama–French Three Factor Model. We also included characteristics for each quintile.

Quintile Sorted on Average Net Return	Alphas and Three-Factor Loadings for US Equity SMA						Quintile Characteristics		
	Average Net Monthly Return	Alpha	MKT	SMB	HML	R-Squared	Manager Tenure Average	Average Gross Monthly Return	Average Annual Expense Ratio
1	0.63	−0.11	1.29	0.78	−1.51	0.89	15.71	0.77	1.11
2	0.85	−0.01	1.01	0.60	−1.19	0.90	15.31	0.94	0.76
3	0.95	0.04	0.85	0.27	−1.11	0.89	14.72	1.03	0.68
4	1.05	0.05	1.23	0.51	−1.13	0.89	14.98	1.14	0.71
5	1.33	0.08	1.26	0.10	−0.94	0.87	14.33	1.44	0.68

Table A3. Characteristics of US equity ETFs by Monthly gross return quintile. Our ETFs samples range from 1999 to 2023 and comprise 460 US equity ETFs after correcting survivorship bias. We divided US equity ETFs into five quintiles based on average monthly gross return and calculated the risk-adjusted alphas using the Fama–French Three Factor Model. We also included characteristics for each quintile.

Quintile Sorted on Average Gross Return	Alphas and Three-Factor Loadings for US Equity ETF						Quintile Characteristics		
	Average Gross Return	Alpha	MKT	SMB	HML	R-Squared	Manager Tenure Average	Ave Monthly Actual Return	Average Annual Expense Ratio
1	0.65	−0.08	0.86	0.07	0.19	0.86	5.02	0.62	0.43
2	0.86	−0.02	0.95	0.22	0.20	0.90	4.95	0.83	0.39
3	0.93	−0.01	1.00	0.23	0.22	0.94	4.58	0.90	0.37
4	1.03	0.00	0.99	0.24	0.18	0.93	3.45	1.00	0.37
5	1.19	0.06	1.00	0.05	0.05	0.95	1.95	1.17	0.33

Table A4. Characteristics of US equity ETFs by Monthly net return quintile. Our ETFs samples range from 1999 to 2023 and comprise 460 US equity ETFs after correcting survivorship bias. We divided US equity ETFs into five quintiles based on average monthly net return and calculated the risk-adjusted alphas using the Fama–French Three Factor Model. We also included characteristics for each quintile.

Quintile Sorted on Average Net Return	Alphas and Three-Factor Loadings for US Equity ETF						Quintile Characteristics		
	Average ACTUAL RETURN	Alpha	MKT	SMB	HML	R-Squared	Manager Tenure Average	Ave Monthly Gross Return	Average Annual Expense Ratio
1	0.62	−0.11	0.85	0.07	0.19	0.85	4.73	0.65	0.47
2	0.82	−0.05	0.96	0.21	0.20	0.91	5.24	0.86	0.41
3	0.90	−0.03	0.99	0.26	0.21	0.94	4.76	0.93	0.35
4	1.00	−0.03	0.99	0.23	0.20	0.94	3.22	1.03	0.35
5	1.17	0.03	1.00	0.05	0.04	0.94	1.99	1.19	0.30

2. Sensitivity analysis focusing on high VIX period and low VIX period.

Besides the pure style-based comparison across all the time horizon, it is beneficial to conduct performance comparisons on different cycle stages. Instead of defining the cycle stages based on crisis or bull market, we use volatility as a quantitative way to divide our sample into high volatility period and low volatility period. Fortunately, CBOE Volatility Index can serve as an unbiased and objective measure to achieve this task. VIX data is from Fred St Louis. https://fred.stlouisfed.org/series/VIXCLS (accessed on 29 February 2024).

Below is a histogram of 25 years data of VIX index (1999 to 2023). A VIX level of 20 seems to be a threshold where we can have equal number of years into either high volatility period or low volatility period. Table A5 below presents the years included in each period.

Table A5. Ranked historical levels of VIX Index from 1999 to 2023.

Year	VIXCLS	
2008	32.70	High VIX
2009	31.48	
2020	29.25	
2002	27.29	
2001	25.75	
2022	25.64	
1999	24.37	
2011	24.20	
2000	23.32	
2010	22.55	
2003	21.98	
2021	19.66	Low VIX
2012	17.80	
2007	17.54	
2023	16.85	
2015	16.67	
2018	16.64	
2016	15.83	
2004	15.48	
2019	15.39	
2013	14.23	
2014	14.18	
2005	12.81	
2006	12.81	
2007	11.09	

Our performance comparisons are based on yearly gross return, yearly net return, yearly gross return risk adjusted alpha, and yearly net return risk adjusted alpha. All those comparisons are conducted on both high and low volatility periods. Figures A1–A4 are over the high volatility periods (i.e., H VIX), and Figures A5–A8 are over the low volatility periods (i.e., L VIX). Figures A3 and A4 provide evidence that SMAs provide better risk-adjusted performance across all the percentiles during high volatility period. Interestingly, during low volatility period, SMAs can't outperform ETFs except the lowest percentiles (Figure A5) on the gross return basis. However, based on Figure A7, SMAs provide better risk adjusted gross alphas than ETFs during low volatility period, especially for the lowest percentiles. However, SMAs can't outperform (even underperform) ETFs on the net return basis (Figures A6 and A8).

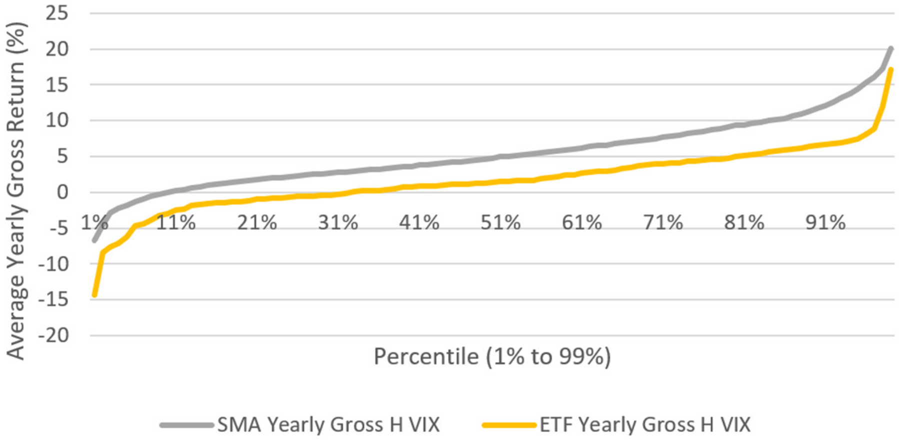


Figure A1. Average Yearly Gross Return Comparison over high VIX period.

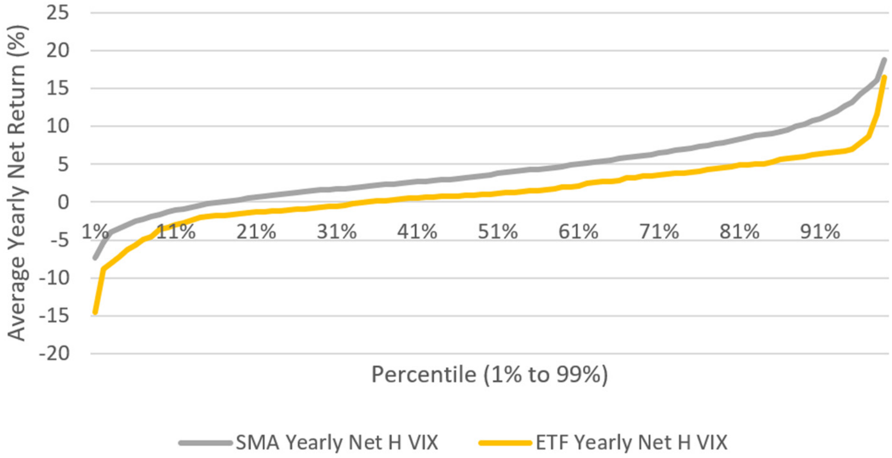


Figure A2. Average Yearly Net Return Comparison over high VIX period.

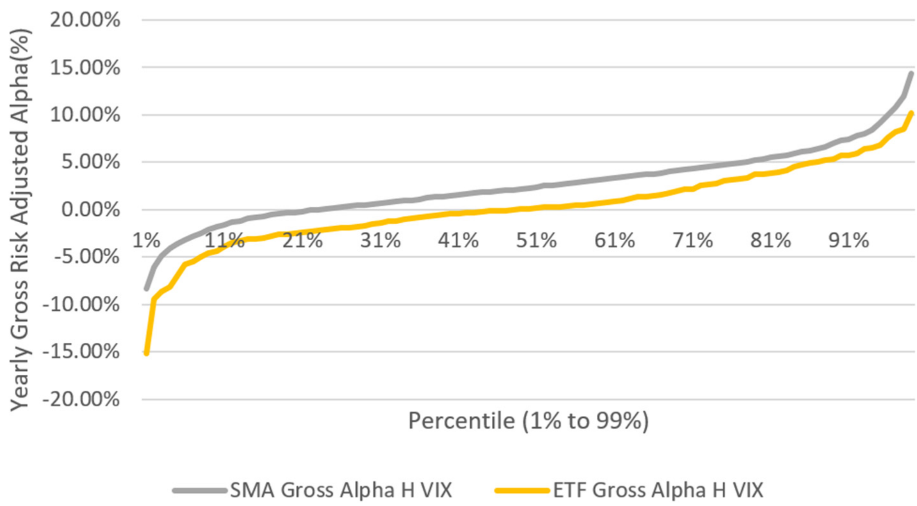


Figure A3. Yearly Gross Risk Adjusted Alpha Comparison over high VIX period.

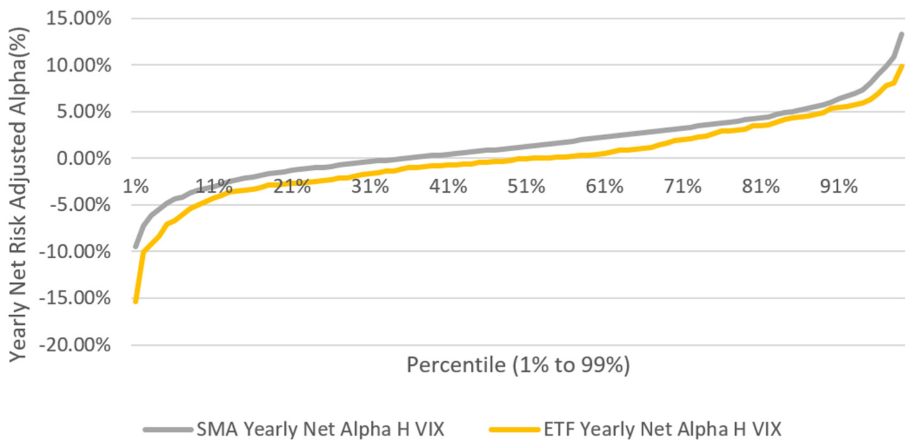


Figure A4. Yearly Net Risk Adjusted Alpha Comparison over high VIX period.

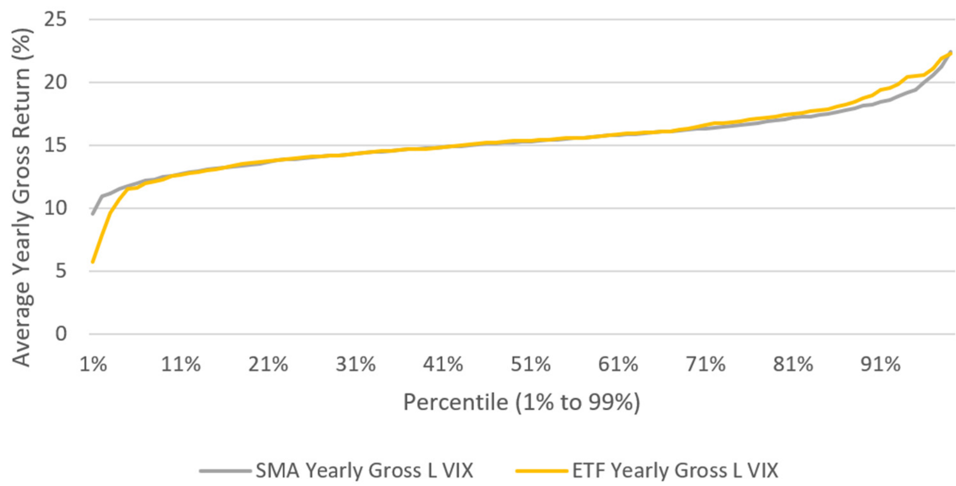


Figure A5. Average Yearly Gross Return Comparison over low VIX period.

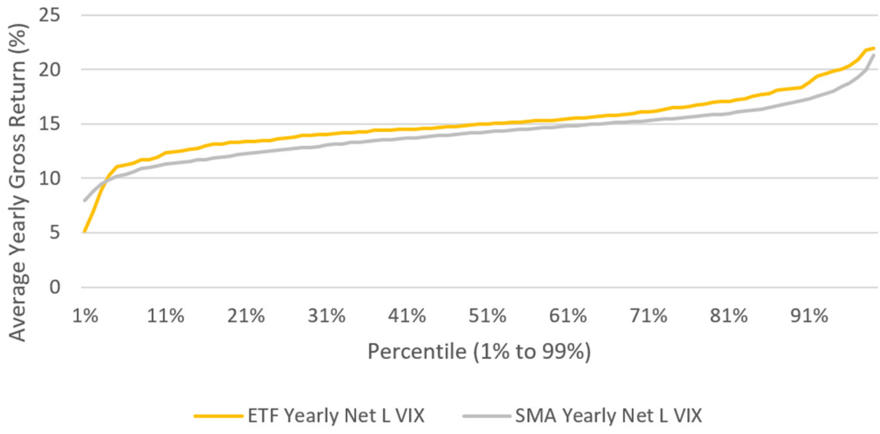


Figure A6. Average Yearly Net Return Comparison over low VIX period.

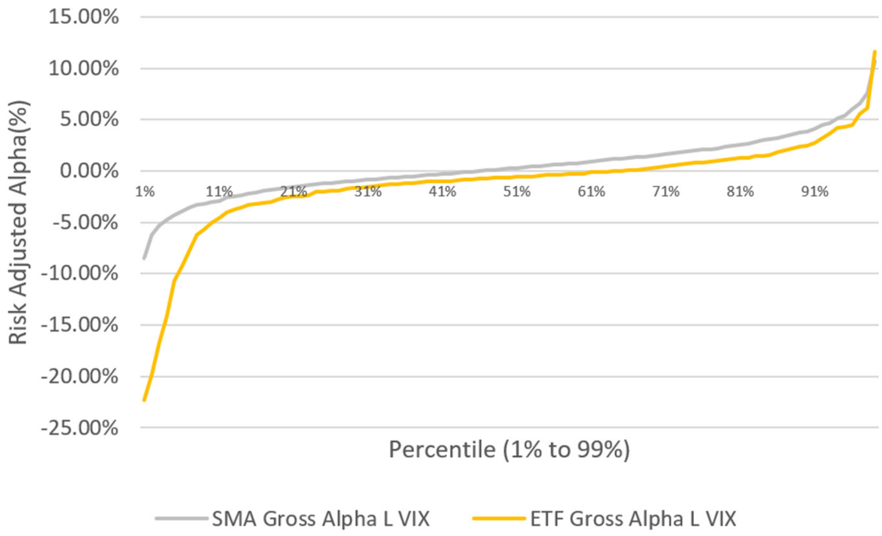


Figure A7. Yearly Gross Risk Adjusted Alpha Comparison over low VIX period.

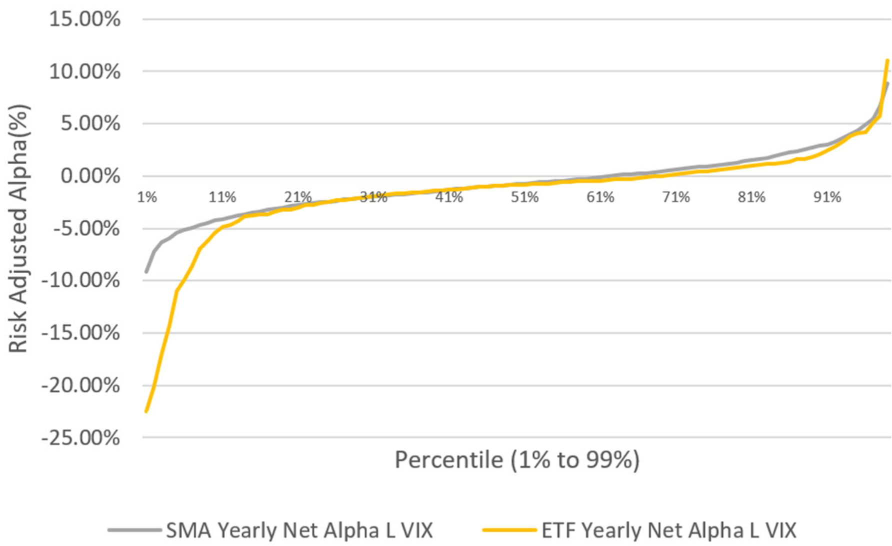


Figure A8. Yearly Net Risk Adjusted Alpha Comparison over low VIX period.

Notes

[1] The investment styles are based on the Morningstar style box.
[2] See Note 1.

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