The Rise and Fall of New Funds
Why Some Funds Succeed and Others Don't

Morningstar Research
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Executive Summary

In this paper, we explore the relationship between observed investor preferences for and eventual investor outcomes in newly-launched funds. Newly-launched funds are particularly interesting to us as they account for an overwhelming share of total global inflows despite usually lacking information investors find relevant, such as a performance track record. With so much information unavailable, we had found it difficult prior to this study to form hypotheses about the types of funds investors prefer and why. Furthermore, by not knowing the types of new funds investors have preferred, we have been unable to make a judgment about whether the types of funds investors choose result in positive outcomes.

To conduct this exploration, we built two models that unpack the historical correlations between both forward risk-adjusted returns and forward cumulative fund flows with observed fund characteristics, economic regimes, and category environs. In isolation, each model offers us a multivariate view of the factors that drive future flows and risk-adjusted returns for newly-launched funds. By comparing the outputs from the two models, we can also identify potential conflicts of interest for asset-managers.

To our knowledge, a larger dataset has never been assembled to approach this question. Indeed, this study may be the first of its kind. We have collected data on every fund launch globally since 2005 to be found in Morningstar's database -- over 57,000 unique funds. To date, it is likely that no study can assert more definite conclusions of what has historically driven the success and, in some cases, failure of new fund launches.

Key Takeaways

- Frequent portfolio disclosure correlates with higher flows and higher risk-adjusted returns.
- Managers who own their fund have historically performed better and garnered more assets.
- Managers who possess a CFA are preferred by investors and have had higher risk-adjusted returns.
- Female portfolio managers have received higher flows.
- High fees hurt both future flows and future risk-adjusted returns.
- Coverage by a Morningstar analyst has had an economically large impact on future flows and returns.
- A cannibalization effect exists at firms that launch multiple products at once.
- Funds launched into monopolistic categories are less likely to attract assets.
- Funds launched from firms with large market shares have an advantage getting additional flows.
- Investors tend to prefer funds that invest according to specific style tilts, but these preferences have not all resulted in positive investor outcomes.

- Investors have revealed specific preferences for types of fund structure
- Economic regimes characterized by high volatility and decreasing oil prices have historically been an advantageous time to invest in new funds.
- Fund ownership patterns suggest that investors discriminate based on manager buying behavior.

Introduction

It's easy to dismiss new funds as an immature, unproven, and unimportant segment of the asset management industry. But the truth of the matter is that the asset management industry is dominated by new funds. Globally, we find that new funds account for the preponderance of new asset flows. In 2015, global fund flows reached approximately $516.4 billion across the three asset classes in our study - equity, fixed income, and allocation. Of the total, new funds with less than 12 months of track record accounted for $379 billion or 73% of all flows. Even in years when the industry experiences net outflows, new funds continue to garner assets. In 2014, new funds grabbed $316 billion in net inflows compared to -$526bn in net outflows for funds with greater than 12 months of track record. This pattern holds in the majority of regions and is especially true for the US. For example, in 2015, U.S. mutual funds had $40.8 billion in new asset flows in total. Out of that universe, funds less than one-year old had new asset flows of $77.7 billion. Of course, a good chunk of these inflows should be considered seed capital, but nonetheless, the simple fact remains that capital is consistently being reallocated away from aging products and into newer, fresher, and younger funds.

Reconciling the facts above with the common refrain that flows go to those funds with successful long-term track records is actually not that difficult. Funds with successful track records do reap a harvest of inflows, but those funds who fail move into net outflows. A portion of those outflows are redistributed to the successful managers but also to new funds recently launched. Nuance, of course, exists as Davidson and Strauts (2015) reveal that other firm-level and fund characteristics beside track record need to be considered. However, the above mental framework can serve well-enough to reconcile seemingly contradictory facts.

We hope, therefore, that it does not come as a surprise why the patterns of flows into new funds should be of interest to us as researchers. It is simply too big and too important to ignore. Furthermore, we are particularly concerned about investor behavior when investing in these unproven products. Do we find that investors prefer what's good for them?

In this paper, we explore the relationship between observed investor preferences for and eventual investor outcomes in newly-launched funds. To conduct this exploration, we built two models that unpack the historical correlations between both forward risk-adjusted returns and forward cumulative fund flows with observed fund characteristics, economic regimes, and category environs. In isolation, each model offers us a multivariate view of the factors that drive future flows and risk-adjusted returns for newly-launched funds. By comparing the outputs from the two models, we can also identify potential conflicts of interest for asset-managers. A variable (e.g. socially-responsible investing) that has tended to result in higher flows but lower returns presents a difficult choice for asset-managers over whose interest to prioritize. This tension between what investors have preferred and the outcomes investors are seeking also highlights poor choices on the part of the investing populace. We find that investors have been inconsistent with how they allocate their assets among newly-launched funds. For example, we find that investors prefer cheaper funds which, not surprisingly, tend to result in better outcomes. But we also find that investors prefer funds that invest in more popular, familiar stocks that have done well recently when the opposite choice would have resulted in better risk-adjusted returns.

Newly-launched funds are of particular interest to us as they often lack information that we know investors use to make decisions. From prior work, we have observed that investors exhibit strong preferences for funds with strong performance track records. While this is perhaps not surprising, it does raise the question of what information investors use to make an investment decision when a performance track record is unavailable. Despite the lack of information on newly-launched funds, we have already presented evidence that new funds can garner immense assets almost immediately.

Given the lack of relevant data early on in the life cycle of a fund, variable selection and variable definition were critical choices in our study. Variables included in the model had to be both widely available in our sample and hypothesized to be relevant drivers. We included 23 variables in the fixed income and allocation models. In the equity model, we were able to expand this number to 39 due to the quality of Morningstar's equity data and portfolio holdings database. Many variables included in the model are to be expected: fees, firm-level characteristics, index fund, socially-responsible, and portfolio disclosure. However, some variables are less common. Category-level data points such as market concentration and firm market share by category were constructed specifically to examine the role of category structure on newly-launched fund outcomes. Furthermore, we also expanded the use of our ownership data by building data points to examine whether a fund manager behaves in a similar fashion to other types of managers. An example of this is the Manager CFA Ownership data point which captures the extent to which a newly-launched fund manager is buying stocks in a manner similar to what the typical CFA manager buys. We will discuss these variables and others in more detail later in the paper. But, in general, we attempted to capture various perspectives of a new fund by focusing on data categories such as: fund structure, manager demographics, firm reputation, category environs, portfolio disclosure, portfolio style, and economic regimes.

For the purposes of this paper, we define newly-launched funds as any fund with less than 12 months of track record. We do not consider a newly-offered share class to be a new fund. We are only interested in brand-new funds. We include open-end funds and ETFs in our sample. All explanatory data we use would have been available within that first year. The variables we are trying to explain are forward 36-month risk-adjusted returns and forward 36-month cumulative fund flows. The study is global and begins in January 2005. The last new funds to be included in our study would have needed to be launched by March 2013.

Asset management firms are only required to disclose net assets and not investment flows. Therefore, Morningstar calculates estimated flows by looking at the change month-to-month in net assets that cannot be explained by the fund's return. The calculation includes an adjustment for reinvested dividends, which can have a large impact on funds where dividend payouts are large and frequent. For a full explanation, please consult the Morningstar Cash Flow Methodology document.

Thus far, we have used the shorthand 'investors prefer' or 'investor preferences' to discuss fund characteristics that result in higher flows. But this is perhaps misleading. The simple fact is that the majority of money in the global investing marketplace is heavily intermediated. The majority of flows are not due to the actions of the retail investor but are directed by the result of some complex interaction between an advisor, an institution, and a platform. The intersection of these three parties can result in varying levels of choice for different types of investment products. Therefore, it is perhaps best to conjure an image of the web of intermediaries who compete for platform placement and attention from advisors. When we say "investors prefer", therefore, it's perhaps more accurate to say these are the types of newly-launched funds that most successfully navigated the network of distribution channels and appealed to advisors most. Nonetheless, for the paper, we will continue using this shorthand.

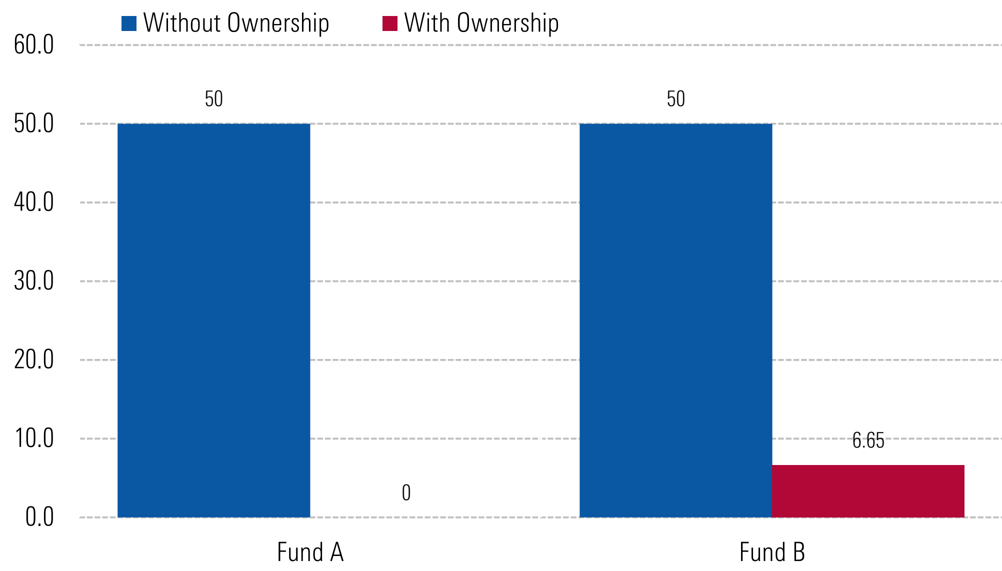
In the next section, we provide a brief explanation of how our results can be interpreted. We realize it's not the easiest to wrap a brain around (even a pliable one). So, we hope that example helps. After the interpretation section, we discuss what we believe are the key takeaways from our modeling exercise. Following the takeaways, we conclude the paper with some general observations and thoughts for further research. In the Appendix, we detail the data used for this analysis, describe the specifics of the methodology we employed, and list our references. The paper concludes with the full data tables.

Interpretation

First things first. We've got two models in here: one to describe forward 36-month cumulative flows and another to describe forward 36-month cumulative risk-adjusted returns. In the paper, we may use the shorthand 'Star Rating' to refer to the forward risk-adjusted return results. This is because the risk-adjusted return calculation we use forms the basis for the Morningstar Rating for Funds (e.g. the "Star Rating"). As a result, relationships we find that correlate with higher forward risk-adjusted returns also correlate with higher Star Ratings by construction.

Let's take an example. Consider two equity funds, A and B. As of today, they have the exact same characteristics. Based on these characteristics, we expect each fund to be placed in the 50th percentile of their category in terms of forward 36-month cumulative flows. They are expected to be average funds. However, now suppose we observe that Fund B's management team decides to align their own financial self-interest with their investors by investing in their own fund while Fund A does not. As a result, we would change our expectation and now expect to see Fund B gather more assets because investors prefer funds with manager ownership. We expect this effect to contribute about a 6.6 percentile increase in category-relative flows. Meanwhile, Fund A is expected to stay at the 50th percentile since its characteristics remain unchanged.

Exhibit 1 Chart Interpretation



Source: Morningstar Direct. Data as of 30/06/2016.

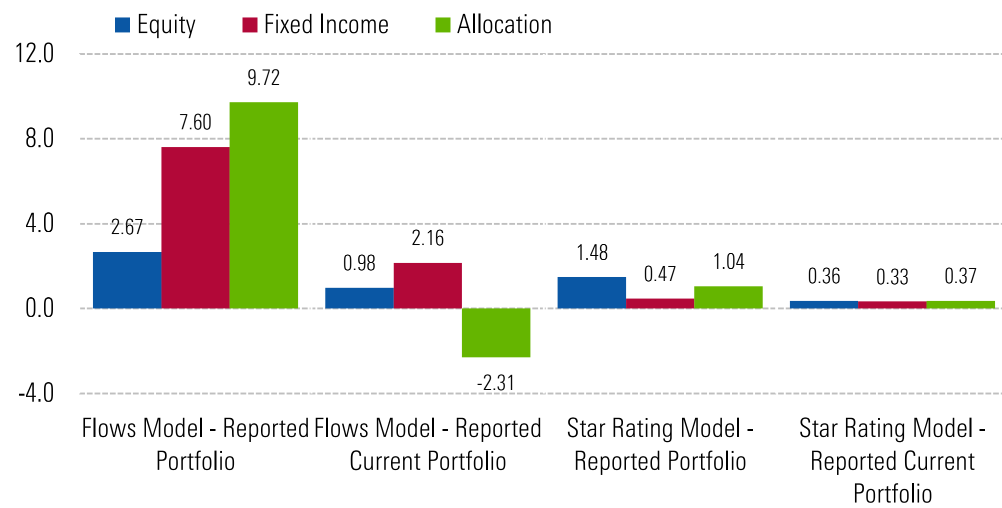
Above, blue bars represent the fund's initial category placement. The red bar represents the projected 6.6 increase in flows to display the movement in the category distribution. Going forward, we will report these effects by citing the expected change. So, for the above example, we would have a column showing 6.6%. That is the change expected to forward flows for a change in manager ownership. All of the characteristics we show in our paper are additive. Meaning as a fund increases or decreases on each dimension, we will consequently expect changes to a fund's forward flows and risk-adjusted returns. Additionally, all of the charts will show the maximum change a fund may experience. For variables placed in category percentiles, we show the movement from the 1st percentile to the 100th percentile. For binary variables, we show the change from not possessing the attribute to acquiring the factor. The raw regression results and the corresponding coefficient multiplication factors are found in the Appendix.

In the next section, we will present the key takeaways from our modeling exercise.

Key Takeaways

No downside to frequent portfolio disclosure in the data. Disclosing portfolio holdings generates higher flows and, in a surprise to us, is correlated to higher forward returns. We defined two measures of portfolio disclosure: whether or not a fund has reported any holdings information within the first year (Reported Portfolio) and an additional measure that captured the frequency of disclosure (Current Portfolio). We find investors highly value the first portfolio and also place additional value on frequent updates to the fund. The initial portfolio can generate an average of 2.7%, 7.6%, 9.7% increase in category flow percentiles for equity, fixed-income and allocation respectively. While additional portfolios can generate 1% and 2.2% percentile flows for equity and fixed-income. For allocation funds, we did not find a flow premium associated with frequent disclosure.

Exhibit 2 Portfolio Disclosure



Source: Morningstar Direct. Data as of 30/03/2016.

Though we do find the act of portfolio disclosure to be significantly correlated with higher risk-adjusted returns, we do not expect this relationship to be causal. We do not expect the mere act of disclosing a fund's portfolio to automatically increase future risk-adjusted returns. Rather, we believe the underlying causes for frequent disclosure and higher returns could be shared: an indication of a higher quality strategy, greater manager confidence, vigorous firm stewardship, and sound investment process. We estimate the added benefit on forward risk-adjusted returns from portfolio disclosure is small, 1.5%, 0.47%, 1.04% increase in risk adjusted returns for equity, fixed-income, and allocation, respectively. These effects are highly persistent and significant. Funds who disclose more frequently find an additional benefit ranging from 0.3%-0.4% return increase. Furthermore, we find these effects are persistent globally.

One potential counterargument to these findings could be that the relationship of portfolio disclosure to flows and risk-adjusted returns actually reflects differences in regulatory requirements rather than differences in investor preference. For example, in the US, funds are required to report holdings on quarterly basis while in other jurisdictions holdings may only be reported annually. Could it be that we are just capturing differences in marketplace? If this bias were present, then our findings would suggest that new funds do better in more regulated environments. Rather than suggesting that investors prefer disclosure.

To insulate our study from these effects as best as possible, we forced each of our dependent variables (e.g. flows and risk-adjusted returns) to be relative to other funds within the Morningstar category. The vast majority of Morningstar categories only sit within one regulatory regime. Therefore, while the

Reported Portfolio variable would still be affected by regulatory differences, we can observe whether investors prefer more disclosure regardless of what is typical by studying the relationship between flows and the variable Current Portfolio. We observe that, globally, funds from more regulated regimes do better but that investors also prefer more disclosure relative to what they are used to. We think that this substantiates the overall claim that investors prefer disclosure in general.

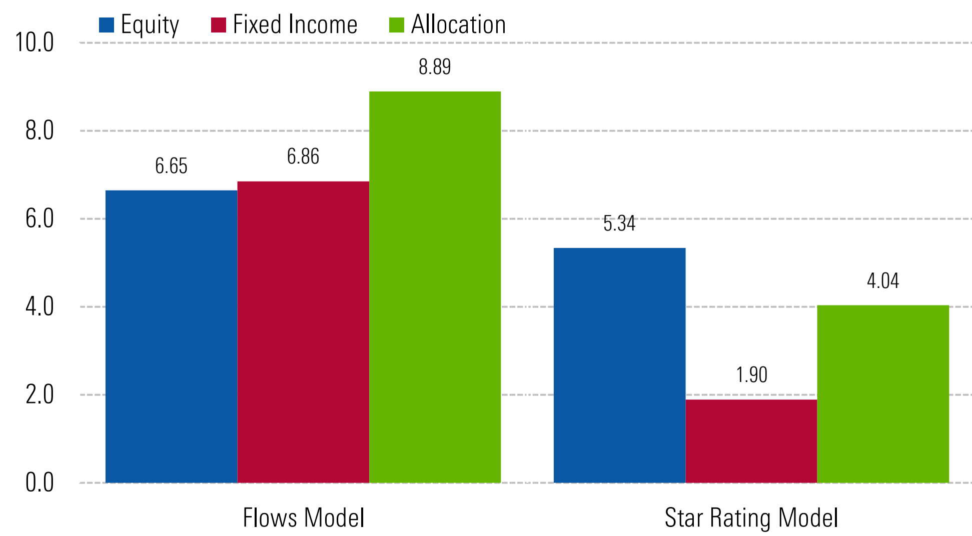
This should make intuitive sense. Since an investor has little information to go off of when deciding to invest, portfolio holdings can play a significant piece in the decision. As prior Morningstar studies show, track record is the key element in driving flows. (Davidson, Strauts) With the lack of a track record, portfolio holdings can be a window into the fund's process and help investors to get a sense for the type of strategy the fund hopes to deploy.

Managers who own their funds do better. Fund management ownership is an excellent signal for investors. Portfolio managers who have their financial interests aligned with the investors run higher quality funds. Investor preference for such funds ownership outpaces the benefit of higher risk adjusted returns. A typical equity fund will have on average 5.5% higher risk adjusted returns and will move up 6.5% percentiles for flows within their category. For fixed income and allocation, the benefit is more dramatic, 1.9% and 4.0% increase in risk adjusted returns with a 6.9% and 8.9% percentile flows increase, respectively. We expect to see fund management ownership correspond positively with risk adjusted returns and the data shows investors understand the benefit too.

Interestingly, we did not differentiate between the levels of manager ownership, just whether or not a single manager had at least $1 in the fund. We noticed a significant number of funds report no manager investment into their fund. By doing so, the fund is effectively sending a signal that the management team's financial interests are not aligned with their end investors and they are not willing to do so, even at a minimal cost. Not doing so suggests that the funds may be losing out on future business. Investors appear to be using the ownership reporting data as a filter when deciding between two comparable new funds. In the absence of historical information about a manager's decision making, investors are using the manager's financial stake in a new fund as a proxy for their stewardship. The decision to do so has shown to be meaningful and positive in terms of a higher forward returns.

If every fund management team changes their behavior as a result of seeing these correlations, investors may stand to lose a signal that has historically proven useful in sorting managers. Of course, manager investment aligns incentives with investors and creates additional motivation for the manager to be a good steward of capital. This should result in better outcomes for investors. That said, we are unsure if the simple act of a manager investing in their fund will in outperformance, especially if done so for marketing reasons. The interplay between these two motivations for manager ownership will be interesting to observe going forward. From our perspective, as we continue to collect ownership data and as more fund managers own their funds, we hope to be able to distinguish between ownership levels and types of ownership in order to differentiate the levels of manager commitment to their investors.

Exhibit 3 Manager Ownership



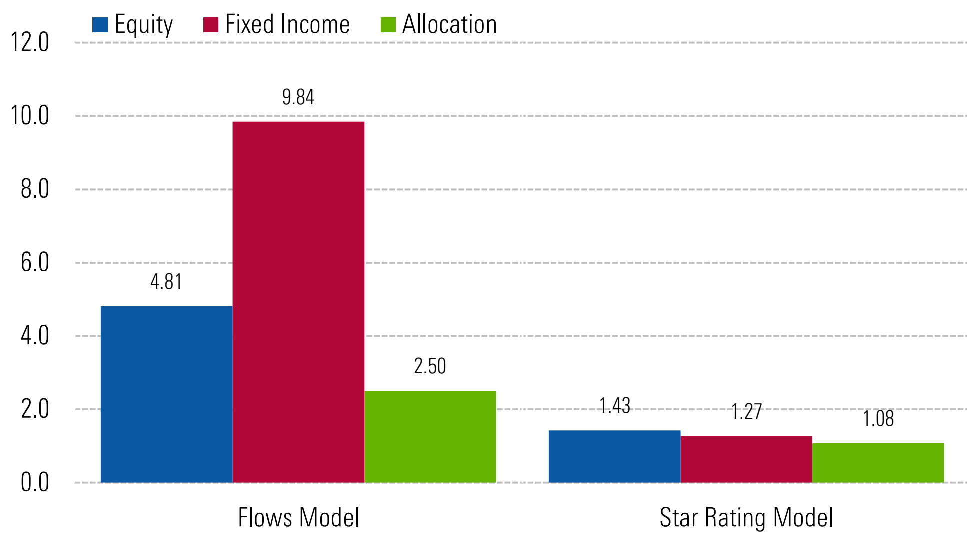
Source: Morningstar Direct. Data as of 30/03/2016.

New funds helmed by CFA managers achieve better outcomes and are preferred by investors. Investor preferences for CFA designated portfolio managers follows similarly as their preferences for manager ownership. While the average increase in fund returns across asset classes ranges from 1.1%-1.5%, the expected average flows varies among fund type. Fixed-income investors display the strongest preference for CFA managers as the average benefit is 9.8% increase in category flow percentiles. Equity and allocation funds receive on average 4.7% and 2.5% percentile increase, respectively.

Investors have imperfect knowledge about a manger's capabilities so they are likely using the CFA charter as a proxy for skill and education. Our study shows the signal is a beneficial metric to investors as well from the perspective of improving their long-term performance. Interestingly, the preference varies dramatically across asset classes. This tells us the importance of a more educated manager differs for investors depending on the investment type. Yet, the effects in terms of outperformance is very similar, regardless of asset class. Regardless of the magnitude, having a fund managed by a CFA manager has resulted in higher flows and higher Star Ratings. The interests of the asset manager correspond to the investor.

Though we only look at managers who hold the CFA, we believe that any other designation that signals a higher educational achievement to the investor would be rewarded in the same direction (though perhaps with differing degrees of magnitude). For example, fund managers that have PhDs, CFPs, or CAIAs are also likely to be preferred by investors. We used CFA designation as the only flag solely due to data availability. Regarding data availability, one potential concern would be that we do may not have sufficient coverage of CFA managers globally to adequately test this hypothesis and ensure that this is not a US vs ex-US phenomenon. We do not believe this to be an issue as we have approximately 7,000 unique funds ex-US with a CFA and 9,000 unique funds in the US with a CFA. With this level of data coverage, we should be fairly confident that the relationships we are observing are global in nature.

Exhibit 3 Manager Education

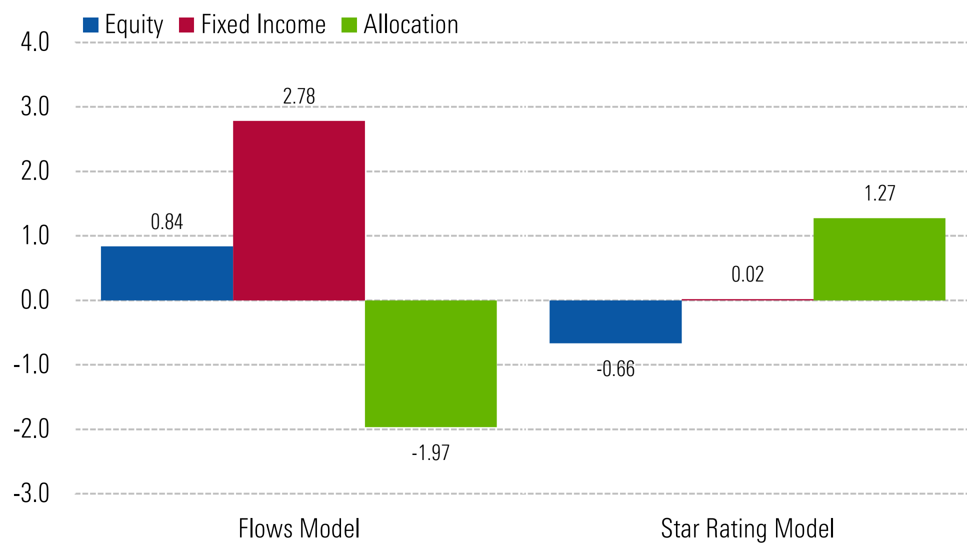


Source: Morningstar Direct. Data as of 30/03/2016.

Female portfolio managers tend to garner more assets. The inherent trait of a manager's gender effects flows into a fund. To determine an investor's perception of a portfolio manager's gender, we calculated the probability of being female given a first name and birth year. For a team managed fund, we used the highest probability of all the fund's managers. Instead of using a binary indicator variable, the continuous probabilities can tell us about an investor's perception of gender. If an investor can automatically assume their portfolio is managed by a woman, do they prefer those funds more than a fund where the naming information is less clear? In doing so, we can test whether there is an overall investor bias for female portfolio managers.

Our study suggests gender does matter to investors. Flows follow women portfolio managers for equity and fixed income asset classes. Our hypothesis for why there is this preference for female management corroborates previous Morningstar studies with our data. Last year, the Fund Manager by Gender report determined women are underrepresented in the fund management industry relative to other professions. (Lutton, Davis) Therefore, we assume women face significant headwinds in advancing their career in the financial industry. So, the average woman who does advance to become a portfolio manager should be higher performing than the average male portfolio manager. Our reasoning implies a female portfolio manager signals to an investor higher management skill which is represented by a positive association between flows and gender. As the demographics change of who is control of private wealth become more split between men and women, we expect to see preference for female portfolio managers to be positive and grow over time. (Lutton, Davis)

Exhibit 4 Gender



Source: Morningstar Direct. Data as of 30/03/2016.

While we can logically reason why an investor may prefer a female portfolio manager, we find mixed effects when studying gender's correlation to higher forward Star Ratings among new funds. Intuitively, the results make sense. We do not expect gender to be a suitable proxy for skill. A portfolio manager is not inherently better at managing a fund due to their gender, regardless of the headwinds faced in a manager's career development. Therefore, we are not surprised to see inconclusive results.

A potential counterargument to our findings is the fact that women are more likely to be part of a management team rather than manage a fund solo. Therefore, our findings could be suggestive that investors simply prefer larger management staffs over small ones. Since we did not control for team size, we cannot rule this possibility out. Arguments from Lutton, Davis (2015) support our hypothesis, however, that there is likely a preference for female portfolio managers and greater diversity in general. Exploring these relationships in greater detail, however, is beyond the scope of this paper. We plan to investigate further the relationship between gender and the fund management industry in a subsequent paper later this year. Hopefully, that work will more concretely address the role gender has to play in fund management.

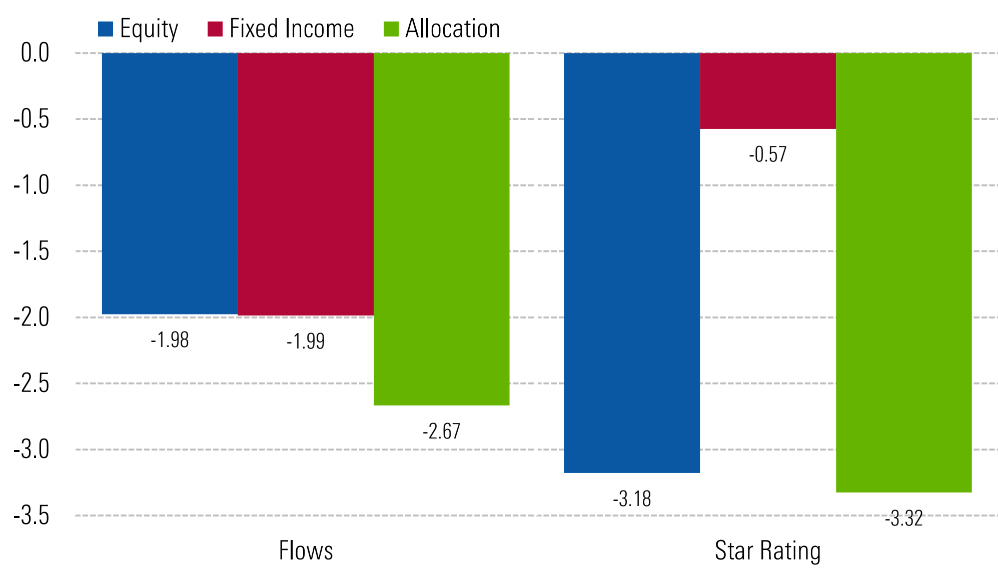
High fees hurt flows and future risk-adjusted returns. Fees are one of the most consistent drivers of flows and returns for new funds. Higher fees led to lower returns and lower flows across all asset classes for new funds; however, the magnitude relative to other factors is smaller than expected. In our study, we control for a host of differences – manager traits, fund structure, portfolio style, firm characteristics, macroeconomic environments, and category characteristics – so we can see the relative economic importance of each factor on forward flows and forward Star Ratings.

Unsurprisingly, fees play an important role in the forward Star Ratings. A category's most expensive fund could lose out on 3% in terms of risk adjusted returns for equity and allocation funds compared to the cheapest fund. The effect is less dramatic for fixed-income funds, as the difference is only on average 0.57% risk adjusted returns. The results of the study lines up with latest Morningstar research which outlines how fees have predictive power of success.

Therefore, knowing fees could be used as a proxy for forward success, we were surprised to see fees were only at minimum the ninth most economically meaningful driver of flows across asset classes. Lowering a fund's expense ratio one percentile change relative to the category will only boost a fund's forward cumulative flows a fraction of a percentile, between .02% -.03% for all asset classes.

For new funds, investors are looking at fees as a decision factor but are taking into account other information – manager, firm and category characteristics - and placing more importance on such factors. Yet, for more mature funds, as a previous Morningstar flows report found, historical performance is the single most important driver of flows. Therefore, while fees may not play a significant role in an investor's decision for buying a new fund, fees will affect a new fund's track record which will later heavily influence investors' decision.

Exhibit 5 Fees



Source: Morningstar Direct. Data as of 30/03/2016.

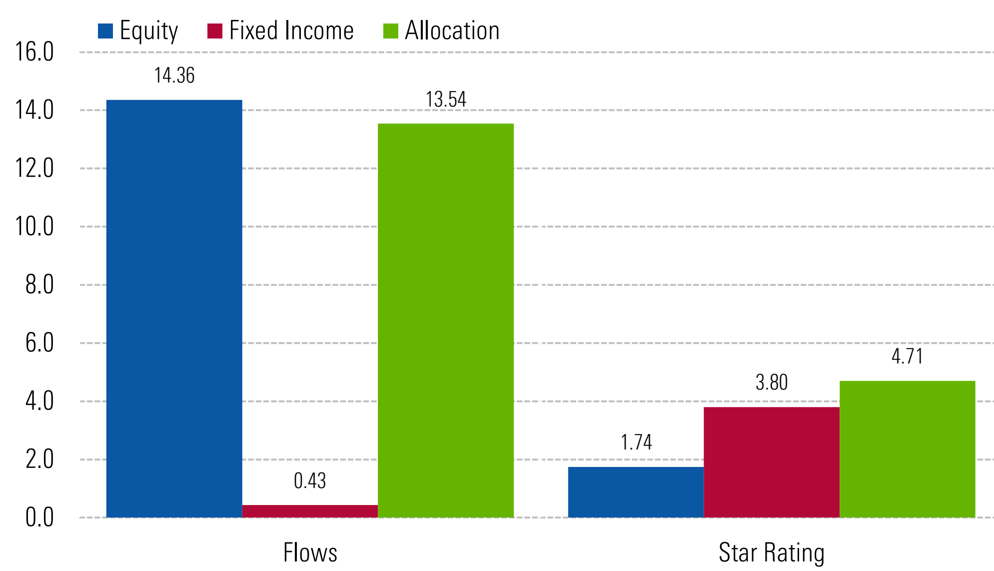
Coverage of a new fund by a Morningstar analyst is suggestive of higher flows and better investor outcomes. Morningstar analysts are skilled at finding successful new funds, and investors take notice. Across asset classes, funds covered by Morningstar generate higher risk adjusted returns. The largest effect is in allocation, where there is a maximum increase in 4.7%, where the smallest effect is in equity as we see only a 1.7% maximum benefit.

Investors look to Morningstar to perform independent due diligence and then often appear to follow our advice. The effect of a Morningstar Analyst rating is immense and compounds over time. The sooner the analyst starts rating the fund, the more time investors have to digest the information and take action. If Morningstar rates an equity fund in the first month, the fund moves into 14.4% higher category flow percentile. The effect is equally large for allocation funds, where the percentile increase is 13.5%. Interestingly, investors are not valuing the rating as much for a fixed income fund. During the same time period, the percentile increase is only 0.4%.

An alternative explanation for why we appear to observe that investors prefer those funds covered by Morningstar could be that Morningstar actually only chooses to cover so-called "discovered managers". For example, Bill Gross was very much a discovered manager when he went to Janus and ended up attracting significant assets. In this case, the popularity of the manager caused Morningstar's coverage and not the other way around. The causal arrow would have been reversed. We can't rule this possibility out, but we also observe that the newly-launched funds that Morningstar has covered have ended up performing admirably. This is suggestive of the fact that Morningstar analysts have some skill and should be a reason why investors may prefer to see a fund rated by an independent shop like Morningstar.

Furthermore, other studies corroborate this interpretation. Morningstar has performed studies on our ratings to determine their success as well as their effect on investor preferences. Internal studies show Star Ratings are indicative of future success (Kinnel) and are the single most important factor driving flows into funds (Davidson, Strauts). The two studies together show investors have come to trust Morningstar, our ratings, and our opinions. With scarce information available, investors derive value by turning to Morningstar for a recommendation on what may be the best funds available.

Exhibit 6 Months Since Morningstar Analyst Rating



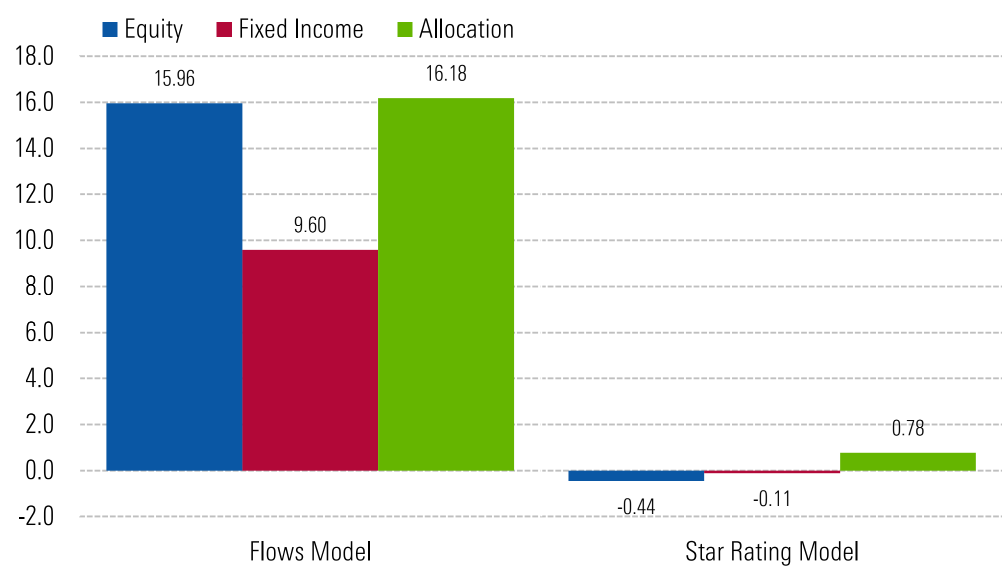
Source: Morningstar Direct. Data as of 30/03/2016.

Firms run the risk of cannibalizing their product prospects. We wanted to understand how firms should operationalize fund launches so we developed a measure of new fund competition within a firm. We hypothesized, the more an individual fund has to compete for resources with other new funds, the less likely that fund would be able to gather assets. From the perspective of forward flows, the cannibalization effect is the most significant factor driving assets into a new fund. When a firm changes practices from launching the most funds in an asset class to launching the least amount, the individual funds gains 16.4, 9.6, 16.2 percentiles in higher category flows for equity, fixed-income, and allocation asset classes, respectively.

We are not surprised by the result. In a centralized firm structure, there is a limited number of marketing and sales resources dedicated to promoting a new fund to garner assets or in a decentralized firm structure, the supporting staff are competing with each other for flows into an asset class. Either way, splitting resources too thinly or causing resources to compete is harmful to the firm on a per fund basis. On the firm level, each fund must gather the minimum amount of assets to be profitable. So to run profitable funds quicker, asset managers should revisit how funds are launched and the frequency of the launches.

Our manager research teams have long argued against the practice of launching many funds at once. Firms exhibiting best stewardship practices do not flood the market with new funds at once but are thoughtful and simplified about their approach. Interestingly, while we have advocated for such types of practices, the effect has not shown to hurt or help forward risk adjusted returns. We do not expect certain operational types of fund launches to be correlated to forward Star Ratings.

Exhibit 7 New Fund Concentration Percentage



Source: Morningstar Direct. Data as of 30/03/2016.

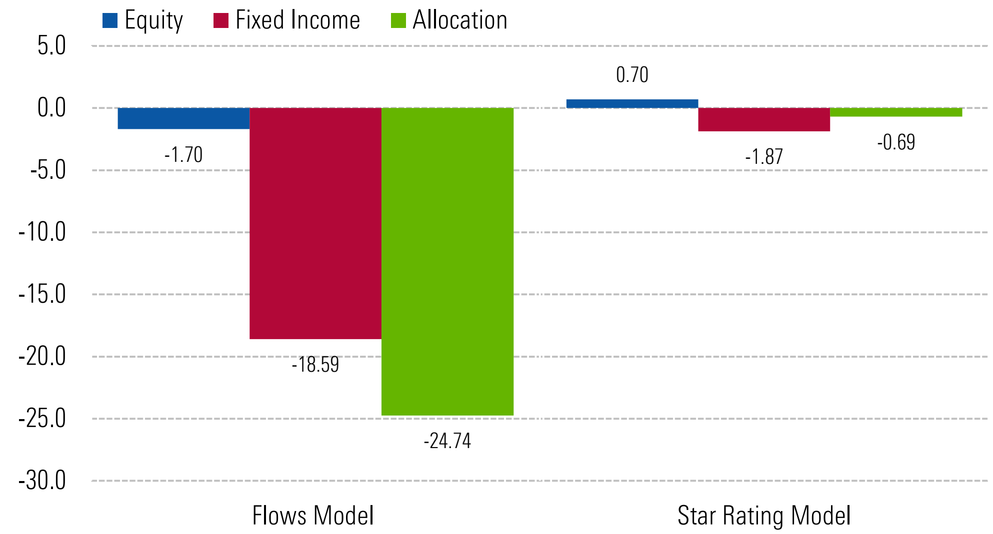
Monopolistic categories produce headwinds for new funds. One of the choices asset managers face is where to launch new products. In the absence of data, reasonable hypotheses could be proposed that either exaggerate or minimize the importance of category market structure on the success of new product launches. Do categories with relatively equal distribution of AUM offer better or worse odds at attracting new assets? Or do new funds launched into categorized dominated by monopolist funds offer an intriguing alternative? There doesn't seem to be an obvious a priori answer. Our research, however, suggests a clear empirical answer.

We construct a Herfindahl index for each Morningstar category globally. The Herfindahl index measures the size of funds in relation to the overall category and can be used as an indicator for the level of competition between funds in that category. This metric is commonly used in industry analysis to determine the amount of market concentration and determine whether or not a company may be a monopolist. By constructing a similar metric using fund assets in place of market capitalization, we can assess the relative competition within a fund category.

Our findings are quite conclusive. New funds tend to do very poorly if they are launched into categories where assets are concentrated amongst only a few pre-existing funds. These relationships hold directionally across all asset classes, but are strongest in fixed income and allocation. For example, a fixed income fund launched into a monopolistic category has historically placed 18 percentiles lower in flows compared to a fixed income fund launched into a category characterized by perfect competition. The situation is more extreme in allocation where a new fund places nearly 25 percentiles lower. The effect is much smaller in magnitude for equity funds though still quite persistent in the data. As with all findings in this paper, this effect holds after controlling for the myriad of differences between products.

Many of the findings in this paper may only be temporary, though persistent, patterns observed in this data sample. While our sample is tremendously broad, it is somewhat short. We purposefully call out findings that may only be statistical mirages unlikely to persist. That said, we do not believe this finding to be accidental. It is not controversial to assert that structural advantages are enjoyed by monopolists in industry. And we believe similar arguments can be made for mutual funds where customer inertia may be even more of a reality. A new fund will have difficulty attracting assets in a category if the vast majority of investing dollars have already voted in favor of a particular fund or set of funds. Furthermore, the magnitude of these effects suggest that these headwinds can only be defeated by herculean performance track records or very creative fund construction. Therefore, we anticipate that these correlations will persist in the data far beyond the confines of this study.

Exhibit 8 Market Concentration



Source: Morningstar Direct. Data as of 30/03/2016.

Asset managers with large market share are advantaged when launching new funds. The prior takeaway suggested that launching new funds into monopolistic categories resulted in tough sledding for the new funds. In the data, we find an exception to this rule -- namely, if a fund is issued by the current monopolist. All else equal, a fund issued by the firm who owns the majority of assets in that category tends to do quite well at attracting assets for its new funds. It suggests that large firms likely have distributional advantages stemming from either their scale, expertise, channel access, pre-existing wholesale relationships, platform priority, or most likely some combination of all the above.

Monopolies can be naturally occurring where there may be high fixed costs associated with gaining entry into that niche. Often times, the first supplier to the market has been observed to have an overwhelming advantage in establishing its position over potential competitors. Monopolies can persist when the product they produce do not have close substitutes and when competing with them would leave to a duplication of efforts and a wastage of resources.

When we think about monopolies in the fund marketplace, they likely arise for similar reasons as those in industry more generally. We generally don't expect there to be high fixed costs for creating new mutual funds and we don't usually expect these to vary between categories. However, if the provider company is interested in issuing an active fund, some categories exist where the supply of experienced and talented management professionals is shallow. This could create a variation in fixed costs between productizing a fund in different categories. Being the first-mover is likely also advantageous and key to establishing a reputation as an expert in a giving investment strategy. New products launched into those categories will be perceived to be higher quality as they are issued from a firm with a better brand and reputation for creating successful products in that area. Furthermore, investors could expect that resources could be shared between the established funds and new funds creating a skill spillover.

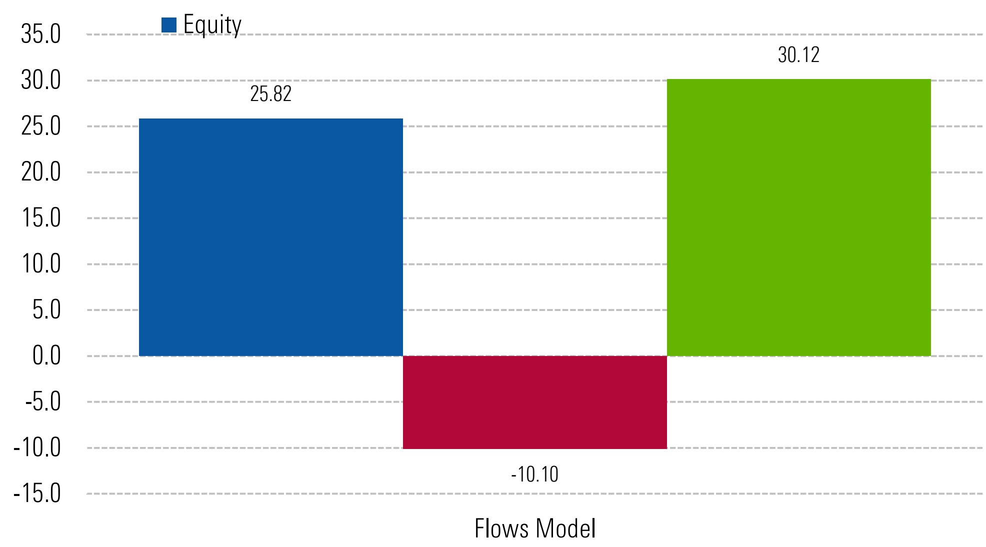
Overall, we think that there are likely good reasons for monopolies to arise in the fund marketplace. Investors seem to recognize this fact by preferring new funds issued by monopolists.

For garnering assets, we find that this effect holds tremendous sway over determining the successful outcomes of new funds in the equity and allocation asset classes. New funds issued from large fund provider companies outpaced new funds issued from smaller providers by 25 percentiles for equity and 30 percentiles for allocation.

The notable exceptions are funds that are issued by category giants in the fixed income asset class where the opposite effect is observed with significance. At face value, this is one of the more puzzling findings in our research study as it fails to square with common sense and historical experience. However, upon a second look, we see that there is a very strong, opposing relationship with the variable Top Ten Firm. Top Ten Firm is a binary variable signifying whether a fund was issued by one of the largest firms in the asset class as measured by AUM. For equity and allocation, we find that these coefficients point in the same direction - being large in the category or the asset class is a benefit to launching new funds. However, in fixed income, we find opposing relationships suggesting that these two variables are likely collinear and cancelling each other out. Top Ten Firm is a more significant, persistent relationship and is also economically larger. This suggests that monopolies hold more cross-category sway in the fixed income asset class than the equity or allocation asset classes where holding a monopoly within a category is of more importance.

Overall, the takeaway here is that market leaders in the equity and allocation asset classes have reaped massive benefits by doubling down in categories where they already possess the upper hand. Asset class behemoths in the fixed income asset class, on the other hand, have enjoyed scale benefits regardless of which specific categories they tend to dominate.

Exhibit 9 Firm Market Share



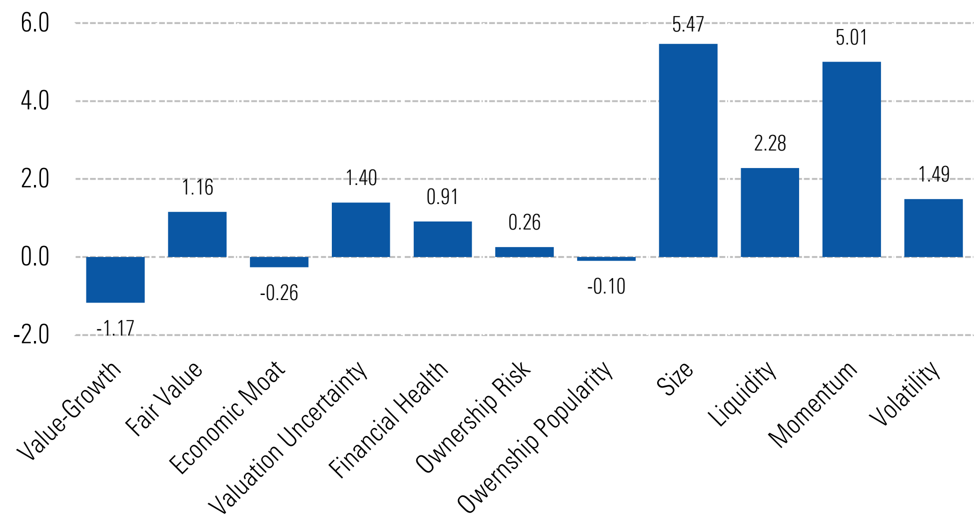
Source: Morningstar Direct. Data as of 30/03/2016.

Style tilts that have resulted in good investor outcomes are not widely preferred by investors. This is the most disappointing finding in our paper from two perspectives: 1) investors don't seem to make good choices when it comes to choosing new funds, and 2) by not making good choices, it creates a conflict of interest for asset managers. Broadly-speaking, we find that investors in new funds prefer to give their money to funds that invest in popular companies that have done well recently when almost all evidence would suggest that the opposite choices would have resulted in better investor outcomes. While we only were able to study this for equity funds, we don't hold much optimism for these results to be reversed in fixed income and allocation asset classes given the magnitude and persistence of these effects in our equity fund sample.

Mainstream asset pricing literature is pretty clear on the fact that variation in average stock returns can be explained by a few, common factors. Moreover, there is virtually no argument over the directionality of these effects -- certain factor tilts offer higher expected returns than others. The main source of debate in the literature is related to why these factors exist at all and what motivates them to occur -- the two camps being primarily risk-based and behavior-based explanations. For the purposes of this paper, we do not concern ourselves with why such effects exist. We only really care that they exist and seek to merely appeal to the consensus that certain factor tilts are rewarded while others are not. Examples include: tilting in favor of value stocks at the expense of growth, tilting towards small cap and away from large cap, and tilting towards high momentum.

At Morningstar, we have built an equity risk model that identifies and measures some of these common drivers. Not surprisingly (since we study the same datasets), we find broadly similar results for which factors drive returns. What we show in Exhibit 10 are the factor premia Morningstar has estimated that explain the variation in average stock returns. In Exhibit 11, we compare these to the tilts investors have seemed to prefer. And we find stark differences.

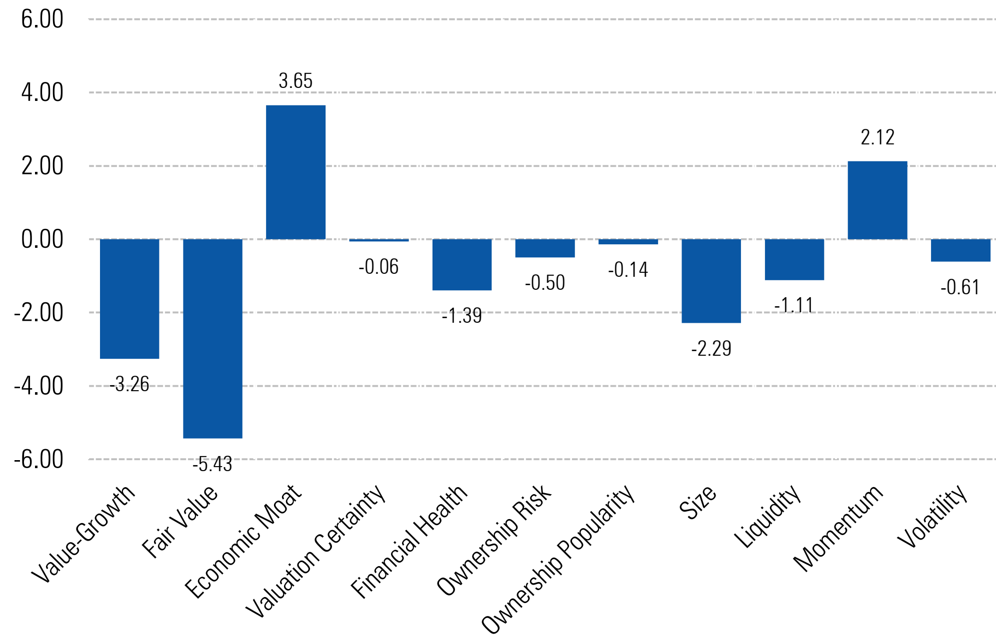
Exhibit 10 Investment Style Premia



Source: Morningstar Direct. Data as of 30/06/2016.

Investors appear to prefer overvalued stocks when undervalued would have served them better. Investors prefer large cap tilts even though small cap tilts are generally better. Investors like low volatility when high volatility resulted in better outcomes. Perhaps the only choice investors seem to make that aligns with the factor premia is choosing to invest with funds that buy high-momentum stocks. However, there is reason to believe that investors into these funds with high-momentum tilts may not realize the benefit of this tilt. For one, momentum strategies are hard to maintain as funds get larger due their high-turnover nature and the resulting accumulation of trading costs. Second, remember that we are studying new funds which have not yet established a track record. These funds may very well not intend to implement a momentum strategy and only be tilted in this direction with their first or second portfolio disclosure.

Exhibit 11 Investment Styles - Flows Model



Source: Morningstar Direct. Data as of 30/03/2016.

Our findings suggest that asset managers, to the extent they know about these revealed investor preferences, are in a real pickle. Do they choose to take style tilts that may be less sexy to investors now but ultimately result in better performance? Or do they tilt in certain style directions that may be more palatable to investors now at the expense of lower expected returns? Further complicating the issue is the fact that we (and almost everyone else) know that the biggest predictor of future fund flows is past performance. If the ultimate goal is garnering assets, asset managers are forced to choose between playing the long-game versus playing the short game.

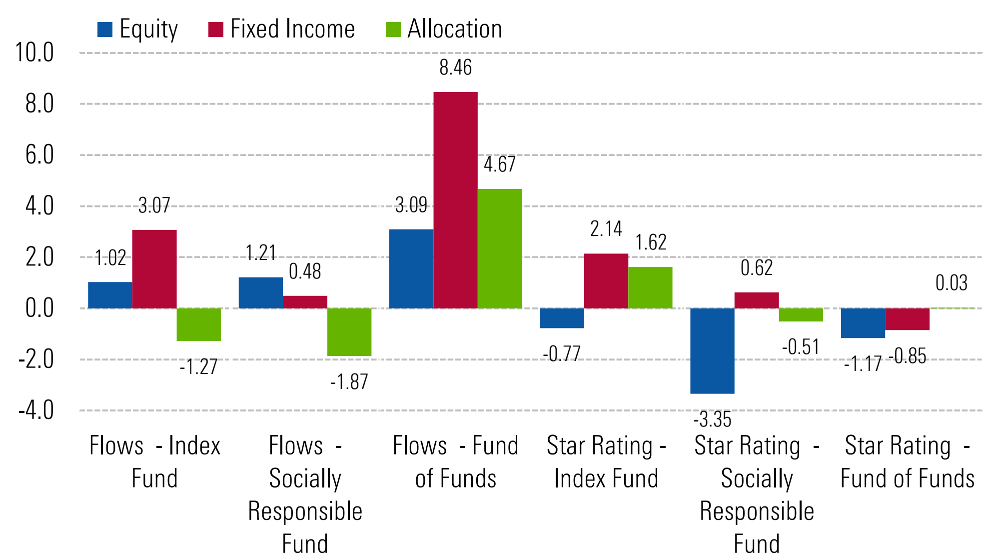
This also suggests that firms like Morningstar have an important role to play in continuing investor education. Although, convincing arguments have been made that suggest that despite best efforts to educate the investing populace on the types of style tilts they should take, we may never see a course correction in aggregate. Premia exist for a reason and the prime reason appears to be related whether or not those characteristics are popular (Ibbotson, Idzorek 2014). Under this theory, we would anticipate that if a course correction did occur (e.g. investors started to prefer small caps and shun large caps) we might see the premia flip directions. Arguing in favor or against this hypothesis is beyond the scope of this paper. Nonetheless, we bring it up here to illustrate the fact that the patterns we observe may not be entirely surprising and may always be an artifact in the data.

Choice of fund structure has had important consequences for flows and returns. There are meaningful differences in investor preferences for fund structure type for new funds than for funds with track records. Our finding expands on the 2015 "What Factors Drive Investment Flows" paper, where Morningstar studied organic growth rates for all funds, by region. This study, in contrast, is strictly limited to entirely new funds less than 12 months old and looks at total forward flows. While there are differences in model structure, we can still see where how preferences stay consistent through a fund's lifecycle and how they change as a fund becomes older. In particular, we looked at the following structures: index fund, fund of funds, and socially responsible funds.

For index funds, global investors are more receptive to new fixed-income index funds as there is a 3.1% percentile increase in cumulative flows than mature active income funds. For reference, there was no correlation between the organic growth rate of all global funds and fixed income index funds, globally. We find when the sample of funds narrows to new funds, the index preference becomes quite significant and positive. As indexing becomes more popular, the trend is shifting to new fixed income funds – an asset class typically not associated with passive investing.

Consistent with our previous study, new index equity funds are more preferred than new active equity funds and there is no correlation between allocation funds and forward flows. Interestingly, during the time period of our study, only actively-managed new equity funds would have produced marginally better risk adjusted returns. We found a benefit of 0.77% higher returns.

Exhibit 12 Fund Structure



Source: Morningstar Direct. Data as of 30/03/2016.

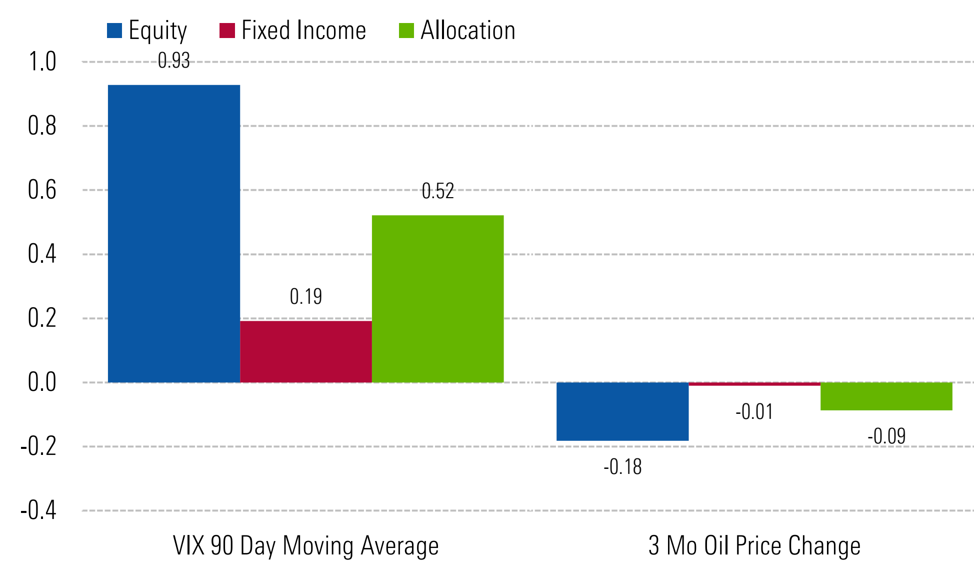
Fund of funds is preferred more for new funds and eventually becomes a nonfactor for investors. In particular, fixed-income funds highly preferred, generating increase of 8.5% category flow percentiles. The benefit has not paid off thus far for investors as there has been a slight negative premia for fund of fund structures of -8.5% risk adjusted return units.

Socially responsible investing still holds favor for new equity and fixed income funds. Notably, the preference for sustainable investing has not paid off during the time period. New equity socially responsible funds lost on average -3.35% in terms of risk adjusted returns.

In conclusion, since investors have less information about a new fund, the structure plays a more significant role in a decision than funds with track records.

Launching funds in periods of economic stress is positive for future performance. In our testing only the star rating model had meaningful results with the economic variables. Which makes sense because short-term economic signals shouldn't have an effect on flows over the next three years. For the star rating model if a fund was launched in a period of high volatility and falling oil prices the new fund tended to outperform over the subsequent three-year period. These results are counterintuitive because the instinct is to gravitate towards more established funds during times of market stress. But during periods of heightened volatility opportunities often arise that larger funds can't take advantage of because the trades are too small to have an impact on their portfolios. New funds are small and can take advantage of these trades. By using their relative small size to their advantage they build up a performance advantage. The benefit of being small is strongest in equities because small traders can trade without moving the market. Conversely, the performance advantage is much smaller for fixed income funds with only a 0.19% increase during high VIX periods. This is because being large is an advantage in fixed income where the best pricing goes to the largest traders. Large firms also get access to new issue bonds that a small firm would not get.

Exhibit 13 Economic Variables - Star Rating Model



Source: Morningstar Direct. Data as of 30/03/2016.

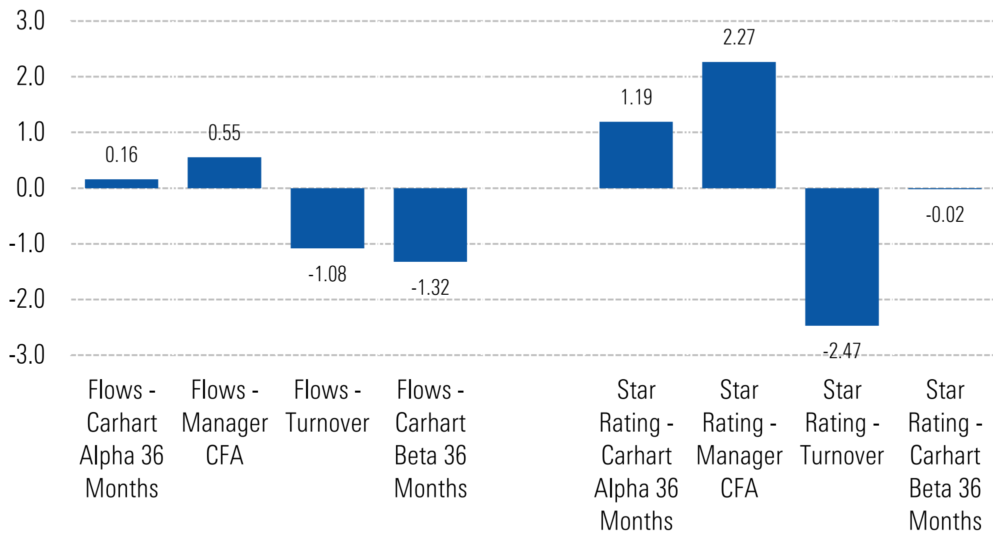
New funds that make similar buy/sell decisions as successful managers have better outcomes and are preferred by investors. Using Morningstar's portfolio holding database, we are able to evaluate a new fund manager's buying patterns and identify how similar or different they are to established fund managers on several dimensions. For each new fund, we construct novel data points that tell us how similar their reported holdings are to the cohort of managers who have exhibited high alpha, high beta, or high turnover historically. We also construct a data point about a new fund that tells us how similar a new fund manager's purchases are to the collection of all purchases made by current fund managers with CFAs. Constructing these data points are useful as many new fund managers may not possess their CFA and none of these new funds have track records to evaluate.

Before we run the model, what would we expect the results to be? We know that investors, in aggregate, show a strong preference for managers who have exhibited high historical alpha. Said differently, investors reward past performance. So, we should expect that new funds who behave similarly to historically good managers in terms of what they buy will be preferred by investors and thus awarded with disproportionately large inflows. On the other hand, investors show little preference for the level of market beta. So, we may not expect to a see a strong relationship between future flows and whether new funds buy stocks that high beta managers buy. Furthermore, we might expect investors to shun new funds that look like they are poised to implement a high turnover strategy as a track record of high turnover is something investors aren't too keen on. Finally, we know that CFA managers have an advantage in attracting inflows likely based on the signaling effect of their credentials. Therefore, we might expect new funds that invest similarly to funds with CFA managers will be preferred in aggregate by investors.

Indeed, we find all the above relationships to be present in the data with strength and persistence. The magnitude of these effects on par economically speaking with portfolio disclosure and style tilts generally. While we were only able to test these hypotheses for equity funds, we anticipate that these types of relationships should hold in other asset classes.

In terms of forecasting future risk-adjusted returns, we find that buying stocks preferred by managers with their CFAs and managers with low turnover tend to result in better investor outcomes. Somewhat surprisingly, new funds that buy stocks preferred by historically highly-skilled managers have not resulted in better outcomes for investors. Despite the strength of these relationships in the equity fund data, we think that the argument for the continued persistence of these relationships is weaker and less convincing for other asset classes. Overall, we would require more evidence to be convinced that these findings are causal and reliable to forecast future risk-adjusted returns. Nonetheless, it does confirm that investors were making decisions that resulted in better outcomes in this sample at least.

Exhibit 14 Portfolio Characteristics



Source: Morningstar Direct. Data as of 30/03/2016.

Conclusion

In this paper, we sought to explain why some newly-launched funds succeed and why others do not. We defined two measures of success. From the perspective of the investor, we defined success as higher forward 36-month cumulative risk-adjusted returns (which serves as the primary input to the Morningstar Rating for Funds or "Star Rating"). From the perspective of the asset manager, we defined success as higher forward 36-month cumulative flows percentiled within the category. The models we constructed revealed the historical relationships between observed fund data, macroeconomic regimes, and category environs with these success measures. Understanding where, what, how, and when to launch or invest in new products certainly has its benefits for many fund industry participants. Furthermore, our method of analysis enables economically-relative comparisons to be made between all these data and the outcome of interest.

What do we find? New funds launched with high fees have worse outcomes -- lower cumulative flows relative to their category and lower risk-adjusted returns. Coverage by a Morningstar analyst has correlated with future success on both measures. There are significant returns to manager education and portfolio disclosure. Diversity of fund management is to be sought out by asset managers. Investors tend to be make poor decisions with how they allocate assets between investment styles. Investors have a preference for firms with higher manager tenure. New funds face headwinds when launching into monopolistic categories, but this is offset if the new fund is issued by the monopolist. Investors should take note of new funds issued during times of crisis -- those funds have historically been advantaged. The full results can be found in the tables in the Appendix.

The main result of our paper is the twofold. First, investors seem to gravitate towards funds that make them feel more comfortable where the interests of the fund management company are aligned with their own. Investors prefer more information more frequently. Investors like seeing funds helmed by good stewards of capital with managers who have experience and credentials. Firm reputation makes difference. Managers with "skin-in-the-game" are noticed. In the absence of a track record, investors are essentially asking themselves "can I trust this manager?" Anything that will likely tilt the answer to that question towards a yes shows up materially in aggregate flows.

Second, the good news for investors is that their preferences have generally paid off in better outcomes. Funds that exhibit the types of traits listed above are generally a better cohort of funds from the investor's perspective. The main exception to this comes from investor preferences for style tilts which are directly contrary to their best interest. If portfolios have been disclosed, the investing populace tends to place a premium on funds that buy popular, large-cap, overvalued, and liquid stocks that done well recently. Investors appear to be asking themselves "have I heard of these stocks?" and responding with additional flows to the new fund when the answer is yes. Unfortunately, in almost all instances, we would expect the opposite choice to result in a higher expected return. This is the most disappointing finding of the paper though perhaps not entirely surprising as discussed in earlier sections.

We conclude this paper by highlighting future work we hope to do soon. As with most papers, several questions were raised by conducting this analysis. Two stand out:

1) Now that we know something about how new funds succeed, what do we know about why some funds die out? Could we build a model to forecast the probability of liquidation?

2) Investors clearly prefer funds with female management. What is the relationship between the fund industry, investors, and gender more broadly?

We anticipate studying these questions and more in the coming months.

Appendix

Data

Our study relies on Morningstar fund data sources, the Federal Reserve Bank of St. Louis for economic data, and the University of Minnesota for gender data. The sample period begins in January 2005 and ends in March 2013. Over the entirety of the sample, 57,512 unique funds are included. Monthly fund counts range from 1686 to 5324 depending on the period and model concerned, with recent periods having higher counts. For the flows model, our sample includes multiple broad asset classes – balanced funds (counts range from 452 to 1812 funds), equity (856 to 2691 funds) and fixed income (378 to 1605 funds). In March 2013, our sample spans a total of 4188 funds. For the Star Rating model, our sample includes multiple broad asset classes – balanced funds (counts range from 500 to 1490 funds), equity (1042 to 2286 funds) and fixed income (393 to 873 funds). In March 2013, our sample spans a total of 2947 funds. Given the small universe of alternative funds, we chose not to include in either model them for the purposes of this study.

We restrict our analysis to new funds which we define as less than 12 months old from the inception of the fund's oldest share class. We do not want to analyze the launch of an additional share class from an established fund. Therefore, we restrict our analysis to the fund level data of entirely new funds incepted after December 31, 2004. Share class data is rolled up to the fund level and the process for doing so each explanatory variable is explained in detail below. Each control variable is lagged by one month to avoid any look ahead bias, therefore any fund less than one month old cannot be included in our study.

At most, each fund appears 12 times in our sample, one for each month of their first year in existence. For example, if a fund is incepted in January 2005, the explanatory variable will be the fund's raw Morningstar Star Rating in January 2008 or the Total Flows accumulated by January 2008. Should a fund become obsolete 40 months after inception, the fund will appear only 4 times in our study, using the first four months of data for control variables and up to first 40 months of data for explanatory variables.

Our sample does not suffer from survivorship bias. Morningstar's global fund databases return a full history of dead funds, and these funds are included in our sample, where applicable. 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. Including only new funds that will survive at least 36 more months is by choice as we hope to identify what factors are correlated with a successful launch of a fund. In the future, we hope to study what factors will cause a fund to become obsolete.

Regression coefficients

The control and dependent variables in our regressions are important to understand. Many continuous explanatory variables are standardized into percentile units across all funds (1 lowest percentile, 100 highest percentile) cross-sectionally by date and category. Economic and category variables are not standardized into percentiles. Imputation by category was performed on all missing data for continuous explanatory variables. We imputed each category's percentile median for each date.

Dependent Variables

Morningstar 36 Month Risk-Adjusted Return

Morningstar uses expected utility theory to determine how much return a model investor is willing to give up to reduce risk. Morningstar Risk-Adjusted Return measures the guaranteed riskless return that provides the same level of utility to the investor as the variable excess returns of the risky portfolio. We call this riskless return the "certainty equivalent" geometric excess return.

Morningstar uses historical excess returns as the basis for expected excess returns, rather than relying on analysts' forecasts or other probabilities of future returns. Morningstar Risk-Adjusted Return is defined as follows:

$$MRAR(\gamma) = \left[\frac{1}{T}\sum_{t=1}^{T}(1 + ER_t)^{-\gamma}\right]^{-\frac{12}{\gamma}} - 1$$

Where:

$$ER_t = \text{ the geometric excess return in month } t = \frac{1 + LR_t}{1 + RF_t} - 1$$

$$LR_t = \text{the load adjusted return for the fund in month } t$$

$$RF_t = \text{the return for the risk} - \text{free asset in month } t$$

$$T = \text{the number of months in the time period}$$

A rating system based solely on performance would rank funds on their geometric mean return, or equivalently, MRAR(0) or Morningstar Return. A rating system that provides a heavier penalty for risk requires that $\gamma > 0$. Morningstar's fund analysts have concluded that $\gamma = 2$ results in fund rankings that are consistent with the risk tolerances of typical retail investors. Hence, Morningstar uses a γ equal to two in the calculation of its star ratings. So Morningstar Risk-Adjusted Return is calculated as follows:

$$MRAR(2) = \left[\frac{1}{T}\sum_{t=1}^{T}(1 + ER_t)^{-2}\right]^{-\frac{12}{2}} - 1$$

The section inside the brackets determines the investor's average utility from this fund's monthly excess returns over 36 months. Then, that level of utility is converted into a return by taking it to the power of –1/2. Lastly, Morningstar annualizes the result by taking it to the power of 12.

We calculate the forward 36 month Morningstar Risk Adjusted Return for each share class of a fund included in our study. For those who provide complete asset information for all share classes, we calculate the asset weighted Morningstar Risk Adjusted Return. For those funds where complete asset information is not available, we compute an equally weighted Morningstar Risk Adjusted Return.

Cumulative 36 Month Flows

We define flow as the organic growth in the fund's net assets not attributable to capital appreciation. Each month, we calculate the monthly flow experienced by individual share classes and convert the amount back into USD. The monthly fund flow is calculated by aggregating the flow information from all the share classes launched in the first 12 months of the fund's existence. We calculate the monthly flows of these share classes up to the next 48 months so we can then calculate rolling cumulative 36 months for the first 12 months of the fund's inception. We then percentile all new fund flows by date and asset class. Higher percentiles indicate higher flows.

Independent Variables

Asset-weighted Manager Tenure

The firm-level tenure number is an asset-weighted average of the longest manager tenure of each fund assigned to the firm. The tenure number at the fund level is the number of months the current manager has been on the fund. For funds with more than one manager, the tenure of the manager who has been with the fund the longest is used in the calculation.

Morningstar 5 Year Success Ratio

Success ratio measures the percentage of a provider company's open-end mutual funds with a Morningstar Category rank of less than 50 over the five-year period through the previous month's end.

Average Net Expense Ratio Rank

The firm-level fee number is an equal-weighted average of the net expense ratio equivalent data point ranked by Morningstar Category of each fund assigned to the firm. Net Expense Ratios are defined per the definition in the preceding sections and ranked by Morningstar Category. Each fund's fee rank is then averaged to arrive at a firmwide estimate of the typical, relative cost of their fund lineup.

New Fund Concentration Percentage

This is a continuous variable from 0 to 1 measuring a firm's concentration of new funds in an asset class. 1 indicates the particular fund in question is the firm's only new fund in an asset class. A number close to zero indicates the fund is one of many new funds a firm is launching. 0 indicates all funds at a firm are older than 12 months. This explanatory variable is standardized into percentiles compared to only new funds in the same category. The variable is calculated each month for each category. The calculation is below:

$$New\ Fund\ Concentration\ Percentage = \frac{Fund\ Assets}{Firm's\ New\ Assets\ in\ Category}$$

Net Expense Ratio

Different regions have different reporting requirements for mutual fund expenses. For example, in the

U.S., Net Expense Ratio is the most commonly used data point that encompasses all fees levied on the investor over the past year, including performance-based fees. In the United Kingdom and Europe, Ongoing Charge is the most commonly used data point to express fees levied on investors in the past year. Unlike Net Expense Ratio, Ongoing Charge does not include performance-based fees. Therefore, to harmonize net expense ratios of U.S., U.K., and Europe-domiciled funds, we add back in performance fees to the Ongoing Charge.

For Fund of Funds, we also included acquired fund expenses.

For all domiciles in our purview, we do our best to harmonize fee-reporting differences across geographies using the following mapping procedure:

$$NetExpenseRatio = \begin{cases} NetExpenseRatio & \text{Domicile} = \text{USA} \\ IndirectCostRatio(or MER) & \text{Domicile} = \text{AUS} \\ ManagementExpenseRatio & \text{Domicile} = \text{CAN or NZL} \\ OngoingCharge + PerformanceFee(or NER) & \text{Region} = \text{UK, EU} \\ JPAf - TaxTotalExpenseRatio & \text{Domicile} = \text{JAP} \\ FoF.NetExp_i = FoF.exp_i + AcquiredFundExpense & \text{FoF} = \text{Yes, Acq Fund Exp} \neq \text{NA} \\ FoF.NetExp_i = FoF.exp_i + \sum_{i=1}^{N} w_i exp_i & \text{FoF} = \text{Yes and Region} = \text{US} \\ NetExpenseRatio & \text{Otherwise} \end{cases}$$

Months Since Rating

This is an integer variable ranging from 0 to 12, indicating the number of months since a Morningstar analyst rated the fund, irrespective of whether the rating is positive, neutral or negative. Funds without a Morningstar Analyst Rating are marked as 0 months.

Socially Responsible Fund

This is a categorical, dummy variable that indicates whether or not a fund has identified itself as socially conscious. This data point indicates if the fund selectively invests based on certain noneconomic principles. Such funds may make investments based on such issues as environmental responsibility, human rights, or religious views. A socially conscious fund may take a proactive stance by selectively investing in, for example, environmentally friendly companies or firms with good employee relations. This group also includes funds that avoid investing in companies involved in promoting alcohol, tobacco, or gabling, or in the defense industry.

Index Fund

This is a categorical, dummy variable that indicates whether or not a fund tracks an index. While an index typically has a much larger portfolio than a mutual fund, the fund’s management may study the index’s movements to develop a representative sampling and match sectors appropriately.

Fund of Funds

This is a categorical, dummy variable that indicates whether or not a fund is structured as a fund of funds – a fund that specializes in buying shares in other mutual funds rather than in individual securities. Quite often this type of fund is not discernible from its name alone but rather through prospectus working (that is, the fund's charter).

Average Monthly Growth Rate
This is a numerical variable indicating the average growth rate of assets into a fund. The data is standardized into percentiles by category and date. 100 indicates the fund is the fastest growing fund in the category while 1 indicates the fund is the slowest growing fund in the category on that date.

Education
This is a categorical, dummy variable that indicates whether or not one of the fund's managers has received the Chartered Financial Analyst designation. Only one fund manager needs to have their CFA for the Education designation.

Ownership
This is a categorical, dummy variable that indicates whether or not the fund management has invested their own money into the fund. Only one fund manager needs to invest one dollar into the fund for Manager Ownership designation.

Gender
This is a continuous variable from 0 to 1 indicating the probability the fund has at least one female fund manager. We collect the first names of the fund managers and then assign each name a score based off the frequency the name is associated with each gender. A high score indicates the name is associated with females where a low score indicates a typical male name. If the fund is managed by multiple people, the highest score is used for the fund.

Reported Portfolio
This is a categorical, dummy variable that indicates whether or not the fund has released their portfolio holding data. The fund only has to have previously released one month of portfolio holdings for the for the Reported Portfolio designation.

Reported Current Portfolio
This is a categorical, dummy variable that indicates whether or not the fund has released their prior month's portfolio holding data.

Holdings-Based Preference Measures
Equity Funds: We calculate preference factors of managers by looking holdings across managers with similar traits. In this study, we look at Manager Tenure, Turnover, CFA designation, Carhart Market Alpha, and Carhart Market Beta characteristics.

To calculate each of the above variables, we run the below process:

$M \equiv \text{the set of managers or funds}$

$N \equiv \text{the set of stocks}$

$X_m \equiv characteristic\ of\ each\ manager\ or\ fund$

$w_{m,n} \equiv the\ current\ weight\ that\ fund\ manager\ \boldsymbol{m}\ places\ in\ stock\ \boldsymbol{n}$

We want to compute the relative amount of stock n held by manager m. First, identify a stock that a manager holds (e.g. AAPL) and the percentage of his portfolio in that stock (e.g. 15%). Then, identify who else owns that stock and in what percentage (e.g. 10 other managers at 10% each), then add divide manager m's weight by the sum of the weights of the other managers (e.g. 15% / (10*10%)). This is expressed below:

$$v_{m,n} = \frac{w_{m,n}}{\sum_{m=1} w_{m,n}}$$

Notice that this term, v, will be estimated for each holding of each manager.

Now, we want to calculate a stock's quality. We will use the manager characteristic and the relative weighting term, v, from above. The calculation should look very similar to a typical weighted average, except we are using v as our weights as opposed to w.

$$Holdings\ Based\ Preference\ (stock) \equiv\ \delta_n = \sum_{m=1}^{M} v_{m,n} X_m$$

This says that the stock's quality is a weighted average of each manager characteristic multiplied by the relative weight he/she holds in the stock. This will simply be a weighted average of the stocks he/she holds and their quality as computed above. Again, the calculation here should be very similar to a typical weighted average calculation.

$$Holdings\ based\ Preference\ (fund) \equiv\ \delta_m^* = \sum_{n=1}^{N} w_{m,n} \delta_n$$

To interpret each of the scores, a high score indicates a fund is buying similar stocks as a manager who represents that characteristic. For example, a high Manager Tenure score indicates the fund manager has similar preferences as those to long tenured managers.

3 Mo Oil Price Change

This is a continuous variable indicating the change in crude oil prices over the past three months. West Texas Intermediate (WTI) from Cushing, Oklahoma prices are used. Increasing one unit of Oil Price Change corresponds to a one dollar. The 3 Month Oil Price Change variable is calculated each month.

GDP YoY change

This is a continuous variable measuring the strength of the US economy. We compare the year over year change in the quarterly GDP. Since the GDP data is available only quarterly, the GDP Rate of Change variable is calculated for each quarter and stays constant for the subsequent two months.

VIX 90 Day Moving Average

This is a continuous variable measuring the volatility in the market. We take a simple average of the VIX index for the previous 90 days. The VIX 90 Day Moving Average variable is calculated for each month.

6 Mo Unemployment Rate

This is a continuous variable measuring the trend of the US job market health. The Unemployment Rate of Change uses the U6 unemployment rate because we feel this rate better captures an investor's understanding of what it means to be unemployed. We calculate the rate of change over the previous six months and recalculate the variable each month.

Market Concentration Index

This is a continuous variable (0,1] that indicates market concentration within a Morningstar Category. 1 indicates one firm has complete monopoly over the category whereas a number close to 0 indicates a competitive category where no single firm can control the category's assets. Market Concentration Index is calculated for each category each month. The calculation is below:

$$Market\ Concentration\ Index = \sum_{i=1}^{n} (\frac{x_i}{C_k})^2$$

$$n = number\ of\ firms\ in\ Morningstar\ Category\ k$$

$$x = Firm's\ Assets\ within\ Morningstar\ Category\ k$$

$$C = Total\ Assets\ in\ Morningstar\ Category\ k$$

Firm's Category Market Share

This is a continuous variable (0,1] that indicates a firm's market share of a Morningstar Category. 1 indicates a firm has a complete monopoly over the category whereas a number close to 0 indicates the firm has a very small market share within the category.

Top Ten Firm (AUM)

This is a categorical, dummy variable that indicates whether a fund is from a firm with top ten assets under management in the respective asset class.

Cumulative 36 Month Flow into Category

This is a forward looking numerical variable indicating the total inflows into a Morningstar category over the next 36 months.

Valuation Exposure

The Valuation exposure indicates a fund's level of exposure to discounted stocks relative to their fair value estimate. A higher score means the fund is holding undervalued securities.

On the stock level, the Valuation factor is the normalized ratio of Morningstar's Quantitative Valuation metric which compares an estimated Fair Value to the current market price of a security. It represents how cheap or expensive a stock is relative to its fair value. Higher scores indicate we believe the company is undervalued and increases the likelihood the company will generate positive returns.

To calculate the Quantitative Valuation metric, we developed an algorithm which attempts to divine the characteristics of stocks that most differentiate the overvalued stocks from the undervalued stocks as originally valued by our team of human equity analysts. Once these characteristics have been found, and their impact on our analyst-driven valuations has been estimated, we can apply our model beyond the universe of analyst-covered stocks. To be more precise, we use a machine learning algorithm known as a random forest to fit a relationship between the variable we are trying to predict (an analyst's estimate of the over- or under-valuation of the stock) and our fundamental and market-based input variables.

To calculate the Valuation exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation, so a score of zero can always be interpreted as the average score, and a non-zero score of n can be interpreted as being n standard deviations from the mean.

On the portfolio level, the Valuation exposure is the asset weighted value of the stock holdings Valuation exposure scores.

Valuation Uncertainty Exposure

The Valuation Uncertainty exposure indicates a fund’s level of exposure to stocks with uncertain valuations. A higher score indicates the fund is holding securities with higher uncertainty ratings.

On the stock level, the Valuation Uncertainty factor measures the level of uncertainty embedded in a company’s Quantitative Fair Value Estimate. Higher scores imply greater uncertainty so we expect to see a greater range of outcomes. Using the Morningstar Valuation Uncertainty factor can help investors evaluate and adjust their portfolio exposure to firms with more certain equity valuations.

To calculate the Quantitative Valuation Uncertainty metric, we use the outputs from the statistical model calculating the Quantitative Valuation Estimate. For each Quantitative Valuation Estimate, the model generates 500 predictions before averaging them at the final prediction. The dispersion (or more specifically, the interquartile range) of these 500 tree predictions is our raw Valuation Uncertainty Score. The higher the score, the higher the disagreement among the 500 tree models, and the more uncertainty is embedded in our quantitative valuation estimate.

$$Quantitative\ Valuation\ Uncertainty = Q_3(\{x_i \mid 1 < i < n\}) - Q_1(\{x_i \mid 1 < i < n\})$$

$$x_i = Valuation\ Estimate$$

$$n = number\ of\ estimates\ produced\ by\ model$$

$$Q_3 = Third\ Quartile$$

$$Q_1 = First\ Quartile$$

To calculate the Valuation Uncertainty exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. A score of zero can always be interpreted as the average score, and a non-zero score of n can be interpreted as being n standard deviations from the mean.

On the portfolio level, the Valuation Uncertainty exposure is the asset weighted value of the stock holdings Valuation Uncertainty exposure scores.

Economic Moat Exposure

The Economic Moat exposure indicates a fund's level of exposure to stocks with Economic Moats. A higher score means the fund is holding securities with strong moats.

On the stock level, the Economic Moat factor assesses the strength of a firm's competitive position and by evaluating the sustainability of their profits. Higher scores indicate a firm will be able to keep competitors at bay for an extended period.

To calculate the Quantitative Economic Moat, we developed a statistical model to replicate the output of an analyst as faithfully as possible. The model calculates two probabilities: one to predict whether a company has a wide moat or not, and one to predict whether a company has no moat or not.

$$Moat\ Score = \frac{P(Wide\ Moat\ Prediction) + (1 - P(No\ Moat\ Prediction))}{2}$$

$$0 \leq P(Wide\ Moat\ Prediction) \leq 1$$

$$0 \leq P(No\ Moat\ Prediction) \leq 1$$

To calculate the Economic Moat exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. A score of zero can always be interpreted as the average score, and a non-zero score of n can be interpreted as being n standard deviations from the mean.

On the portfolio level, the Economic Moat exposure is the asset weighted value of the stock holdings Economic Moat exposure scores.

Financial Health Exposure

The Financial Health exposure indicates a fund's level of exposure to financially sound stocks. A higher score means the fund is holding securities with high financial health scores.

On the stock level, the Financial Health risk factor assesses the strength of a firm's financial position and ranks companies on the likelihood that they will tumble into financial distress. Higher scores imply stronger financial health and therefore a lower risk of bankruptcy.

To calculate the Quantitative Financial Health metric, we developed a linear model approximating the Distance to Default definition by measuring the interaction between the percentile of a firm's leverage and the percentile of a firm's equity volatility relative to the rest of the universe. Our model has the benefit of increased breadth of coverage, greater simplicity of calculation, and more predictive power while maintaining the timeliness of a market-driven metric.

$$Financial\ Health\ Score = 1 - \frac{(EQVOLP + EVMVP + EQVOLP \times EVMVP)}{3}$$

$$EQVOLP = Percentile\ of\ Annualized\ Trailing\ 300\ Day\ Equity\ Total\ Volatility$$

$$EVMVP = Percentile\left(\frac{Current\ Enterprise\ Value}{Market\ Cap\ ratio}\right)$$

To calculate the Financial Health exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation, so a score of zero can always be interpreted as the average score, and a non-zero score of n can be interpreted as being n standard deviations from the mean.

On the portfolio level, the Financial Health exposure is the asset weighted value of the stock holdings Financial Health exposure scores.

Ownership Risk Exposure

The Ownership Risk exposure indicates a fund's level of exposure to stocks preferred by managers with high levels of Morningstar Risk preferences. A higher score means the fund is holding securities preferred by riskier managers.

On the stock level, the Ownership Risk factor represents, for a particular stock, the ownership preferences of fund managers with different levels of risk exposure. The Ownership Risk factor relies on current portfolio holdings information and the raw Morningstar 36-month Risk score. High Ownership Risk scores signify that those stocks are currently owned and preferred by fund managers with high levels of Morningstar Risk. If high-risk managers are purchasing these stocks, then those stocks are likely to be high-risk. A stock's characteristic is therefore defined by who owns it.

The Ownership Risk factor for stock n is calculated as the weighted average of each manager m's Morningstar Risk 36-month score multiplied by the relative weight he/she holds in stock. If a manager exhibits extreme risk behavior over the past 36 months, then their Morningstar Risk 36-month score would be very high to reflect that. If we observed that every high risk manager owned a significant amount of a specific stock, then the inference would be that this stock is going to exhibit extreme risk behavior going forward.

$$Ownership\ Risk_n = \sum_{m=1}^{M} v_{m,n} MRISK36_m$$

$$Where:$$

$$v_{m,n} = \frac{w_{m,n}}{\sum_{m=1}^{M} w_{m,n}}$$

$$MRISK36 = Morningstar\ Risk\ Score\ 36 - month$$

The raw scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation, so a score of zero can always be interpreted as the average score, and a non-zero score of n can be interpreted as being n standard deviations from the mean.

On the portfolio level, the Ownership Risk exposure is the asset weighted value of the stock holdings Ownership Risk scores.

Size Exposure

The Size exposure indicates a fund's level of exposure to small stocks.

On the stock level, we calculate the size factor as the normalized value of the logarithm of a firm's market capitalization.

$$Size_{i,t} = -ln(MV_{i,t})$$

To calculate the Size exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. A score of zero indicates an average level of market capitalization, and a non-zero score of n can be interpreted as being n standard deviations from the mean.

On the portfolio level, the Size exposure is the asset weighted value of the stock holdings Size scores.

Liquidity Exposure

The Liquidity exposure indicates a fund's level of exposure to liquid stocks.

On the stock level, we define liquidity as share turnover. We calculate the Liquidity factor as the normalized value of the stock's raw share turnover. The raw share turnover score is calculated as the logarithm of the average trading volume divided by shares outstanding over the past 30 days. It is essentially a churn-rate for a stock and represents how frequently a stock's shares exchange hands.

$$shareturnover_{i,t} = ln\left(\frac{1}{T}\sum_{t=1}^{T}\frac{V_{i,t}}{SO_{i,t}}\right), where\ T = 30$$

To calculate the final Liquidity exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. A score of zero indicates an average level of liquidity, and a non-zero score of n can be interpreted as being n standard deviations from the mean.

On the portfolio level, the Liquidity exposure is the asset weighted value of the stock holdings Liquidity scores.

Momentum Exposure

The Momentum exposure indicates a fund's level of exposure to momentum.

On the stock level, we calculate a raw Momentum score as the cumulative return of a stock from 365 calendar days ago to 30 days ago. This is the classical 12-1 momentum formulation except using daily return data as opposed to monthly. To compute, US dollar currency returns are used.

$$momentum_{i,t} = \sum_{t-365}^{t-30} \left(ln\left(1 + r_{i,t}\right) - ln(1 + rf_t) \right)$$

To calculate the final Momentum exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. A score of zero indicates an average level of momentum, and a non-zero score of n can be interpreted as being n standard deviations from the mean.

On the portfolio level, the Momentum exposure is the asset weighted value of the stock holdings Momentum score.

Volatility Exposure

The Volatility exposure indicates a fund’s level of exposure to volatility.

On the stock level, we calculate the Volatility score as the normalized range of annual cumulative returns over the past year. Each day, we compute the trailing 12-month cumulative return. Then, we look over the past year and identify the maximum and minimum 12-month cumulative returns. We compute the range by taking the maximum minus the minimum 12-month cumulative returns.

$$range_i = \left(ln\left(1 + r_{i,t}\right) - ln(1 + rf_t) \right)^{max} - \left(ln\left(1 + r_{i,t}\right) - ln(1 + rf_t) \right)^{min}$$

To calculate the final Volatility exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. A score of zero indicates an average level of volatility, and a non-zero score of n can be interpreted as being n standard deviations from the mean.

On the portfolio level, the Volatility exposure is the asset weighted value of the stock holdings Volatility score.

Methodology

To evaluate the fund-specific drivers of Star Rating and Flows, we employ a panel regression. We regress the forward 36 month Star Rating and Cumulative Flows on a set of contemporaneous explanatory variables.

The set of explanatory variables we use for equity funds is slightly different than the set of explanatory variables we use for fixed income and balanced funds. As constructed, we believe that this model offers a glimpse at the underlying decision-making process investors go through when choosing to allocate their money and how their preferences affect forward risk adjusted returns. We purposefully re-estimate the models by asset class so that we are capturing the within-asset-class variation in Star Rating and Flows rather than the between-asset-class variation.

We apply the following framework to the data globally across asset classes:

Panel Regression

Flow Model

$$\sum_{j=1}^{36} flow_{i,t+j} = \gamma + \phi_t Z_{i,t} + \lambda_t X_{i,t} + \sigma_t B_{i,t} + \varepsilon_{i,t+1}$$

Star Rating Model

$$36\ month\ Risk\ Adjusted\ Return_{t+36} = \gamma + \phi_t Z_{i,t} + \lambda_t X_{i,t} + \sigma_t B_{i,t} + \varepsilon_{i,t+1}$$

Where $flow_{i,t+j}$ is defined as the change in a fund's net assets from month *t* to month *t+j* not attributable to returns. X_i is vector of explanatory characteristics at time *t*.

The contents of the vectors Z_i, X_i, B_i are as follows:

Exhibit 15 Variables Included in the Model

$\mathbf{Z_i}$ (equity only)	$\mathbf{X_i}$	$\mathbf{B_i}$ (yes/no)
Value-Growth	Months Since Rating	Index Fund
Fair Value	Avg Growth Rate (Star Rating)	Socially Responsible Fund
Economic Moat	Expense Ratio	Fund of Funds
Valuation Certainty		
Financial Health	Asset Weighted Mgr Tenure	Ownership
Ownership Risk	Success Ratio 5 Yr	Education
Ownership Popularity	Avg Net Expense Ratio Rank	
Size	New Fund Concentration Index	Is Firm Top Ten
Liquidity		
Momentum	Proportion Female	Reported Portfolio
Volatility		Reported Recent Portfolio
	3 Mo Oil Price Change	
Carhart Alpha 36m	GDP YoY Change	
Manager Tenure	VIX 90 Day Moving Average	
Manager CFA	6 Mo Unemployment Rate	
Turnover		
Carhart Beta 36m	Market Concentration Index	
	Firm's Category Market Share	
	Category Cumulative 36m Flow	

Source: Morningstar Direct. Data as of 30/06/2016.

How to Obtain Final Estimates

The panel regression, as specified above, is run for each model and asset class. As a result, we are left with six vectors of coefficients, standard errors, and t-statistics. To account for autocorrelation through time, we re-estimate the standard errors using robust standard errors, and then recalculate the t-statistics. The coefficients are left the same from the original estimation but the level of significance for each variable is more accurate.

Data Tables

In the tables below, we show the panel regression results. Coefficients are expressed in percentage terms and are bolded when statistically significant at the 5% level and are expressed as follows. Below the coefficients, t-statistics are presented in the row below. Coefficients can be interpreted as the benefit a fund can obtain by moving from one percentile to another or in the case of dummy variables, when the factor moves from False to True. For the flows model, the coefficients represent the change in category forward 36-month cumulative flows percentile of a fund. For the Star Rating model, the coefficients represent the change in the forward 36-month risk adjusted return.

Exhibit 16 Regression Results by Asset Class and Model

	Equity		Fixed Income		Allocation	
Factors	Star Rating	Flows	Star Rating	Flows	Star Rating	Flows
(Intercept)	**-21.50**	**41.64**	**-2.98**	**42.58**	**-10.76**	**39.35**
	-74.02	71.53	-22.12	75.12	-52.94	60.92
Firm						
Asset Weighted Manager Tenure	**-0.79**	**5.18**	0.02	**9.49**	0.19	**1.68**
	-5.77	17.80	0.23	29.73	1.82	3.97
Success Ratio 5 Yr	**-1.73**	**-0.65**	**0.55**	**-1.78**	-0.10	**1.06**
	-12.91	-2.36	7.52	-5.35	-0.87	2.67
Avg Net Expense Ratio Rank	**-1.00**	**-4.22**	**0.29**	**-4.51**	**-0.49**	**1.46**
	-7.45	-15.54	4.02	-13.30	-4.60	3.76
New Fund Concentration Percentage	**-0.44**	**15.96**	-0.11	**9.60**	**0.78**	**16.18**
	-3.56	65.36	-1.54	30.92	7.72	46.20
Fund Structure						
Months Since Rating	1.74	**14.36**	**3.80**	0.43	4.71	**13.54**
	1.33	2.69	2.29	0.10	1.50	2.05
Index Fund	**-0.77**	**1.02**	**2.14**	**3.07**	**1.62**	-1.27
	-6.03	3.62	26.96	7.70	6.63	-1.67
Socially Responsible Fund	**-3.35**	**1.21**	**0.62**	0.48	**-0.51**	**-1.87**
	-18.84	3.54	5.10	0.57	-2.95	-2.70
Fund of Funds	**-1.17**	**3.09**	**-0.85**	**8.46**	0.03	**4.67**
	-9.66	12.93	-12.03	25.82	0.39	18.33
Average Monthly Growth Rate	**-0.65**	--	**-0.49**	--	**0.93**	--
	-5.40	--	-7.15	--	9.40	--
Expense Ratio	**-3.18**	**-1.98**	**-0.57**	**-1.99**	**-3.32**	**-2.67**
	-23.62	-6.50	-6.52	-4.49	-29.87	-6.33

Source: Morningstar Direct. Data as of 30/06/2016.

Exhibit 16 Continued

	Equity		Fixed Income		Allocation	
Factors	Star Rating	Flows	Star Rating	Flows	Star Rating	Flows
Manager Characteristics						
Ownership	**5.34**	**6.65**	**1.90**	**6.86**	**4.04**	**8.89**
	19.06	10.97	7.27	3.71	11.69	5.79
Education	**1.43**	**4.81**	**1.27**	**9.84**	**1.08**	**2.50**
	14.63	21.06	19.36	28.35	10.60	5.74
Gender	**-0.66**	**0.84**	0.02	**2.78**	**1.27**	**-1.97**
	-6.38	3.43	0.34	8.08	13.25	-5.07
Economic Variables						
3 Mo Oil Price Change	**-0.18**	0.00	**-0.01**	-0.01	**-0.09**	0.01
	-48.89	-0.72	-4.67	-0.58	-27.06	1.23
GDP	**0.70**	0.03	**-0.23**	0.57	0.01	0.21
	5.50	0.12	-3.46	1.92	0.06	0.68
VIX 90 Day Moving Average	**0.93**	0.02	**0.19**	**0.06**	**0.52**	**-0.06**
	106.23	1.39	37.84	3.07	69.28	-2.47
6 Mo Unemployment Rate	**-0.45**	0.00	**-0.04**	0.01	**-0.28**	**0.07**
	-47.79	0.04	-7.13	0.23	-36.40	3.13
Category Characteristics						
Market Concentration Index (HHI)	**0.70**	**-1.70**	**-1.87**	**-18.59**	**-0.69**	**-24.74**
	3.23	-2.97	-17.25	-24.04	-3.45	-25.95
Top Ten Firm	0.07	**8.47**	**0.36**	**13.66**	0.17	**6.44**
	0.24	11.30	2.76	25.06	0.87	6.43
Firm's Category Market Share	**7.78**	**25.82**	**-0.50**	**-10.10**	**4.29**	**30.12**
	18.68	27.37	-2.58	-12.73	11.22	21.82
Category Cumulative 36 Month Flow	0.00	0.00	0.00	**-0.07**	**0.06**	**1.49**
	-1.82	-0.93	-0.28	-2.27	3.50	24.54
Portfolio Characteristics						
Reported Portfolio	**1.48**	**2.67**	**0.47**	**7.60**	**1.04**	**9.72**
	11.55	10.58	5.90	20.60	8.63	23.63
Reported Current Portfolio	**3.18**	**3.90**	**0.33**	**2.16**	**0.37**	**-2.31**
	0.11	0.25	4.19	5.41	3.07	-5.20

Source: Morningstar Direct. Data as of 30/06/2016.

Exhibit 16 Continued

	Equity		Fixed		Allocation	
Factors	Star Rating	Flows	Star Rating	Flows	Star Rating	Flows
Portfolio Characteristics						
Carhart Alpha 36 months	1.08	**3.82**	--	--	--	--
	0.00	0.00				
Manager Tenure	**-11.51**	0.89	--	--	--	--
	0.00	0.00				
Manager CFA	**0.55**	**2.27**	--	--	--	--
	4.00	7.64				
Turnover	**-1.08**	**-2.47**	--	--	--	--
	-7.12	-7.49				
Carhart Beta 36 months	**-1.32**	-0.02	--	--	--	--
	-8.95	-0.05				
Style						
Value-Growth	**-0.37**	**-3.26**	--	--	--	--
	-1.98	-8.12				
Fair Value	**-1.15**	**-5.43**	--	--	--	--
	-5.35	-12.91				
Economic Moat	**6.57**	**3.65**	--	--	--	--
	27.02	7.14				
Valuation Uncertainty	**-1.30**	-0.06	--	--	--	--
	-5.48	-0.11				
Financial Health	**4.24**	**-1.39**	--	--	--	--
	18.12	-2.87				
Ownership Risk	**-5.81**	-0.50	--	--	--	--
	-25.54	-1.09				
Ownership Popularity	**-3.29**	-0.14	--	--	--	--
	-19.50	-0.41				

Source: Morningstar Direct. Data as of 30/03/2016.

Exhibit 16 Continued

Factors	Equity Star Rating	Equity Flows	Fixed Income Star Rating	Fixed Income Flows	Allocation Star Rating	Allocation Flows
Style						
Size	**5.82**	**-2.29**	--	--	--	--
	26.02	-4.73				
Liquidity	**0.91**	**-1.11**	--	--	--	--
	5.00	-2.96				
Momentum	**-0.90**	**2.12**	--	--	--	--
	-5.18	5.79				
Volatility	**3.73**	-0.61	--	--	--	--
	14.03	-1.08				

Source: Morningstar Direct. Data as of 30/03/2016.

Exhibit 17 Coefficient Multiplication Factors for Chart Displays

Category Characteristics	Factor	Firm	Factor
Market Concentration Index (HHI)	1	Asset Weighted Manager Tenure	100
Top Ten Firm	1	Success Ratio 5 Yr	100
Firm's Category Market Share	1	Avg Net Expense Ratio Rank	100
Category Cumulative 36 Month Flow	1E+10	New Fund Concentration Percentage	100

Economic Variables	Factor	Fund Structure	Factor
3 Mo Oil Price Change	1	Months Since Rating	12
GDP	1	Index Fund	1
VIX 90 Day Moving Average	1	Socially Responsible Fund	1
6 Mo Unemployment Rate	1	Fund of Funds	1
--	--	Average Monthly Growth Rate	100
--	--	Expense Ratio	100

Source: Morningstar Direct. Data as of 30/06/2016.

Exhibit 17 Continued

Manager Characteristics	Factor
Ownership	1
Education	1
Gender	1

Portfolio Characteristics	Factor
Reported Portfolio	1
Reported Current Portfolio	1
Carhart Alpha 36 months	100
Manager Tenure	100
Manager CFA	100
Turnover	100
Carhart Beta 36 months	100

Style	Factor
Value-Growth	100
Fair Value	100
Economic Moat	100
Valuation Uncertainty	100
Financial Health	100
Ownership Risk	100
Ownership Popularity	100
Size	100
Liquidity	100
Momentum	100
Volatility	100
--	--

Source: Morningstar Direct. Data as of 30/06/2016.

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About Morningstar® Quantitative Research™

Morningstar Quantitative Research is dedicated to developing innovative statistical models and data points, including the Quantitative Equity Ratings and the Global Risk Model.

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