Determining Capacity Effects With Actively Managed Funds

A study of U.S. equity strategies.

Morningstar Quantitative Research
11 April 2022
Version 1.0

Contents

Darshan Savant,
Associate Quant Analyst
darshan.savant@morningstar.com

Sabeeh Ashhar
Director of Quant Research
sabeeh.ashhar@morningstar.com

Executive Summary

Actively managed funds are focused on generating alpha that more than compensates investors for the underlying risks. Fund managers exploit asset mispricing as alpha opportunities and become popular among investors, attracting higher flows. Certain underlying alpha attributes may start to demonstrate constraints at a higher level of flow and create implementation issues for a manager. Hence, there is a differential ability for managers to generate high average returns but on a decreasing return to scale in deploying these abilities. Capacity drivers also differ across asset classes.

In this paper, we are focused on understanding the capacity constraints of actively managed U.S. equity funds. The paper demonstrates that capacity effects are important in analyzing the underlying return-generating mechanism. Our findings will be of interest to anyone looking to identify funds with associated attributes that influence whether a manager can implement the stated strategy with ease without burdening the end investor.

Key Takeaways

- Rapid pace of fund flows, coupled with low liquidity and increase in size exposure, is indicative of managed funds starting to demonstrate constraints with the underlying alpha-generating mechanism.
- Small-cap and growth funds test capacity limits more frequently than large-cap and value funds.
- Capacity effects impact liquidity and motivate fund managers to tap into higher-capitalization holdings. Accordingly, a manager's inability to maintain the alpha-generation process by extending to a different area of the Morningstar Style Box may justify a rating review.
- Availability of alternative investment strategies from fund houses enables investors to deploy capital to better use and helps limit the fund's capacity effects.
- In absence of available options at the hands of the fund manager, there may be an increase in a cash position for funds demonstrating capacity effects.

Unable to maintain higher flows, funds may eventually soft-close to new investors, thereby delaying capital entry and allowing more time to deploy the capital to better use.

Introduction

To achieve high returns, fund managers must implement a differentiated strategy to trade in mispriced assets. A manager's skill set is determined by the ability to identify and implement mispricing opportunities with ease. The skill set translates to the generation of higher returns for investors and to some extent justifies the associated expense.

As per the Mind the Gap study published by Morningstar, there is a performance gap between the realized return made by investors and the reported fund returns. As per Ciccotello et al (2010), the gap arises from two primary sources. The first is the timing effect attributed to abnormal investor flows by looking at the historical performance of funds. The second is the "capacity effects," which are based on specific fund attributes that make it difficult for a fund manager to continue with return-generating technology on every level of incremental flows. In the equity asset class, some pricing anomalies are the result of exposure to low capitalization, fast growth, and illiquid and concentrated holdings. In equilibrium, the profit-seeking actions of investors create implementation issues for managers and essentially deplete alpha opportunities. We are more interested in exploring the underlying capacity effects as part of this paper.

Berk & Green (2004) also explain impacts for investors once the capacity constraint sets in. Capacity effects attributed to liquidity squeeze may drive fund managers into buying other liquid alternatives, preferably from the benchmark. This may lead to a decrease in tracking error, and the fund is forced to become more like an index fund. Investors still pay the fee on this portion of the fund, but because it is not actively managed, it does not earn excess returns. Alternatively, the manager may start going out of their comfort zone by playing into a different area of the Morningstar Style Box. The manager may not have the required skill sets to operate in a different area of the style box, warranting a rating review. Additionally, being unable to deploy the rapid inflows, funds may be soft-closed for some time or additional charges are levied to deter investors from buying into the fund. Soft closure allows more time for a fund manager to deploy extra flows into a differentiated alpha strategy and also prevents new investors from pouring their money in to the fund. Both actions are detrimental for investors as they must re-evaluate their investment journey. Given the impact on investors, it becomes important to help them identify funds that are demonstrating capacity effects.

As part of uncovering the capacity effects, we first explain the methodology for determining capacity effects with funds. To this end, we create a blended capacity-effects score, which in turn is created from three attributes—namely, flows capacity gap, level of liquidity, and change in size scores. To determine the flows-based performance gap, we draw upon work from Ciccotello et al (2010) accounting for the impact of fund size on performance. The developed flows-based performance gap is a mix of timing effect and capacity constraint. We further isolate the flows capacity gap by accounting for the timing effect through a factor model. Following on earlier papers from Morningstar—namely, Evaluating Capacity and Liquidity for Equity Strategies & Mutual Fund Capacity, we try to attribute the blended capacity effects as a function of potential factors like cash composition, other fund family assets, change in holdings, organic growth rate, turnover ratio, and style exposure. This is done by regressing potential factors against the capacity-effects score through a cross-sectional regression model. Finally, we demonstrate some case studies based on newly generated capacity-effects scores that allow for better insights into the evaluation of fund capacity effects.

Capacity-Effects Score Methodology

In this section, we elaborate on the methodology to determine the flows-based performance gap. We first estimate a time-weighted return metric, followed by a flows-weighted return metric. We then determine a performance gap as a differential between the two metrics. We next isolate the flows-based capacity effect by estimating the timing effect from a factor-based model. After that, we study the universe of funds soft-closed between 2010 and 2021 and identify additional parameters that help identify soft-closed funds. We call this new score the *blended capacity-effects score*.

► Universe used for analysis

For analysis, we will focus on a universe of equity funds domiciled in United States. We also limit our analysis to funds having more than 100 million in assets under management to avoid any data gaps in modeling.

► Time-weighted returns calculation

We calculate time-weighted returns for all funds by taking the arithmetic average of monthly returns of the fund over a rolling window of 36 months given by following expression:

$$TWR = \frac{1}{T}\sum_{t=1}^{T} r_{,t}$$

where we assign equal weights to the monthly series of total returns where w_t (weight at time t) is equivalent to 1/T for all time t

► Flows-weighted returns calculation

For the calculation of flows-weighted returns, a weight scheme is adopted such that it accounts for changes in fund size over the period of time. This is measured through an influx coefficient (phi) that is calculated as follows:

$$influx_t = \frac{Flow_t}{FundAsset_{t-1}(1+r_t)}$$

After deriving the influx coefficient for funds over period of time, we then calculate the period weights recursively as follows:

$$\widehat{w}_t = \widehat{w}_{t-1}(1 + influx_{t-1}), \text{ for } t > 1$$

Where $\widehat{w}_t$ at time t is calculated using values of weight and flux coefficient at time t-1. The initial flow weight is taken as unity . We then normalize the weights computed in the previous steps. Finally, the flows-weighted return (FWR) is calculated as below:

$$FWR = \frac{1}{\sum_{t=1}^{T} \widehat{w}_t}\sum_{t=1}^{T} \widehat{w}_t \times r_t$$

As evident from the weighting scheme above, the weights adjusts as per the flows into/out of the fund. Fund outflows at any period result in the influx coefficient being negative, and vice versa for fund inflows. This in turn enables us to isolate the effect of flows on the fund from the growth in the existing asset base. Compared with time-weighted returns, more weight is allocated to periods of higher flows.

- **Performance-gap calculation:**

We measure the performance gap as the difference between the flows-weighted returns and the time-weighted returns of the fund. A negative performance gap is the result of either flows being timed poorly or presence of capacity constraints in the actively managed strategy.

$$Performance\ Gap = FWR - TWR = Diff_{\text{Timing}} + Diff_{\text{Capacity}}$$

We are more interested in isolating the second capacity effect by accounting for the timing component

- **Timing effect calculation:**

To estimate the timing effect we leverage a Fama-French four-factor model using size, value, momentum, and market return factors. The regressions are rolled over the past 36 months to allow for sufficient history of data in the model. We adopt the following empirical factor model for the determination of factor loadings:

$$r_t = \alpha_t + \beta_1 MktRM_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + e_t$$

where $MktRM_t$, SMB_t, HML_t, MOM_t, is the fund's monthly return over and above the risk-free rate, size, value, and momentum factors for the U.S. market, respectively.

We then calculate the time weighted component of the timing effect by taking average over a rolling window of 36 months of the sum product of factor loadings and factor return series to get the time-weighted benchmark returns,

$$TW_{\text{Fund/Timing}} = \frac{1}{T}\sum_{t=1}^{T} \sum_{i=1}^{N} \beta_i r_{i,t}$$

where betas are the estimated factor loadings for every fund in our universe and $r_{i,t}$ is the return series of the factor. We also estimate the flows-weighted component of the timing effect over the same rolling window using a similar methodology presented earlier. The mechanism used in the computation of flows-weighted component of the timing effect alternatively flows-weighted benchmark returns is given by,

$$FW_{\text{Fund/Timing}} = \sum_{t=1}^{T} w_t \times \sum_{i=1}^{N} \beta_i r_{i,t}$$

where w_t are the weights generated by employing the same weighting scheme used for computing the flows-weighted return of the fund.

We then take the difference of the flows-weighted component and time-weighted component of the timing effect, naming it as *timing gap*. We assume this difference to represent the timing component of the performance gap manifested by the fund's investment strategy.

$$Diff_{\text{Timing}} = FW_{\text{Fund/Timing}} - TW_{\text{Fund/Timing}}$$

While we have interpreted the difference in flows- and time-weighted returns to a multifactor benchmark as a *timing* component, we assume that this effect could be a market wide or factor-related capacity constraint. As an example, if the size of assets under management becomes large for funds, the factor returns start to saturate as they are exposed to similar market factors. On this end, we are not differentiating between timing effect and factor-capacity constraint but refer to them jointly as *timing effect* here. Finally, the flows-capacity gap is the remainder of the performance gap net the timing effect

$$Flows\ Capacity\ Gap = Performance\ Gap - Diff_{\text{Timing}}$$

- **Blended capacity-effects score:**

Our major focus here is to develop a metric indicative of capacity effect with funds. The earlier section covered how the flows-capacity gap shows early indications of capacity effects creeping in. We also want to look at other attributes that are indicative of fund capacity issues. To determine additional attributes, we looked at historic data of over 150-plus soft-closed funds for the period 2010 till 2021. We studied various attributes that were indicative of funds getting soft-closed. This is measured through an ability to detect soft-closure with more than 50% rates. As the notification of fund closure is generally available close to two months before the soft-closure date, we used this as the cut-off date to understand the attribute changes. We then studied the changes in attribute levels three months before the cut-off date, as we were keen to develop a pre-emptive factor. Referring to earlier research from Evaluating Capacity and Liquidity for Equity Strategies & Mutual Fund Capacity, we studied the level of liquidity, change in holdings, level of flows-capacity gap, size IQR, level of cash position, style IQR, and other attributes as potential indicators of soft-closure. We provide brief explanation of the factors in the Appendix

Exhibit 1 Soft-Closed Funds Attribute Analysis

Particulars	Liquidity	Delta Size IQR	Flows Capacity Gap	Delta Cash Position	Delta Style IQR	Change in Holdings	Blended Capacity Effects
Increase	43.85%	53.72%	41.44%	41.84%	48.10%	46.15%	35.81%
Decrease	56.15%	46.28%	58.56%	44.68%	51.90%	23.85%	64.19%
No change	0.00%	0.00%	0.00%	13.48%	0.00%	30.00%	0.00%

Source: Morningstar Quantitative Research Data as of November 30, 2021.

In Exhibit 1 above, we find that the liquidity level of the soft-closed fund was extreme for 56.15% of funds near the cut-off date. This makes sense as the majority of soft-closed equity funds are small cap and growth-oriented. Most underlying holdings have low liquidities and are difficult to trade in, given high flows. Apart from this, we also observe that the size score of the funds is increasing as managers have been rapidly trying to deploy capital. A positive change in size factor can be the result of two scenarios. First, given the rapid AUM growth, the capitalization of underlying holdings may naturally undergo a change, and the fund manager is taking a style drift. Second, there are not enough opportunities available for a fund manager to deploy capital to better use. So, the fund manager would be drifting toward other liquid areas of the market. For example, if a successful small-cap manager has had to move into mid-caps as the fund's cash flow has grown, we would assess that strategy as a mid-cap offering. While the team's skills and expertise are inclined toward small-cap investors, we will want to understand if it has the requisite skill set to perform in a different area of the market. Both scenarios would need careful evaluation and possibly a rating review by the analysts. The size attribute change can detect 54% of the funds that got soft-closed. We also observe that our flows-based capacity-gap attribute saw negative values for over 58% of the soft-closed funds. We hence propose to use the top three factors that can detect most of the soft-closed funds. Accordingly, we create a capacity-effects score as an equally weighted score from level of flows-based capacity gap, liquidity, and change in size inter-quartile range. Through the rest of paper, we will refer to this blended score as the *capacity-effects score.* We test this blended score on the universe of soft-closed funds and could identify approximately 65% of the funds before the cut-off date.

$$Capacity\ Effects\ Score\ = Equi\_Weight(Flows\ Capacity\ Gap +\ Liquidity + \Delta\ SizeIQR)$$

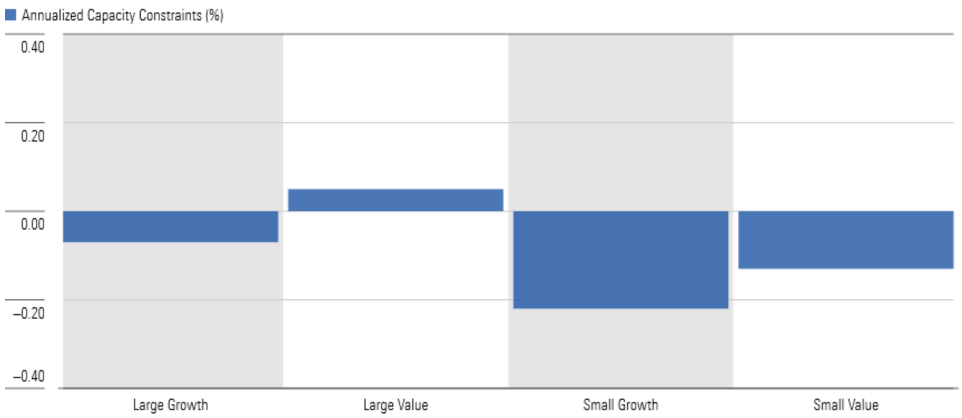
After deriving the capacity-effects score, we investigate the drivers of capacity effects. To that end, we perform monthly Fama-Macbeth-type cross-sectional regression, controlling for factors like organic growth rate, other fund managed assets, fund turnover, cash positions, change in holdings, past returns %, and fund style. Based on available literature, Evaluating Capacity and Liquidity for Equity Strategies & Mutual Fund Capacity**,** these factors are commonly known to affect the capacity constraints of any investment strategy and hence are included in our cross-sectional regression analysis. A brief explanation of these factors and the universe used in analysis can be found in the Appendix. The final model thus takes the form:

$$\begin{aligned} Capacity\ Effects_{i,t+1} = \alpha_0 + \beta_1 Organic\ Gr.Rate_{it}\ +\ \beta_2 Fund\ Family_{it}\ + \\ \beta_3 Turnoverratio_{it} +\ \beta_4 Asset\ Alloc\ Cash(Long)_{it} + \\ \beta_5\ Change\ in\ \#\ Holdings_{it} +\ \beta_6 StyleIQR_{it}\ + \\ \beta_7 Trailing12mExcessReturn_{it} +\ e_{it} \end{aligned}$$

Results

We now move to understand the underlying impact of capacity effects on funds across equity style families. First, we aggregated the capacity-effects score of all of the funds in our universe over the modeling time frame from 2006 till 2021 over key areas of the style box. As can be seen in Exhibit 2, growth and small-cap funds generally experience more capacity effects and accordingly have negative capacity scores.

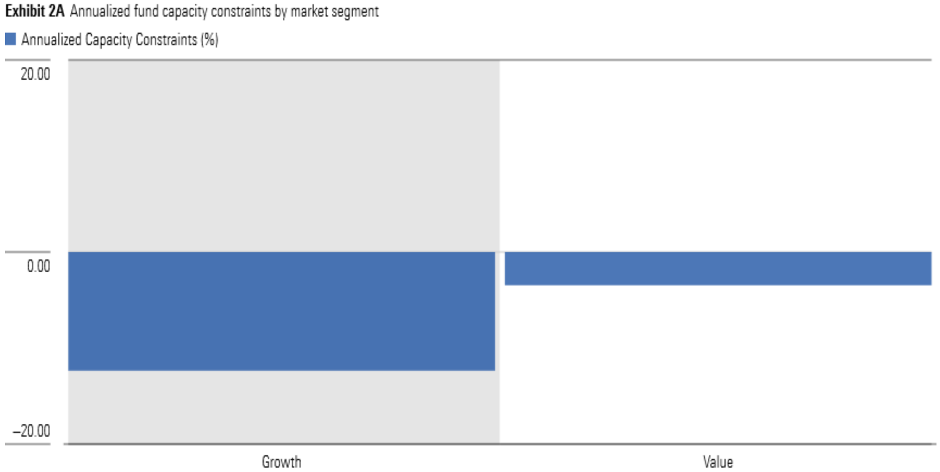
Exhibit 2 Annualized fund capacity constraints by investment style



Source: Morningstar Data as of November 30, 2021.

Similarly, the growth funds generally demonstrate more capacity issues than the value funds. This may

Exhibit 2A Annualized fund capacity constraints by market segment



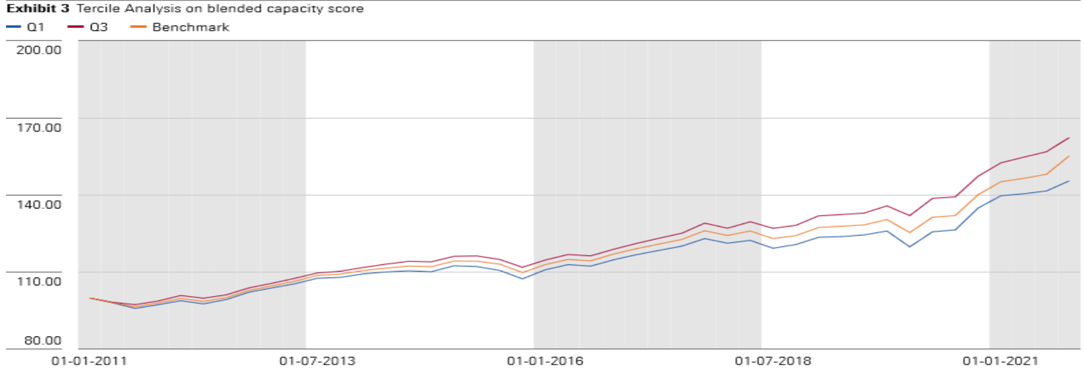
Source: Morningstar Quantitative Research Data as of November 30, 2021.

have a natural explanation that, as small-cap funds buy larger shares of the market of underlying holdings, the liquidity may eventually dry up, making it harder to execute meaningful, alpha-generating trades. In that sense, the fund may not be able to maintain its initial investment strategy of restricting to small-cap growth funds. The underlying alpha inefficiencies in the market are small and temporary. Furthermore, as a fund approaches the limit of total market share (that is, it becomes the market), absolute alpha potential shrinks to zero.

Tercile Portfolio Analysis

To evaluate the efficacy of the capacity scores, we built tercile portfolios on our defined universe, where Q3 is indicative of funds having capacity-effects scores at the higher (positive) end of spectrum. In contrast, Q1 resembles portfolios with lowest capacity-effects scores. We perform a quarterly rebalancing of this strategy on our defined universe. As can be seen in Exhibit 3, the Q3 portfolio outperformed the Q1 portfolio. The compound annual growth rate and Sharpe ratio for the Q3 is better than the Q1 Tercile. This indicates that the capacity-effects score can be used to filter out funds and help improve investor outcomes

Exhibit 3 Tercile Analysis on blended capacity score



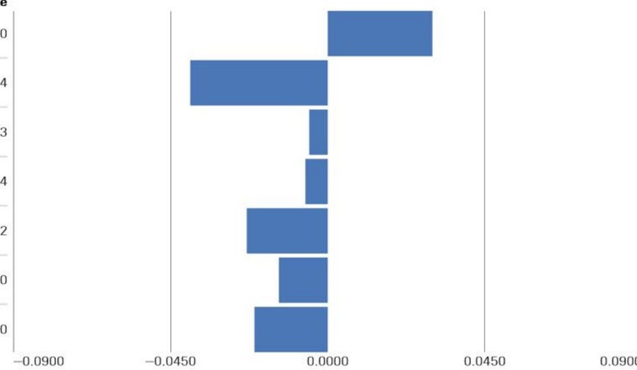
Stat	Q1	Q3	Benchmark
Yearly Sharpe	0.56	0.87	0.69
CAGR	3.69%	4.73%	4.14%

Drivers of Capacity Constraints

We now move to attributing capacity effects on associated attributes, the definitions of which are in the Appendix. The model came out statistically significant, with t-statistics indicating that the associated attributes can help explain capacity issues. Exhibit 5 explains the contribution of each factor in the U.S. equity fund universe for the period 2006 to 2021 to capacity effects. The insights are displayed to showcase the typical change in capacity-effects score for a fund given a change in one of the underlying attributes of holding, while keeping all other constant. All coefficients and estimates should be interpreted, therefore, as adding to capacity effects of the fund. For simplicity going forward, we may refer to this as *increase or decrease in capacity effect*. As an example of how to interpret one of the factors, we look at cash composition of the holdings. Cash composition of the holdings has an average contribution to capacity effect of negative 0.0394. This means that a fund whose cash composition increases by 1% standard deviation above the mean sees a capacity effect going further down to the negative zone by approximately 0.0394 units. We now do a deep-dive analysis to further understand the underlying attributes.

Exhibit 4 Drivers of capacity effect (one month forward)

Charecteristics	Coefficient Estimate
Fund Family	0.0300
Asset Alloc Cash % (Long)	−0.0394
Trailing 12m Excess Returns	−0.0053
Organic Growth Rate	−0.0064
Style IQR	−0.0232
Turnoverratio	−0.0140
Change in Holdings	−0.0210



Source: Morningstar Quantitative Research
Data as of November 30, 2021.

A higher proportion of fund family assets is indicative of more available strategies for investors. It may also be beneficial for investors when funds are soft-closed, and they could look at other available investment opportunities from the fund house. Larger fund families can also provide economies of scale by reducing fund costs. Providing in-depth research for multiple portfolios can also relate to better security-selection characteristics.

Funds having more cash holdings in their portfolios are indicative of having capacity effects. This may be because the portfolio manager has been finding it hard to put all the cash to good use. There may be some illiquid holdings in the portfolio for which there are not sufficient trading opportunities available.

A higher past performance measured through trailing 12-month excess returns for the funds leads to biases in investment decisions among the investors in the form of chasing past performance and thus buying more of the fund. This may be challenging as there may not be sufficient investment opportunities available to put the incoming cash to good use.

A higher organic growth rate is indicative of the speed of growth of flows. It is much harder to put large sudden inflows of capital to work than flows spaced evenly over a longer period. Funds that show big monthly inflows may well have performance diluted in a rising market until that money can be put to work. Managers may opt to hold more cash, tempering performance in an upmarket, or purchase securities that are larger and more-liquid than their typical to keep cash levels in check. A rising organic growth rate is indicative of funds showing capacity effects.

The attributes that make a fund a growth fund (based on the style box) also indicate that the fund would experience capacity constraints. This phenomenon was explained at the start of the Results section. There is also a limit on alpha available in any given area of the style box. A skilled manager can also be hindered by the area of the style box in which they operate.

A higher turnover ratio with a rise in holdings relates to higher capacity constraints. High turnover accompanied by a rise in holdings often indicates tactical trading is taking place to resolve liquidity issues, something that is much harder to do at scale. Momentum strategies, for example, would be more at risk from liquidity issues which could lead to higher turnover or bloated holdings. A corollary is that strategies that require less turnover may have higher capacity than those that trade more rapidly. Further, contrarian offerings that tend to be liquidity providers could also potentially handle more money because of their proclivity to trade against the market.

Case Studies

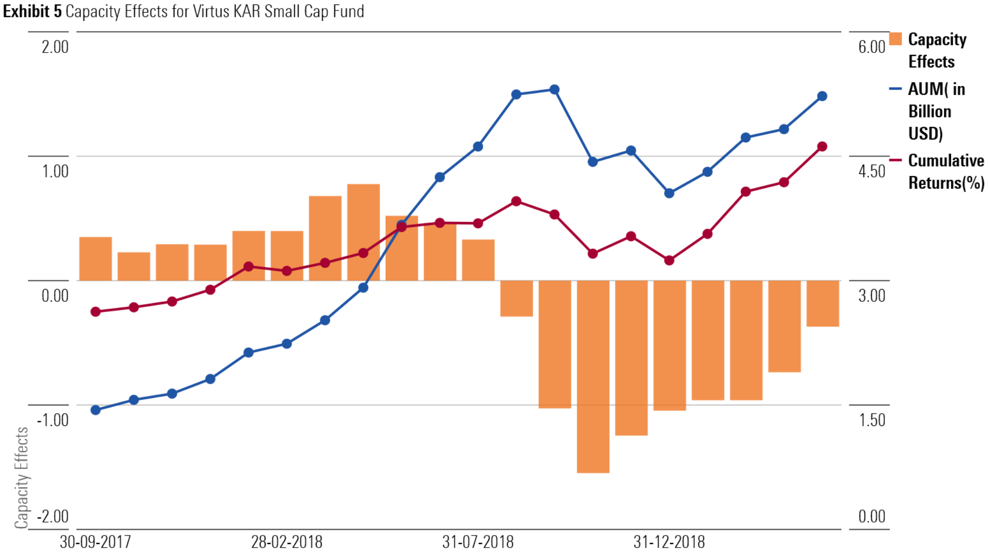
We now move on to discuss some real case studies demonstrating the insights that capacity-effects scores could bring to investors. We specifically focus our effort on two funds to uncover the benefits of the capacity-effects score.

Case Study 1: Virtus KAR Small-Cap Growth PXSGX
U.S. Small-Cap Fund
Morningstar Analyst Rating of Bronze (2022)

The fund saw a rapid growth in AUM from the beginning of 2017 to the end of September 2018, whereby the fund size increased from USD 500 million to USD 5.5 billion. The fund tracks Russell 2000 Index and delivered great returns during the period. However, on Sept. 28, 2018, after multifold growth in AUM, the fund was soft-closed to new users. We would now like to use our capacity-effects scores to uncover insights for the fund in focus.

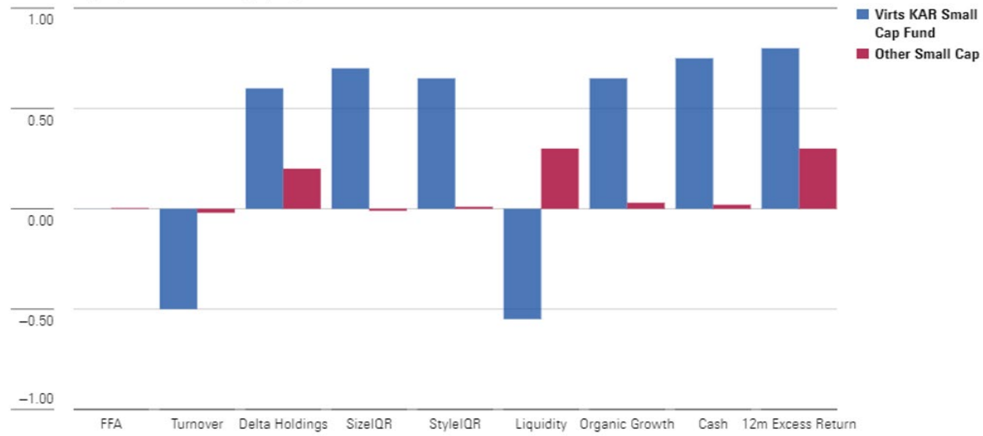
Exhibit 5 shows the return versus AUM growth of the fund over 12 months before soft-closure. As we can see, the growth of the flow was strong and outpaced the return growth (stagnating) from the second quarter of 2018. In line with our model outcomes, the fund started showing capacity issues from the middle of 2018, months before it got soft-closed.

Exhibit 5 Capacity Effects for Virtus KAR Small Cap Fund



Source: Morningstar Quantitative Research Data as of November 30, 2021.

Exhibit 6 Avg. Exposure Fund vs. Category Avg

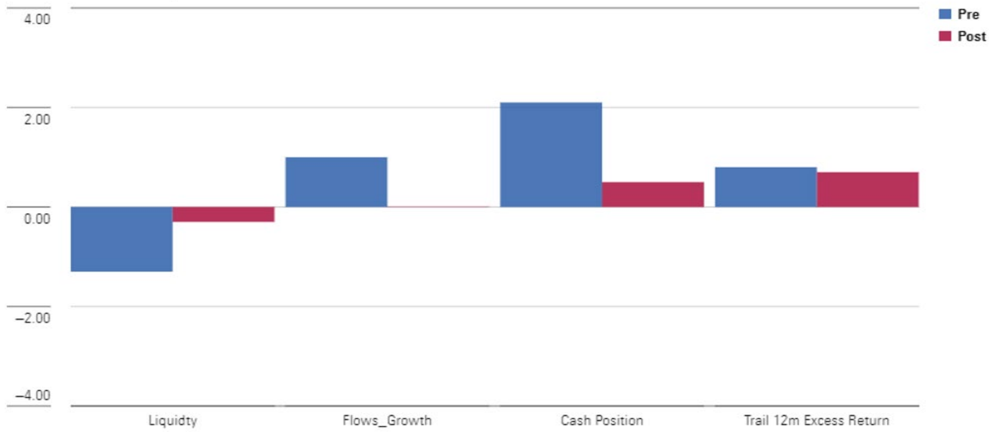


Source: Morningstar Quant Research. Data as of November 30, 2021.

We also refer to Exhibit 6, which shows the exposure of the fund to key attributes that are indicative of capacity issues. Alongside, we present the average exposure of all other funds in the category. To make comparison easier, the exposures are Z-scored. As can be seen from Exhibit 6, the fund saw a strong returns growth that outpaced category returns in the past 12 months. This would have essentially driven more investors to buy in the fund reflected by a significantly high organic growth rate compared with other small-cap funds. The fund possibly had concentrated holdings in illiquid stocks, which is also evident in the comparison of liquidity to other small-cap funds. Given the rising cash levels, the fund manager also tried to dilute the holdings by increasing their number to an amount greater than at other small-cap funds. Compared with other fund families, Virtus KAR fund family had relatively few equities strategies, indicating less flexibility at the hands of the investors to deploy their capital within the same branding umbrella. Left with fewer options at the asset manager, the cash positions kept piling up. In addition, there was an increase in the size score of the funds compared with other small-cap funds. It also looks like the managers were tactically trying to add more positions, measured through a higher turnover, which is also evident in the above graph. Given the tactical shift in style scores, the fund may require a thorough analyst review.

We also evaluated the pre- (12 months before soft-closure) and post-effects (12 months after soft-closure) on key fund attributes. After soft-closing the fund, the managers had more time to better deploy the accumulated capital. As can be seen from Exhibit 7, after soft-closure, liquidity gradually improved and the cash position went down. We feel that, after the soft closure, the liquidity for underlying holdings would have gradually improved as more market participants appeared and trading underlying assets was feasible. The managers would also have more time to rethink their strategy and deploy the cash flows to newly identified market anomalies to generate a balanced return. This is evident as the returns traced back to levels before soft-closure.

Exhibit 7 Fund Pre-Post Exposure to Soft Closure

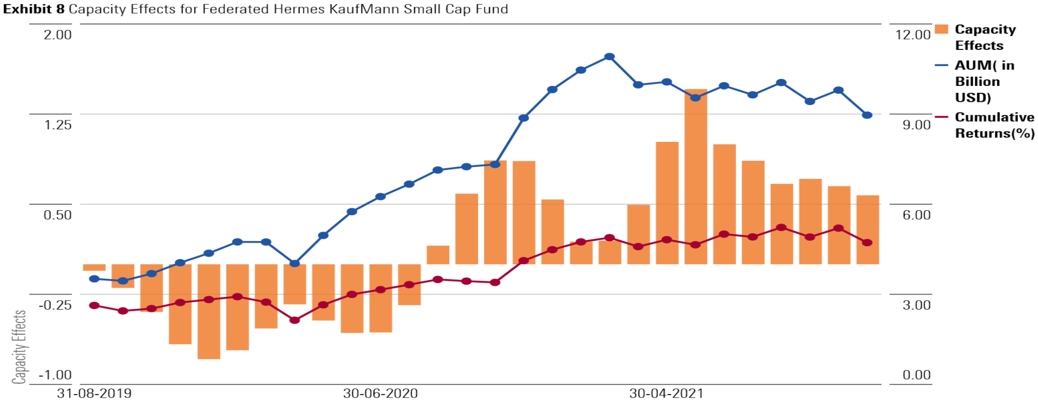


Source: Morningstar Quant Research Data as of November 30, 2021.

Case Study 2: Federated Hermes Kaufmann US Small Cap Fund Institutional Shares FKAIX
Morningstar Quantitative Rating of Silver (2022)

Like the earlier fund example, the fund under evaluation demonstrated rapid growth in AUM from USD 888 million at the start of 2018 to USD 10.1 billion by the end of 2020. As can be seen from Exhibit 8, the fund saw return tapering in early 2020 while flows grew at a fast pace. The fund was eventually soft-

Exhibit 8 Capacity Effects for Federated Hermes KaufMann Small Cap Fund

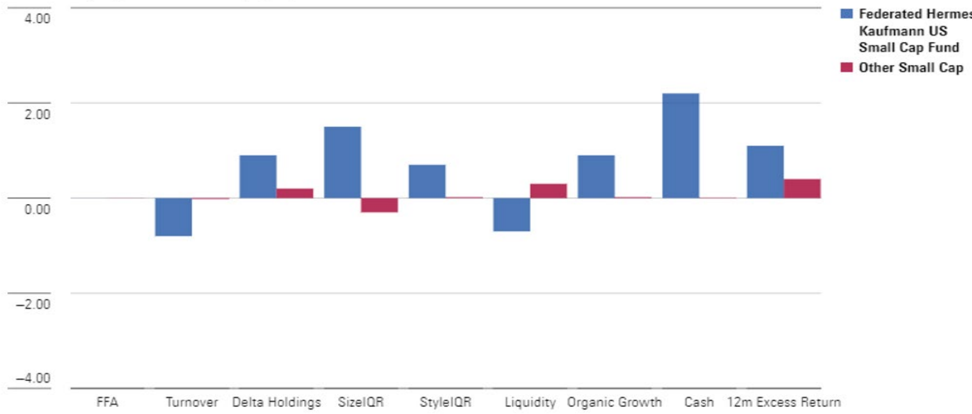


Source: Morningstar Quantitative Research Data as of November 30, 2021.

closed on March 31, 2021. We can see the capacity constraint setting in quarters before the soft-closure. Alongside, if we check the exposures relative to peers in Exhibit 10, they are also in line and building a similar story as the earlier case study. Compared with category peers, the fund had a higher return alongside a faster pace of organic growth rate.

While cash kept piling up, the manager started buying into higher-capitalization holdings, indicative of a higher change in holdings and higher turnover alongside bloating size score.

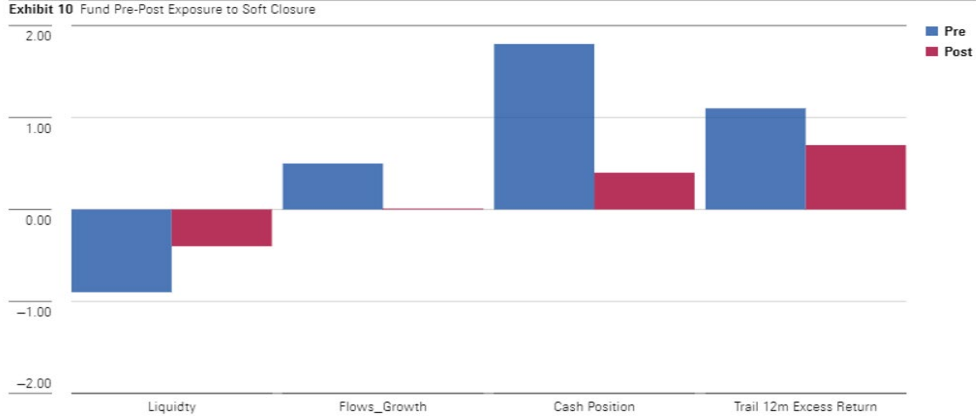
Exhibit 9 Avg. Exposure Fund vs. Category Avg



Source: Morningstar Quant Research Data as of November 30, 2021.

This change in size score would have warranted a change in rating. As the fund is covered under Quantitative Ratings, we could refer to Exhibit 10 and find that the fund was downgraded to Bronze in early 2021 months before the soft-closure. While we suspect the capacity issues impacted ratings, this aspect must be investigated further. In Exhibit 10, we can see that the post-soft-closure fund has a reduced cash position, allowing more time for managers to deploy the capital. The liquidity of the holdings also gradually improved over the period. Most possibly, the fund switched to a Quantitative Rating of Silver in the latter part of the year before soft-closure.

Exhibit 10 Fund Pre-Post Exposure to Soft Closure



Source: Morningstar Quant Research Data as of November 30, 2021.

Open End Funds | Global Open-End Funds

Action View Untitled | Save | Search | Edit Data | Sort | Locate | Export | PDF | Refresh

	Name	Morningstar Quantitative Rating 2021-01	Morningstar Quantitative Rating 2021-02	Morningstar Quantitative Rating 2021-03	Morningstar Quantitative Rating 2021-04	Morningstar Quantitative Rating 2021-05	Morningstar Quantitative Rating 2021-06
1	Federated Hermes Kaufmann Small Cap IS	Silver	Bronze	Bronze	Bronze	Bronze	Bronze

Conclusion

There is no limit to the amount of money a certain type of strategy can run. This aspect is affected by specific attributes of the underlying alpha-generating strategy. All the tools and techniques that we have discussed here are used to help us understand if a strategy may have the capacity to take on more money. The capacity-effects score, alongside the underlying drivers, must be viewed in tandem to have a better understanding of fund capacity. In this sense, our study allowed us to broaden our understanding of mutual fund capacity constraints and correlate poor investor outcomes with specific capacity characteristics. We have been able to isolate an individual factor's directional effect and measure the magnitude of its impact on the fund's capacity. This has allowed for a better understanding of what is meant by funds having decreasing returns to scale.

This paper develops a blended capacity-effects score as the accumulation of flow performance gap, level of liquidity, and change in size score. The capacity effect is related to the underlying strategy positioning in the style box. Hence, small-cap and growth strategies demonstrate more capacity effects. Also, as capacity constraints hit, it becomes difficult for managers to maintain the alpha-generating mechanism. This frequently leads to higher cash holdings or drift in the style strategy through exposure to a higher-capitalization zone having better liquidity score. In some cases, soft-closures of actively managed funds are consistent with sponsors' recognition of capacity constraints to active management that we have measured.

While the current paper mostly focuses on actively managed funds based in the U.S., we can extend the research to global funds as a later piece of research. We can also extend the study to passively managed funds, which exhibit more timing issues in the broader market. In our analysis, we revealed a couple of Gold- and Silver-rated funds that experienced capacity effects at various times. This may require a further rating review as well and possibly follow-up work. Also, a lot of thematic equity funds betting on secular growth themes have exposure to small-cap and illiquid holdings. Such funds have recently seen a rapid rise in flows and new product launches. A study of capacity effects of thematic funds would be useful, and we plan to extend our study in this direction.

Appendix

Data

Our study relies entirely on Morningstar fund data sources. We filter U.S. funds with less than USD 100 million in assets. We also do not include index funds in our sample, as index funds should follow an index weighting and therefore hypothetically would not be positioned to confront capacity concerns. We run our model on approximately 2,200 active U.S. equity mutual funds from the year 2006 through 2021. Our sample does not suffer from survivorship bias. Morningstar's global fund databases retain a full history of dead funds, and these funds are included in our sample. Moreover, our evaluation technique dynamically incorporates monthly changes in fund universe composition, providing a more holistic and realistic picture of historical performance. Each monthly snapshot captures any funds that were subsequently merged or liquidated away.

Time-Weighted Return vs. Flows-Weighted Return Calculation

The below table shows a numerical example of derivation of the performance gap of the fund using hypothetical data. The time-weighted return is simply the arithmetic mean of past n observations whereas flows-weighted return is the sum product of returns and weights, which are adjusted for the level of flows.

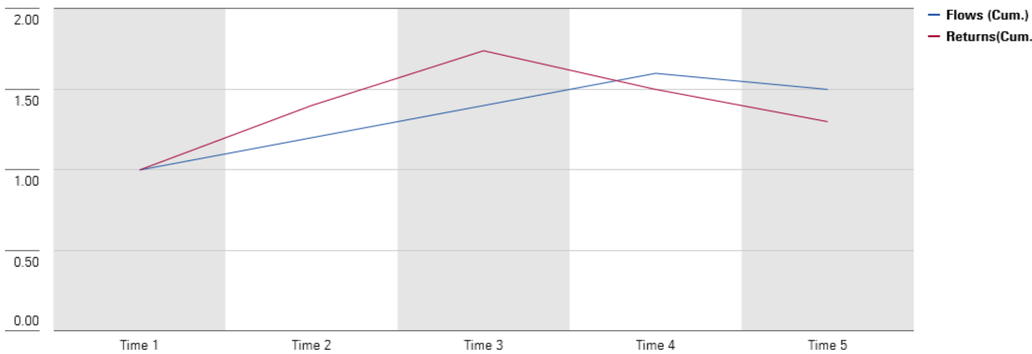
From the cumulative returns vs flows plot in Exhibit 12, we see that investors may chase higher returns, leading to increased inflows to the fund. At a certain point, the fund manager is not able to generate positive returns from these incremental flows, leading to a performance gap.

Exhibit 11 Example showing difference between time weighted return and flow weighted return

TimeFrame	FundAsset	Fund Flow	Return	Flow Coeff	Flow weight	TWR	Flow Weighted Return	Perf_Gap
Time 1	1	0.1	0.01	0.00	1.00	0.1025	0.085	-0.0177
Time 2	1.1	0.2	0.50	0.30	1.30			
Time 3	1.32	0.1	-0.02	0.09	1.42			
Time 4	1.452	0.1	-0.02	0.07	1.52			
Time 5	1.5972	0.2	-0.05	0.13	1.72			

Source: Morningstar Quantitative Research

Exhibit 12 Cumulative Returns vs Cumulative Flows



Source: Morningstar Quantitative Research

Mutual Fund Factors Explained

Organic Growth Rate

This is growth in the market value of investments managed by a mutual fund. Instead of AUM, we use organic growth, which is changes in assets not attributable to returns and indicative of the speed of growth of AUM. We calculate this by dividing fund flows for a month by AUM from the previous month-end.

$$Organic\ Growth = \frac{FundFlow_t}{AUM_{t-1}}$$

Change in the number of holdings

This is the change in a total number of differentiated holdings of a fund. The figure is calculated from the most recent available fund holdings versus the past three months. It does not include a fund's short positions. At Morningstar, we make every effort to gather the most up-to-date portfolio information from a fund.

Turnover Ratio

This is a measure of the fund's trading activity, which is computed by taking the lesser of purchases or sales (excluding all securities with maturities of less than one year) and dividing by average monthly net assets. A turnover ratio of 100% or more does not necessarily suggest that all securities in the portfolio have been traded. In practical terms, the resulting percentage loosely represents the percentage of the portfolio's holdings that have changed over the past year. Morningstar does not calculate turnover ratios. The figure is culled directly from the financial highlights of the fund's annual report. For our model, we use linear interpolation from annually reported figures to create a monthly estimate of the turnover ratio.

Liquidity

By rolling a fund's daily trading volume, we get a more reasonable expectation of how a fund is expected to trade on an average day. If t^{30} represents a holding's rolling 30-day trading volume average at time t, w represents a holding's weight at time t, then a fund's liquidity score at any given month t is equal to:

$$Liquidity = \frac{\sum w(t^{30})}{\log(AUM)}$$

Change in size and style inter quartile ranges

Using Morningstar's size score, which is computed monthly, we can measure the interquartile range of the size of the funds' holdings. This dispersion of scores is useful in measuring whether a fund's breadth of holdings affects its performance. The smaller a fund's size, the more targeted or concentrated the fund's strategy may be. We take the difference between the 25th and 75th percentile of the size score and style score of individual holdings at every time point to get the size and style interquartile ranges, respectively. Using this, we can get an idea of how a fund's buying opportunity is constrained by its own strategy. Significant changes in size score indicate that a fund manager may be straying from its typical holding choices.

Fama-French Regression

We performed Fama-French benchmark regressions on a 36-month rolling basis to compute benchmark fund returns (also to capture alpha). The equity factor returns for SMB (Small Minus Big), HML (High Minus Low), and Mkt-RF (excess return over the risk-free interest rate) of the four-factor Fama-French model were regressed against monthly fund returns. A summary of benchmark regressions is given for a portfolio formed using the last three years of factor data is given below:

Exhibit 13 Fund Benchmark Regressions

Factor	HML	MktRF	Mom	SMB	Intercept	R2-adj
Over all Sample Mean	0.062	0.9079	-0.03008	0.2022	-0.1022	88%
t-stat	1.174	20.52	-0.285	1.904	0.067	

Source: Morningstar Quant Research

Fama-MacBeth Analysis

To evaluate the capacity constraint drivers for funds, we conduct cross-sectional regressions. Each month, we regress the one-month forward magnitude of capacity constraint with capacity-influencing factors. Thus, the Fama-MacBeth estimator computed by performing monthly regressions, one for each time, using all available entity observations. While doing so, even though we do not model time effects explicitly, the process of conducting regression of all variables in a single period is akin to including time effects. The functional form of the Fama-MacBeth model is as follows:

$$y_{i,t+1} = \beta' x_{i,t} + u_{it}$$

Where $x_{i,t}$ is the matrix of capacity factors at time t for fund i
$y_{i,t+1}$ is the vector of capacity effects for fund i at time t+1
u_{it} is the vector of error terms at time t for fund i
β' is the vector of coefficients of capacity factors indexed by time t
If the estimated model parameters are β_t, then the reported estimator is given by β_{avg} as follows,

$$\beta_{avg} = \frac{1}{T}\sum_{t=1}^{T} \beta_t$$

References

Ciccotello, C., Greene, J., Leng. L., & Rakowski, D. 2010. "Capacity and Factor Timing Effects in Active Portfolio Management."

Berk, J., & Green, R. 2004. “Mutual Fund Flows and Performance in Rational Markets.” *Journal of Political Economy,* Vol. 112, P. 1,269.

Fama, E.F., & MacBeth, J.D. 1973. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy,* Vol. 81, P. 607.

Pastor, L., & Staumbaugh, R., & Taylor, L. 2017. “Fund Tradeoffs.”

22 West Washington Street
Chicago, IL 60602 USA