The Fall of Funds: Why Some Funds Fail

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Executive Summary

In this paper, we explore the relationships between fund mergers and liquidations (also known as full closure) with observed fund characteristics. Investors often refer to these funds as "dead." We intend to explore the feasibility of forecasting the full-closure rate of mutual funds across regions, firms, and categories. Full fund closures can result in significant costs to investors, as the event compels investors to sell at a time not of their choosing, may result in a net loss, and may force investors to pay taxes on embedded capital gains. It is therefore advantageous for investors to understand the patterns that tend to precede a full fund closure in order to avoid those undesirable outcomes.

Our findings suggest that much of the common wisdom about why funds close may be incorrect or incomplete at best. Rather than being fully explained by performance track records, we find that full fund closures have virtually no relationship with past performance unless other conditions are also met. Rather, full fund closures are tied much more closely to commercial success, fund structure, firm type, firm behavior, regional differences, management status, and Morningstar Category popularity. In this paper, we unpack these correlations and the economic reasoning likely supporting them. We also demonstrate how to create an "at risk" score for funds that would allow investors to track the risks associated with full fund closure for their investments.

Key Takeaways

- ▶ Fund performance does not forecast full fund closure unless other conditions are met.
- ▶ Index funds are less likely to be shut down.
- ▶ The survival rates of socially responsible funds differ by region.
- ▶ Unsurprisingly, the smallest and slowest-growing funds are at the highest risk of becoming obsolete.
- ▶ By region, the size and type of firm plays a different role in predicting fund closures.
- ▶ If a firm has historically shut down many funds, it is likely to continue to do so.
- ▶ Funds in categories with high historical rates of fund closure are more at risk of closure.
- ▶ Funds in the fastest-growing categories are less likely to shut down.
- ▶ Management changes forecast fund closure.
- ▶ In the United States, mixed-gender teams navigate new funds better.

Introduction

While much of the attention has been focused on the fund industry's 70,000 new product launches during the past 10 years, more than 24,000 funds have quietly closed. Since the 2008-09 financial crisis, the market has settled into a state where a higher percentage of funds is being opened than closed. In 2016, the global fund marketplace added 6,195 new funds while removing only 3,540. Common sense suggests that as the market becomes saturated, more funds will fail to achieve commercial success.

Full fund closures can have significant negative consequences for investors. In the case of a liquidation, investors are forced to sell at a time that they cannot choose. Forced asset sales often result in lower prices due to liquidity constraints, and investors may experience a lower return of their capital than they anticipate. Furthermore, the mutual-ownership structure of mutual funds could mean that there are embedded capital gains in the holdings of the fund, on which the investor would be forced to pay taxes. The investor may not have even been a shareholder while these gains were accumulated. Therefore, all in all, a liquidation is an event best avoided for investors of all stripes.

More often than not, however, funds are not liquidated — instead, they are merged into another product. Several reasons exist for the prevalence of this practice. First, it allows investors to avoid the forced sale that comes with liquidation. Their assets are merged into another fund and continue to benefit from the oversight of a management team. This postpones the need to pay full capital gains taxes on the assets. Second, asset managers are usually loath to liquidate a fund and return capital to fund shareholders, when they can just as easily continue to collect fees on those assets in a different vehicle.

Nonetheless, mergers are often net-negative events for investors. Schlanger and Philips (2013) estimate that 73% of post-merger funds underperform their benchmarks, compared with 64% of unmerged funds over the same period. Even if an investor's assets are merged into a successful fund, there are due-diligence costs, and there is a decent likelihood that this new product may not be a fit in their portfolio allocation and would lead to the investor needing to exit the fund eventually. Upon exit, the investor could be subject to capital gains taxes and any early-redemption fees.

At Morningstar, we believe in long-term investing. This philosophy has several aspects: Keep costs low, trade infrequently, and select good products. But part of investing for the long term means finding investments that will be around for a long time. A long-term investor may buy and plan to hold a high-quality, low-cost product, but if that product liquidates soon after, then the objective will not have been met. Therefore, we believe there is a need to distinguish between funds capable of lasting for the long run and those that are more likely to be shut down soon.

Our latest study sets out to do just that. Our goal was to determine if certain characteristics are more prevalent among obsolete funds than their surviving counterparts. Prior to starting this study, we had expected performance to be a leading indicator. And we also expected commercial success — as proxied by fund size, fund flows, and asset growth rates — to play an important role. But we did not know to what extent performance and commercial success would affect full-closure rates. Furthermore, we did not know the role fund managers played in a fund-closure process, or if funds run by women and those

run by men held to the same standards. We were also curious to see if regional differences, firm behavior, or even category popularity could lead to different outcomes. We explore all this in the paper.

Explanation of the Modeling Approach

The goal of our modeling exercise was twofold. First, we wanted to determine if certain characteristics are more prevalent among obsolete funds relative to their surviving counterparts. Second, we wanted to determine the time horizon over which fund closures are more likely given a specific characteristic.

For the purposes of this study, we define an "obsolete" fund as one where all share classes have been liquidated or merged. We do not consider a liquidation or a merger of a single share class; rather, we consider only when the entire fund shuts down. Our sample includes both open-end and exchange-traded funds from the equity, fixed-income, and allocation asset classes. The remaining funds in our sample represent the global investable universe from July 2006 to June 2016.

To do this, we explored the relationship between fund and manager characteristics and the likelihood that a fund survives another three months, six months, 12 months, and 24 months by building four survival models to unpack the historical correlations for each time period.

To begin, we defined four dependent variables: the last three months of a fund's existence, the last four to six months, the last seven to 12 months, and the last 13 to 24 months. For each dependent variable, we deployed a lasso, logistic regression to our data with the same set of explanatory characteristics. Our technique allowed us to measure the likelihood of a fund becoming obsolete among each independent variable. So, for example, our four- to six-month model told us the change in odds of a fund not surviving the next four to six months for a typical, one-unit increase in each variable.

For example, consider two U.S.-domiciled funds, Fund A and Fund B. They have the same characteristics and we do not know whether each fund will survive the following 24 months. So, the relative odds of each fund becoming obsolete are 1.00:1.00. Each fund not surviving is equally likely.

Now suppose we gather additional information, learning that Fund A is an index fund while Fund B is actively managed. For argument's sake, let us say that we had observed that only actively managed funds have ever closed. We might reasonably expect a higher likelihood that Fund B will become obsolete in the next 24 months. As a result, we would change our expectation, surmising that Fund B has higher odds of closure than Fund A.

Conceptually, this is what the logistic regression accomplishes. Using our data set, we find that active funds are more likely to become obsolete than passively managed ones, holding all else equal. We expect this effect to increase the odds of closure by 31.8%.

Exhibit 1 Odds Interpretation
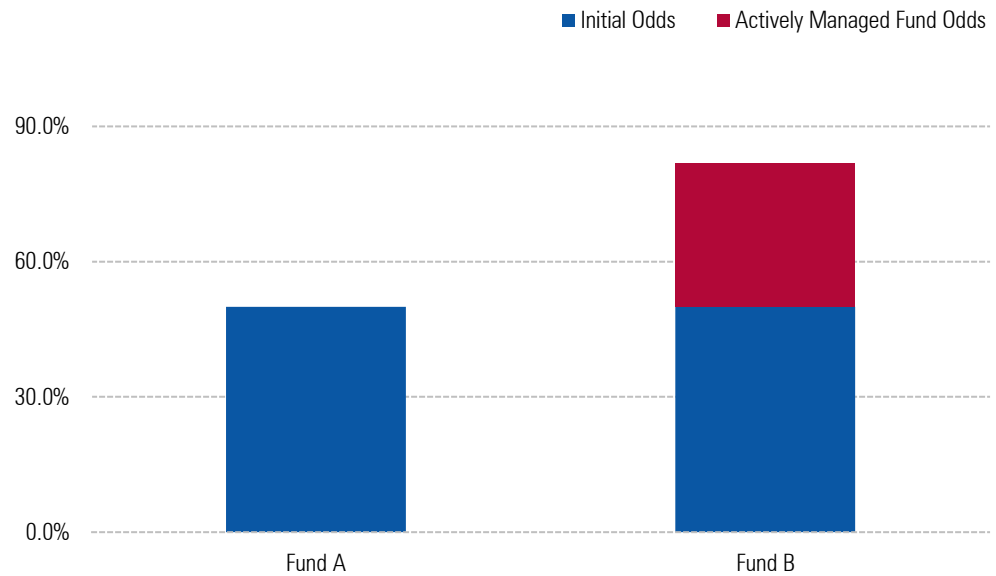
Source: Morningstar, Inc. Data as of June 30, 2016.

In Exhibit 1, the blue bars represent the initial relative odds of each fund closing within 24 months. The 50% odds—or 1:1 odds—mean Fund A and Fund B are equally likely to close. However, our model tells us that this is not true. If the fund is managed actively, then we find such funds are 31.8% more likely to close than index funds within the next two years. The odds of closure are now 1.00:1.32, in favor of index funds. Going forward, we will report these effects by the expected percentage change in odds, so the odds are relative to the 50% or 1:1 norm. For the above example, Fund B is plotted 31.8% above the 50% norm, reflecting a higher likelihood of closure for active funds.

Going forward, we will report the effects by citing the expected change from the 50-50 norm. The exhibits in the rest of this paper will follow the general rule. When odds are positive, the fund exhibiting such a characteristic is more likely to close within the model's time period. Those results are plotted above the X-axis. When odds are negative, the fund exhibiting that trait is less likely to close within the model's time period. Those results are plotted below the X-axis.

Finally, to compare the magnitude of the effects across variables, we will report these effects by citing the maximum change in odds. 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. For numerical variables, where there is no constraint on the input, we will show the change for the increase corresponding to the interquartile range. The corresponding coefficients' multiplication factors used in the exhibits are found in the Appendix.

Key Takeaways

Fund Performance

Fund performance does not forecast full fund closure unless other conditions are met. Let us be unequivocally clear: Poor performance harms investors and the firms running the funds. We are not advocating for the long-term survival of unsuccessful funds. We are, however, stating that it is not poor performance alone that causes fund closures. It is the rippling effects caused by poor performance that cause fund closures. For example, imagine what happens when a bad bout of performance leads many investors to withdraw assets from a fund. Lower and lower asset levels not only reduce fee revenue and increase the costs of running the fund, but require the manager to keep larger levels of cash on hand to meet redemption requests, further affecting performance. It would more likely be the outflows and the continued lack of profitability that would lead a firm to close the fund, but it was all precipitated by poor performance.

How do we see this data play out? Let's take a U.S.-domiciled fund, forecasting over a one-year time horizon. The fund is in the bottom of its category in terms of organic growth rate. Looking at this fact alone, we project that the fund is 30% more likely to become obsolete than the fastest-growing fund in the category. Now, what if we find out the fund is the highest-performing? This fact decreases the fund's survival risk by 58.3%, which more than offsets the closure risk posed by the poorer growth rate. Yet, in reverse, the worst-performing fund is 58.3% more likely to close. So, if the fund is in the bottom-performing ranks, as well as bottom in terms of growth, the effect for the fund compounds, with the closure rate increasing to 88.3%.

The performance metric is only significant when considering its interaction with growth rates. Looking just at performance, the model deems it as not significant on its own. In constructing this study, we utilized a "lasso regression" technique. The main difference between a lasso and the more commonly known "least squares" regression is that the lasso penalizes insignificant variables down to zero. The goal is to minimize variable selection in order to avoid overfitting. Variables that do not contribute to closure are removed. As such, we see our past performance metric eliminated from almost every region and time period forecast. The interaction between performance with fees, growth rates, and management change, however, is informative for fund closure. Therefore, we see that performance alone does not indicate closure. Performance only seems to matter when other conditions are met, such as having low organic growth rates or losing a star manager.

Exhibit 2 Alpha's Effect on Fund Closure

	24 Months	12 Months	6 Months	3 Months
Alpha	—	—	—	—
Net Expense Ratio — Alpha Interaction	-43.7%	-35.8%	-44.6%	-67.4%
Organic Growth Rate — Alpha Interaction	-58.3%	-58.3%	-54.2%	-50.5%
Management Change 24 Months — Alpha Interaction	10.2%	31.2%	—	—

Source: Morningstar, Inc. Data as of June 30, 2016.

Fund Structure

Index funds are less likely to be shut down. This finding is, of course, unsurprising given the success of index funds over the past 10 years. However, it acts as a litmus test for our models. Are we seeing output that is rational? Yes, we expected to find that index funds, on average, have higher rates of survival and therefore are less at risk of closure. Digging deeper in to the results, though, we found the explanation to be a bit more nuanced.

As we consider a fund's survival probability over shorter time horizons, the weight given to an index fund diminishes. If a fund is displaying characteristics of closure in the zero- to three-month time frame, the difference between whether the fund is active or passive is meaningless. Passive investments are essentially at the same risk of closure as an active investment, which means that a firm is equally as likely to shut down an ailing fund in the immediate short term regardless of fund structure. However, as we lengthen the fund's time horizon for survival, index funds are at a much lower risk of closure than active investments.

Let's take an example. As an investor selecting between two comparable investments, the distinguishing factor is that Fund A is actively managed and Fund P is passively managed. Today, Fund A has a 31.8% higher likelihood of closing within two years than Fund P; an 11.1% higher chance of closing over one year; and a 4.0% greater chance of closing over the next six months. Yet, over the three-month time span, both Fund A and Fund P are equally likely to close. The trend of decreasing odds is duplicated in the cross-border, Europe, Middle East, and Africa region as well. In Exhibit 3, we plotted the odds curves through time as a fund nears closure.

The takeaway for long-term investors is that if you are investing in a healthy index fund, there is a higher chance that fund will not be liquidated or merged. Yet, for an index fund exhibiting sickly characteristics, the passive investing strategy will not save the fund from becoming obsolete in the short term.

**Exhibit 3** Index Fund Effects on Fund Closure
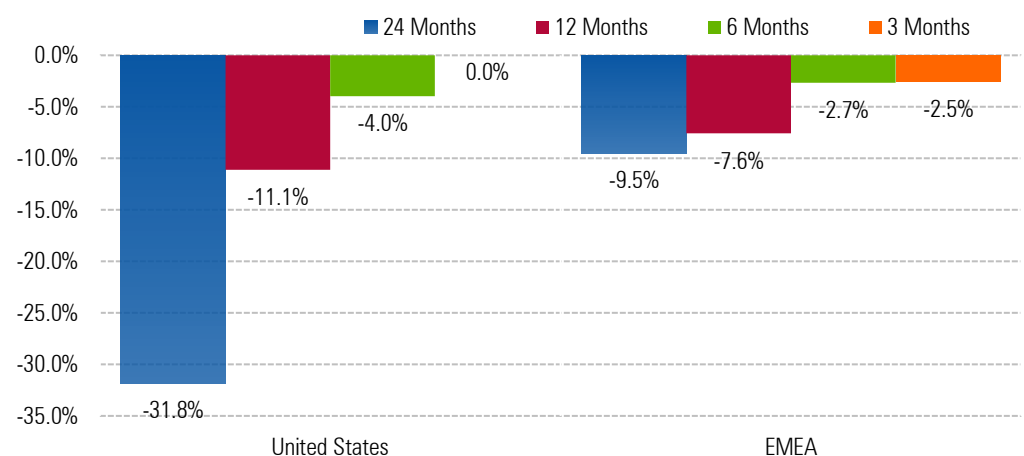
Source: Morningstar, Inc. Data as of June 30, 2016.

The survival rates of socially responsible funds differ by regions. In Europe, the socially responsible mandate lowers the risk of closure for funds. However, the effect reverses in Asia and Canada, and has no effect in the United States. In practice, we see that on a one-year time horizon, the socially conscious mandate decreases the likelihood of fund closure in EMEA by 17.9%, while it increases the odds in Asia and Canada by 29.8% and 23.8%, respectively.

This is the first instance where we see that there are regional variations in factors causing funds to become obsolete. One way to proxy for investor preferences is through fund flows. In a 2015 Morningstar study, Davidson and Strauts found that fund flows differ by region. In particular, investors in Europe have higher preference for SRI funds, as measured by the additional flows a fund receives because of the socially conscious designation in Asia and Canada, funds experienced consistent outflows due to the socially conscious mandate. If in certain markets, SRI funds are popular, then logic would suggest that decreases their odds of closure. If in other markets, SRI funds are unpopular or no less popular, then logic would suggest that increases or has no effect on their odds of closure.

**Exhibit 4** Socially Responsible Fund Effects on Fund Closure
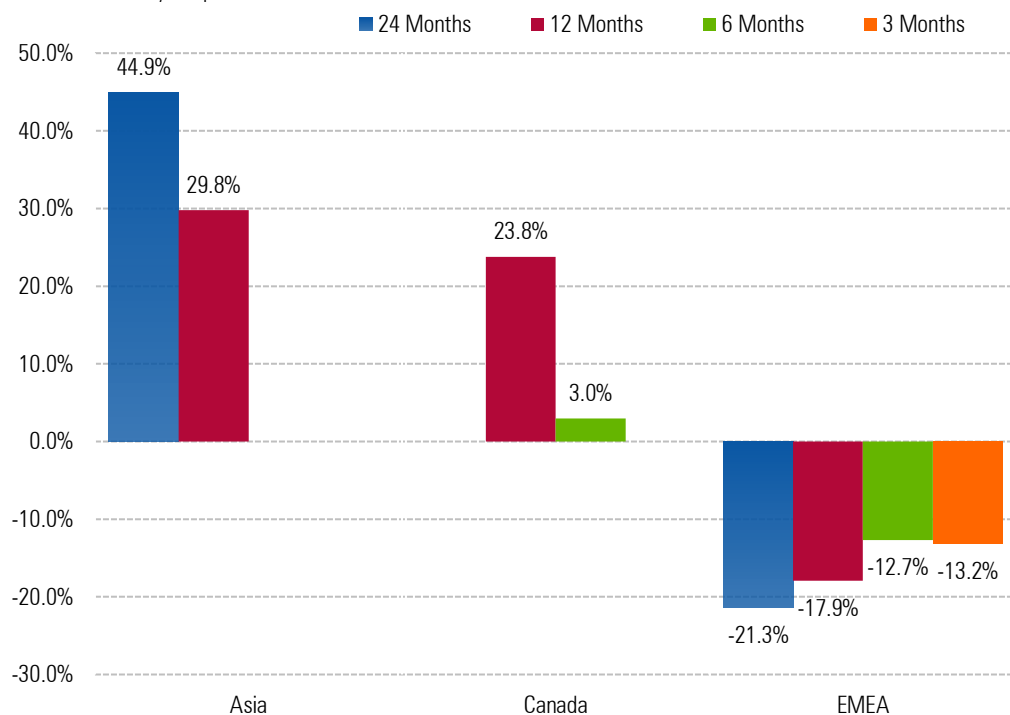
Source: Morningstar, Inc. Data as of June 30, 2016.

Assets Under Management
Unsurprisingly, the smallest and slowest growing funds are at the highest risk of becoming obsolete. Our data suggest that a category's smallest fund is twice as likely to become obsolete as its largest fund. This result is as expected. Funds that do not have enough assets under management cannot generate enough revenue in terms of fees to sustain the fund-management process. A small fund is simply not as profitable as its larger peers. Interestingly, the magnitude of the effects is the same, regardless of region

or time horizon. That is, a category's smallest fund is as likely to close over a three-month time span as it is a two-year time span. In Exhibit 5, we show the relative odds of fund closure, comparing a category's largest fund to the smallest fund.
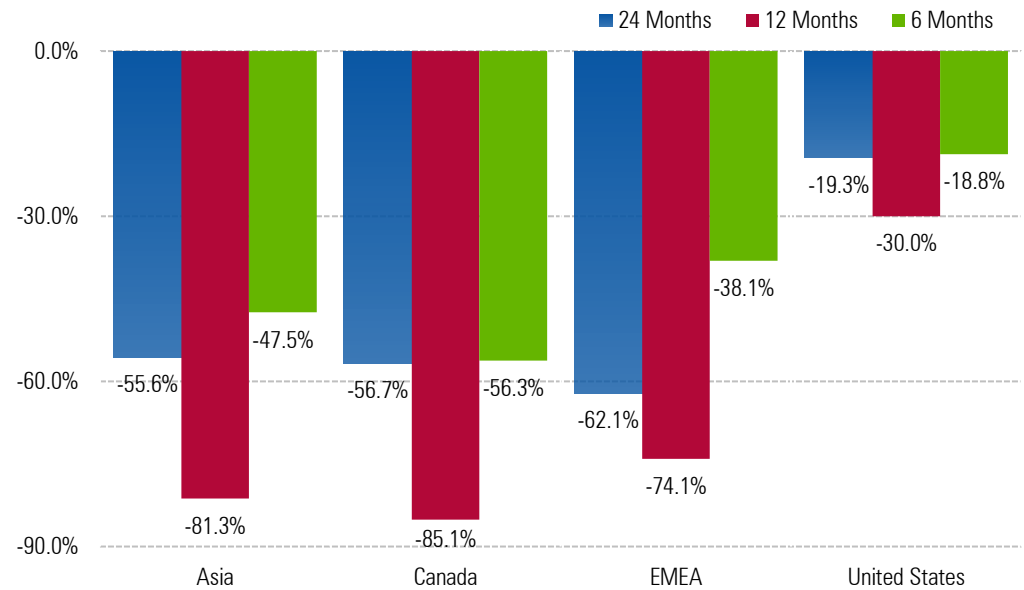
Exhibit 5 Fund Size's Effect on Fund Closure
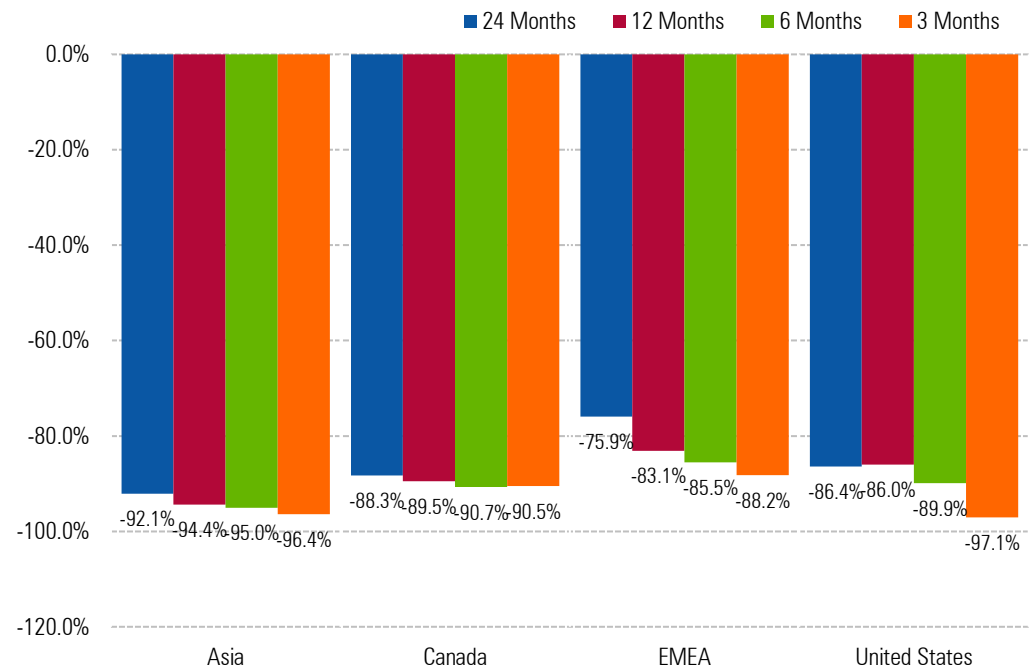
Source: Morningstar, Inc. Data as of June 30, 2016.

While we do not see much variation in the fund size information, fund flows provide differentiated information when forecasting fund closure. When considering whether a fund would shut down on a one- to three-month or four- to six-month time horizon, the organic growth rate is either insignificant or has the smallest effect relative to the other time horizons considered. This makes sense — the time horizon is too short. In most cases, the firm has already decided to shut down the fund and is now in the process of doing so.

Yet, as soon as we expand our length of time to forecast fund closure, we see that the organic growth rate over the trailing 12 months has the largest impact on the odds of survival on the following one-year time frame. This finding holds across all regions. The fastest-growing fund in the category is 81.3%, 85.1%, 74.1%, or 30.0% less likely to become obsolete than the slowest-growing fund in Asia, Canada, EMEA, or the U.S, respectively. The data suggests that when considering winding down unsuccessful funds, historical growth rate information from one year prior weighs more heavily on the decision than more current organic growth information.

Exhibit 6   Organic Growth Rate's Effect on Fund Closure

Legend: ■ 24 Months   ■ 12 Months   ■ 6 Months

Region	24 Months	12 Months	6 Months
Asia	-55.6%	-81.3%	-47.5%
Canada	-56.7%	-85.1%	-56.3%
EMEA	-62.1%	-74.1%	-38.1%
United States	-19.3%	-30.0%	-18.8%

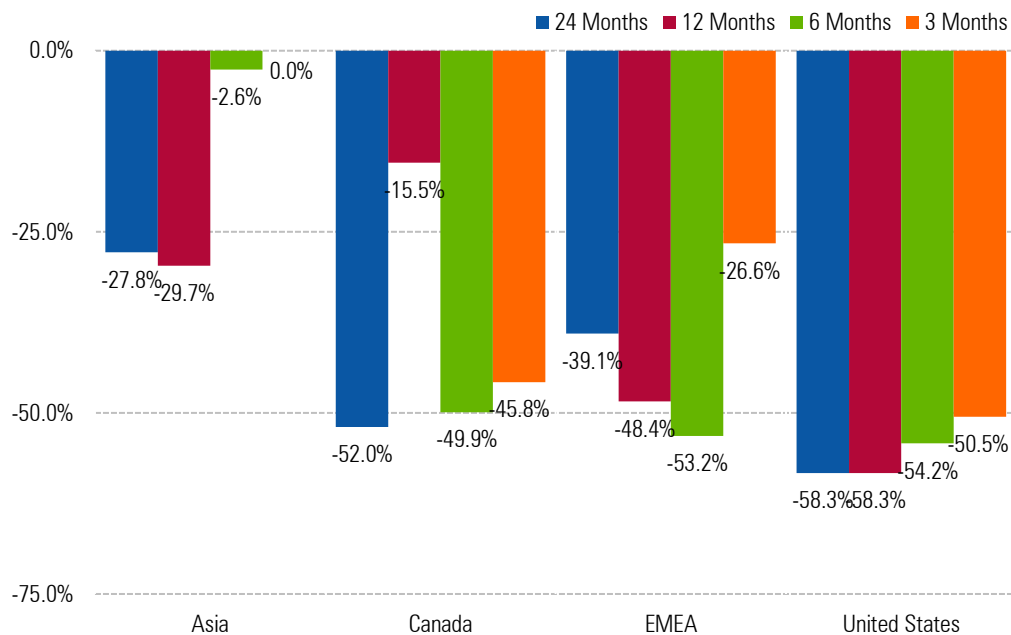Source: Morningstar, Inc. Data as of June 30, 2016.

Managers with skill can change firm decision-making. Clearly, we expect to and do see funds with low levels of AUM and those experiencing weaker organic growth rates closing at a much higher rate than peers. But it's reasonable to ask whether a highly skilled manager could overcome this situation and cause firms to alter their perceptions about a fund's prospects. We expect that the firm must consider the manager's skill as a forward-looking metric when determining their ability to attract assets in the future. To test this hypothesis, we constructed an interaction term between organic growth rates and a manager's level of alpha. Finding a negative relationship here would signify that highly skilled managers are granted extra leniency by firms, lowering the risk of fund closure, even when they are managing funds with low organic growth rates. Indeed, we find, for all four time periods and regions, that a high level of historical alpha can offset a fund's risk of closure due to low growth rates.

Prior to this study, we knew growth rates would be a meaningful factor in determining whether a fund is kept alive. Yet, we did not know the extent of the relationship that exists between the value a manager adds, the potential for asset growth, and ultimate fund survival. Would a firm keep a low-growth fund that is generating a lot of alpha? Or would the firm disregard the fund's level of alpha when deciding to wind down a strategy?

We interacted the two terms: category relative alpha and category relative growth rate. Our results suggest, for a given level of organic growth, higher alpha funds decrease the risk of becoming obsolete. The results make sense. Fund size and fund flows are one aspect of a fund, but the skill of the management team is another. The decision to wind down a fund is more nuanced than relying simply on organic growth rates. Firms make decisions about fund survival by looking at factors in combination with each other. Managers who are not adding value to investors and cannot attract assets should not be

kept around. The market is responding to unskilled managers by eliminating these funds from the investable universe at a higher rate than skilled managers.

Exhibit 7   Organic Growth Rate and Alpha Interaction's Effect on Fund Closure

Source: Morningstar, Inc. Data as of June 30, 2016.

By region, the size and type of firm plays a different role in predicting fund closures. Within a region, we find minimal variation for closure rates, across time horizons, for a given firm. That is, the firm's characteristics do not change the likelihood a fund will shut down within the next zero to three months or the next 13-24 months. Instead, we find the firm's structure varies the likelihood of fund closure by region. That is, certain firm characteristics can increase survival rates in one region but decrease survival rates in another.

To test for the role a firm plays in fund closures, we first tested the size of the firm. Our hypothesis was that larger firms can easily shut down funds without significant implications to their business. As a thought experiment, consider a small fund shop with five funds with equal assets. Closing one removes 20% of its source of revenue. A large firm, by contrast, might shut down funds more readily because the marginal cost of doing so is lower. We only find this hypothesis to be true in the U.S. A U.S.-domiciled fund, from the category's smallest firm, is on average, 17.4% less likely to become obsolete than the fund from the category's largest firm. However, this is not the case in Europe or in Canada — in fact, it's the opposite. The same fund is 11.9% and 59.8% more likely to close, respectively.

We believe the main drivers for these differences across regions are due to the differing distribution practices of mutual funds. In the U.S., wealth managers operate their own fund platforms composed of funds from a variety of asset managers. In Europe and Canada, however, the asset managers and wealth managers are more vertically integrated. For example, consider the European-domiciled firm

UBS. During 2016, approximately 28%[1] of the firm's flows for its asset-management business came from UBS wealth management. Captive firms like UBS are much less enticed to shut down unsuccessful funds if the wealth-management division has assets in the fund. In this case, it is easier to do nothing than to close the fund and move the clients' money somewhere else.

It is important to note: We were only able to test firm size, not whether a firm is vertically integrated due to the lack of clean data regarding distribution. However, we surmise there is significant correlation between the largest firms in Europe and Canada and the captive distributors.

Exhibit 8 Firm Size's Effect on Fund Closure
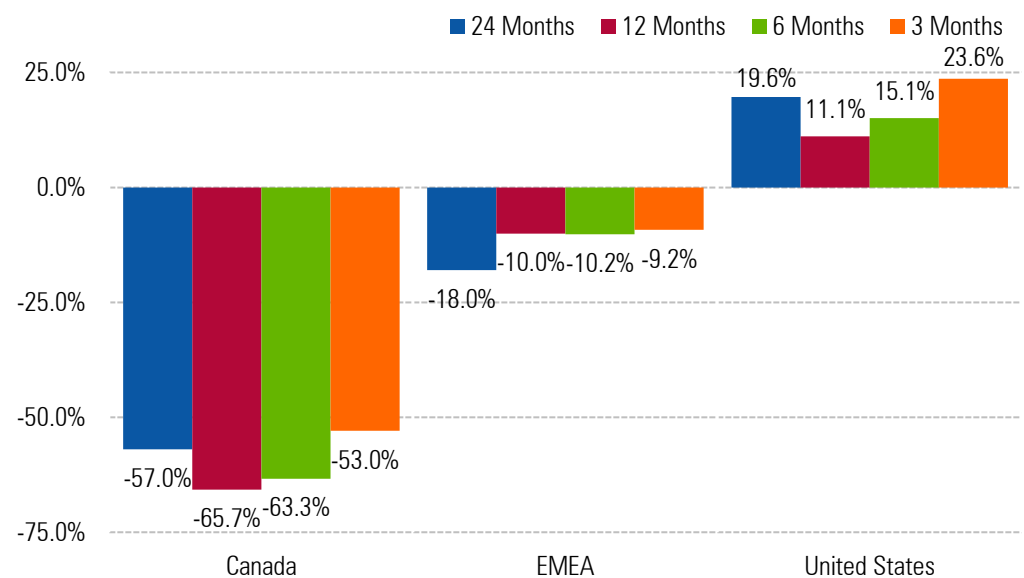
Source: Morningstar, Inc. Data as of June 30, 2016.

Popularity Measures

Firms with a history of shutting down funds will continue to do so. The second firm characteristic tested was the fund-closure rate. We calculated this metric by dividing the number of a firm's obsolete funds by its total number of funds opened. Each month we recalculated the percentage based off of all historical data made available to us. Since our data begins in 2006, this number does not account for funds that both opened and closed prior to the study. However, this is a sufficient approximation of a firm's ability and willingness to keep funds around.

Unsurprisingly, a fund from a firm that historically shuts down a lot of funds is at much higher risk of closure than a fund from a firm with more patience. This applies across regions and time horizons. Interestingly, excluding the U.S, the firm-closure rate's effect has a greater ability to forecast fund closure over shorter time horizons. The converse is true in the U.S., where the firm-closure rate is more correlated with closures over a two-year time horizon.

1 https://www.ubs.com/content/dam/static/epaper/index.html?id=5f49e3ac

In the short term, a fund from the firm with the highest rate of closure is 61.9%, 49.0%, or 42.3%, more likely to close in Asia, Canada, or the EMEA, respectively, but only 10.3% more likely to close in the U.S. However, in the long term, the same fund's odds of closing are 35.2%, 12.3%, 6.3%, and 45.4% higher in those respective regions.

Again, this could have to do with the ease of closing funds regionally. In the U.S., it has been historically very difficult to close a fund. As such, the time to closure—the time at which the fund-management team has recognized a fund should be shut down to completion—tends to be longer in the U.S. than elsewhere around the world. Even so, the data overwhelmingly suggest that on a global basis, firms with historically high rates of closure are likely to continue to shut down more funds in the future.

**Exhibit 9** Firm-Closure Rate's Effect on Fund Closure
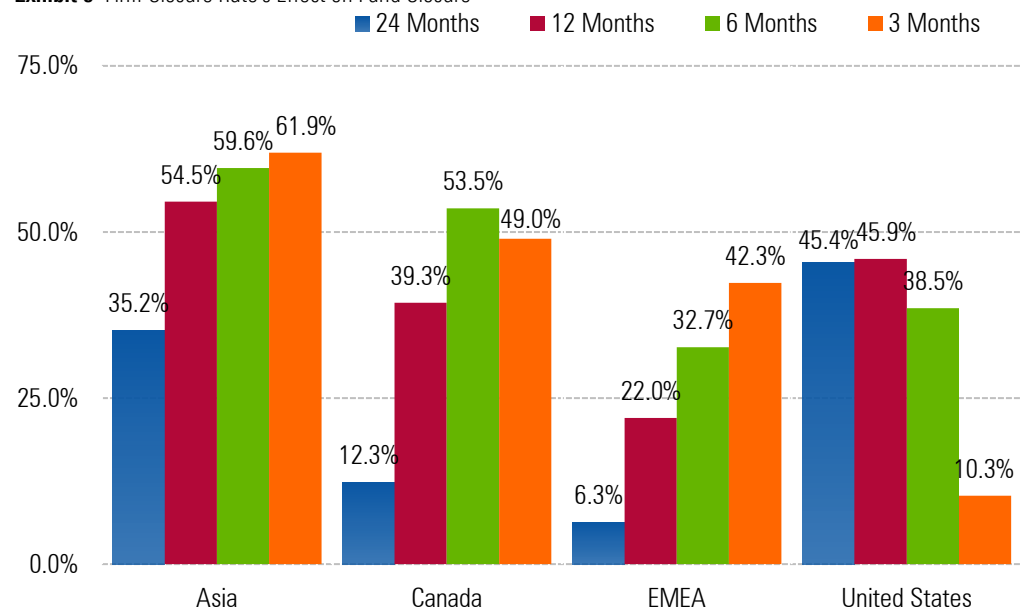
Source: Morningstar, Inc. Data as of June 30, 2016.

A high closure rate may identify the bad firms, the firms who seem to be unable to launch successful products. However, firm closure does not tell the whole story. An asset manager that rapid-fires off 12 new products in year, with hopes of keeping eight alive, would have the same closure rate as a similarly sized firm that launches four new funds but only manages to keep three of them going after a year. Since we are looking only at rates of closure, we are not identifying differences between firms that saturate the market with new funds versus those that pursue a more thoughtful approach. In all likelihood, the firm that can launch a multitude of funds is large, which has been controlled for through firm size. As for the firm following the more thoughtful approach, our model is less likely to pick up on what we assume would have been a longer vetting period, strong processes, and more patience on the part of the parent to keep these funds running longer-term, the combination of which indicates higher quality and lower risk of closure. Thus, perhaps firm closure is best used in conjunction with another firm stewardship metric.

Funds in categories with high historical rates of fund closure are more at risk of closure. Similar to the firm-closure variable, we calculated a category closure rate. In a similar fashion, we calculated this metric by dividing the number of funds that became obsolete while in the category by the total number of funds in the category. Since our study begins in 2006, this metric does not include funds that opened and closed prior to the study, nor does it count funds that entered the category but subsequently changed prior to 2006. Again, this is a sufficient approximation of the category's ability to sustain funds.

A category's closure rate increases a fund's risk of closure only in the U.S. and Asia. Within the subsequent six months, a fund from the category that closes down funds the most is 108.3% (U.S.) and 66.7% (Asia) more likely to close than a fund from a category that has closed funds the least. Elsewhere, we found no effect. As such, we only include results from Asia and the U.S. in Exhibit 10.

**Exhibit 10** Category Closure Rate's Effect on Fund Closure
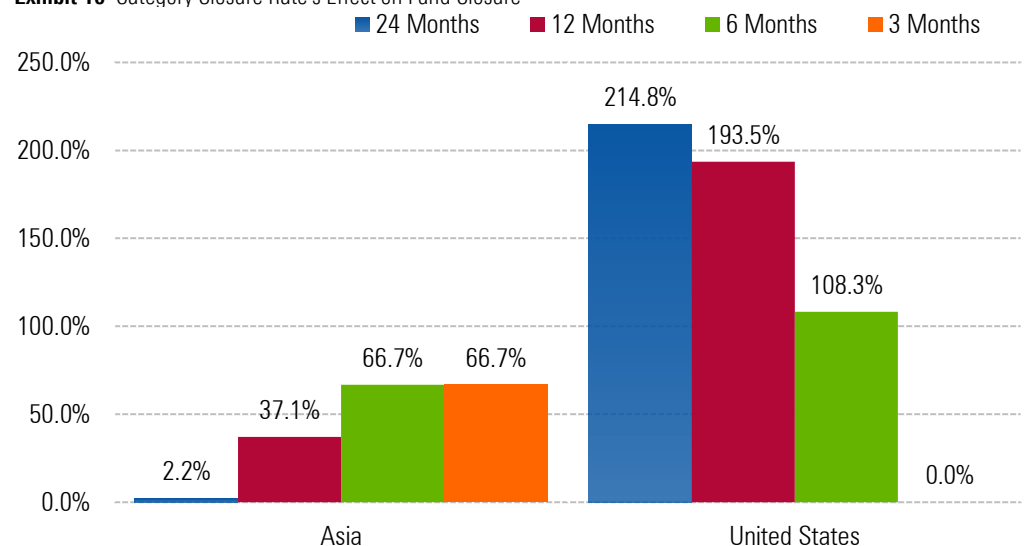
Source: Morningstar, Inc. Data as of June 30, 2016.

As shown above, the effect is the largest in the U.S., which is perhaps more of a reflection that the Morningstar Category system is the more robust and homogenous, than anything else. To examine the U.S. data further, we plotted the closure rates as of June 30, 2016 (the end date for our 10-year study), for the categories with the 10 highest and the 10 lowest rates. Our main takeaway was that allocation and target-date categories close the fewest funds. This was as expected. These funds are designed to be around until they meet their target date, which can be many decades or half a century away. While almost all of these funds are fund-of-funds, the data does not suggest anything about the closure rates of the underlying funds held by the target-date funds — simply that the wrapper funds are far less likely to close.

Exhibit 11 Category Closure Rate
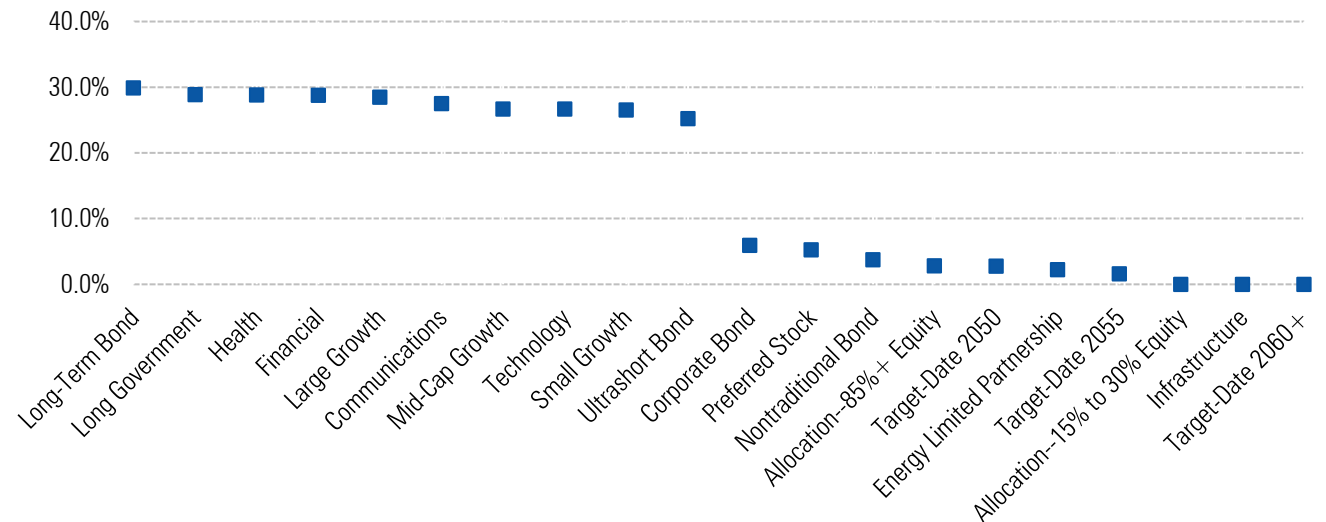
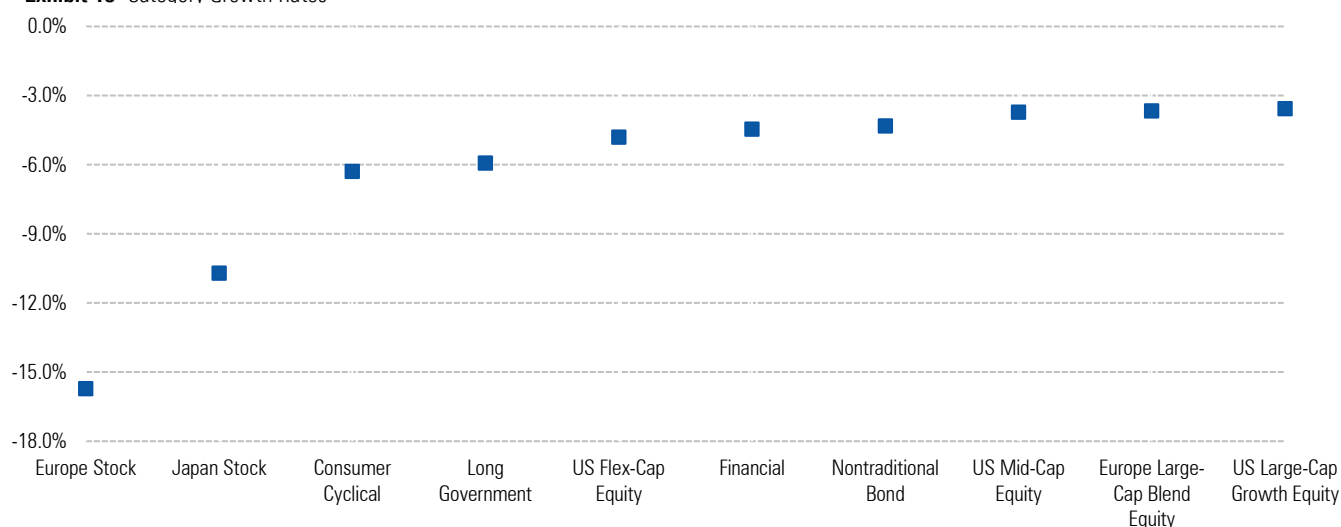Source: Morningstar, Inc. Data as of June 30, 2016.

The fastest-growing categories are less likely to shut down funds. This effect holds across region and time horizon. Within the next four to six months, a fund from the fastest-growing category in Asia, Canada, EMEA, or the U.S., is 20.1%, 27.3%, 25.5%, or 63.2%, respectively, less likely to shut down than the slowest-growing category. This effect persists over the longer time horizons as well. The respective increases in fund closures are 38.4%, 42.9%, 46.7%, and 26.6% less likely to shut down over the next one to two years. Overall, a category's popularity with investors has a greater effect on fund closure than the category closure rate. We see this as the result of the category's popularity being more persistent across regions and time frames than the category closure rate.

Exhibit 12 Category Growth Rate's Effect on Fund Closure
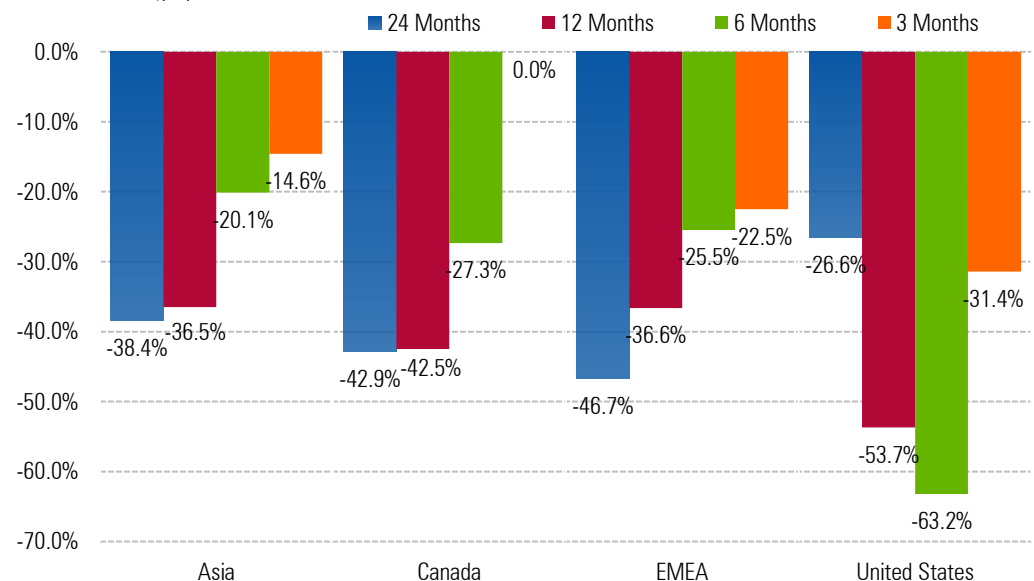
Source: Morningstar, Inc. Data as of June 30, 2016.

The category growth rate is an aggregate measure of fund flows in or out of a category. While we understand the effects of flows on a particular fund, category flows play an additional role, as many firms use them as a benchmark for investor preferences. Flows into a specific fund are a testament to how well that particular fund is doing. Flows into a specific category indicate how that that particular area of the market is doing. Therefore, a fund with the largest organic growth rate could still have a high probability of closure if it is in an unpopular category. This effect can stay with a fund for the following two years. For the benefit of the reader, we plotted the 10 slowest-growing U.S. categories by their growth rates.

Exhibit 13 Category Growth Rates

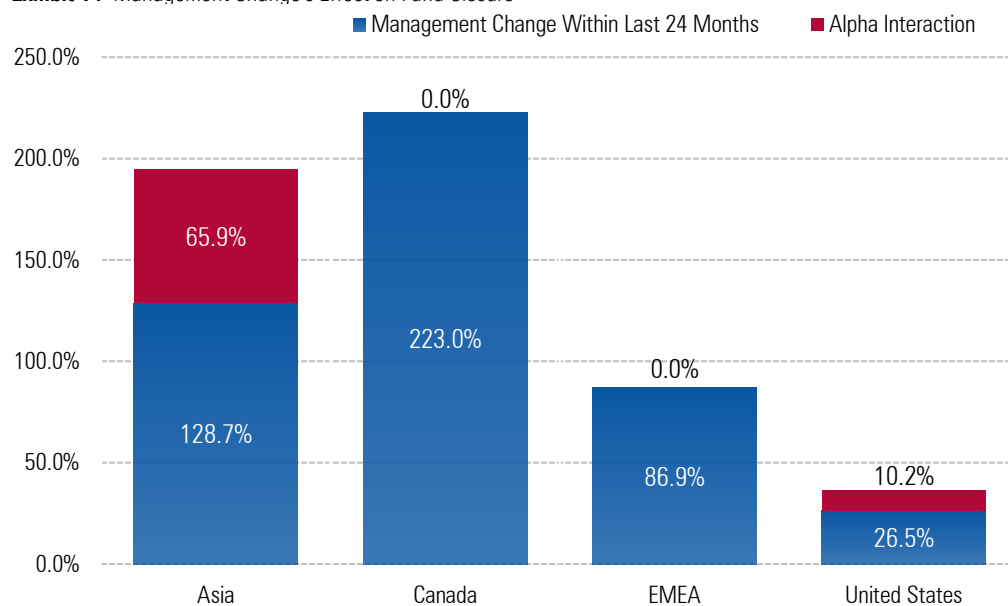Source: Morningstar, Inc. Data as of June 30, 2016.

Fund Management

Management changes forecast fund closure. A fund-management change is highly indicative of a fund closing, regardless of region. We defined a change as the addition or removal of a manager to the management team, irrespective of the individual manager's characteristics, such as tenure, firm position, or gender. We tested this over three distinct time horizons: zero to six months, six months to one year, and one to two years prior to the time period tested. For all regions, the effects of each were meaningful.

In the short term, management changes within the past one to six months, or six months to one year, do forecast fund closing on a three- or six-month time horizon. Exhibit 14 displays a matrix listing the regions, fund-closure time horizons, and the relative likelihood of fund closure. Intuitively, such findings may be statistically significant but not surprising. A fund company knows it is in the process of shutting down a fund six months prior to closure. Therefore, they are more likely to reallocate the time the managers of this fund would normally spend on it to more important tasks. For example, the Fidelity European Aggressive fund was merged with the Fidelity European Dynamic Growth Fund, effective July 17, 2015. However, the Dynamic Growth fund manager took over the reins of the Aggressive fund in October 2014, nine months before the merger. As a secondary example, Manning & Napier Focused

Opportunities shut down on Jan. 25, 2016. Yet, it removed its managing director from the fund management team the previous May. A fund management change within the prior year may not seem interesting, as the fund has already reported that the fund will be liquidating or merging at a predetermined date in the near future.

Exhibit 14 Management Change's Effect on Fund Closure

Source: Morningstar, Inc. Data as of June 30, 2016.

In the long term, what is more interesting—and may be more indicative of an unforeseen fund closure—is a management change within the previous 12 to 24 months. Funds in Asia, Canada, EMEA, or the U.S. are 128.7%, 223.0%, 86.9%, or 26.5%, respectively, more likely to close within the next two years.

To make matters worse, the effect of management changes on fund closures depends on the skill of the departed manager. Losing a high-alpha manager further exacerbates the likelihood of closure by 65.9%, 26.7%, 0.0%, and 10.2%, for Asia, Canada, EMEA, and the U.S., respectively. The message to investors should be clear: If a highly successful manager leaves a fund, there is a much greater likelihood that the fund will experience a raft of problems and may shut down over the next several years, as the task to replace him/her is quite difficult.

Overall, it would appear that adding or removing a manager is a last-ditch effort for a firm to looking to revive an unsuccessful and likely-to-be-liquidated fund. Certainly, there could be a turnaround, and there are plenty of examples where a change in management has led to higher returns and continued flows of assets into the fund. However, the data show that on average a manager change is a sign of a failing fund. A highly successful manager leaving only strengthens the signal of fund closure.

In the U.S., mixed-gender teams navigate funds better. As previously stated, understanding the role that the fund manager plays in relation to a fund's survival is of primary interest. In a simplified look at the data, we generated high-level statistics regarding male and female fund managers. Historically, on average, 20% of fund closures are from mixed-gender or all-women-run funds. This number is in line with the percentage of funds that have women on the management team. In aggregate, without implementing any controls, we see in Exhibit 15 that the rates of closures for both men and women are roughly parallel to the percentages of funds they cover.

Our study takes a deeper dive into the data, adding controls for areas of the industry where women are more likely to run funds, and for characteristics likely leading to fund closure. We looked at two measures: whether the fund is run by both men and women, and whether the team is run by all women. Testing these two values gives us the comparison for looking at funds run by all men. Finally, we look across regions to see how mixed-gender and all-female teams fare in terms of closure.

Our model found that mixed-gender teams are more likely to survive the next four to six, seven to 12, and 13 to 24 months, than funds run by teams of a single gender, but did not have an effect on the zero- to three-month time horizon. The data suggests a more diverse set of people, on average, do a better job navigating funds away from closure, than all-male or all-female teams. After all other considerations, such funds survive at a faster rate. The finding lines up with research into new funds where mixed-gender teams found a benefit in terms of higher flows (Davidson, Sargis, Strauts, 2016).

On the other hand, the indicator flagging teams run by only women is not significant in our regression, for both time periods. However, we find fund of funds, index funds, and socially responsible funds are all less likely to become obsolete. Prior research (Sargis & Lutton, 2016) suggests that these are characteristics associated with higher rates of funds with women at the helm. Therefore, our data indicates that after we have controlled for types of funds that women are more likely to run, there is no additional effect on the likelihood of fund closure because the fund manager is a woman.

Our final finding has a meaningful implication. After considering a manager's skill, the profitability of the fund, and a host of fund structure characteristics — region, fund age, index fund, socially responsible fund, fund of funds — funds run only by women are no less likely to be shut down than if they were run by men. The data suggests women and men are given the same time period to turn around a fund or prove success. With respect to fund closures, a bias by gender does not seem to exist.

Exhibit 15   Mixed-Gender Management Team's Effect on Fund Closure
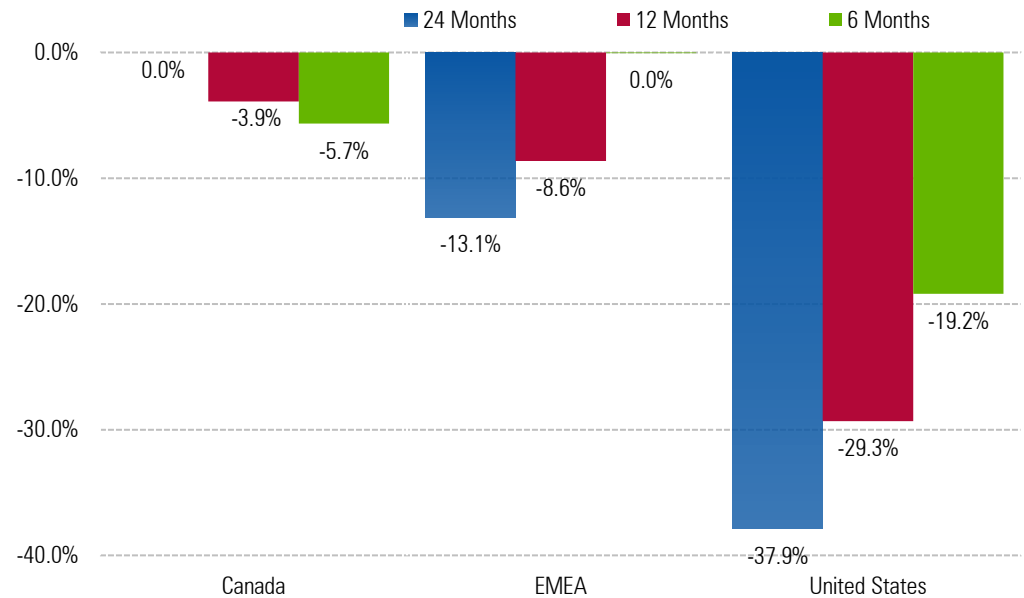
Source: Morningstar, Inc. Data as of June 30, 2016.

Factors Not Affecting Fund Closure

In the U.S., high-fee funds, all else equal, have been less likely to close than lower-fee funds. At first glance, this seems wrong. But let's think about who is actually in charge of the process of closing down funds — whether they are being liquidated or merged into other funds — in the U.S. Shutting a fund down is time-consuming, painful, and costly. Before a mutual fund's board can decide whether to approve closing or merging a fund, they must analyze the effects of a closure on each class of shareholders. Legal must then draft and file the appropriate documents for a closure/merger. Marketing has to inform shareholders, and public relations must manage any associated press. All internal employees supporting the fund's daily operations need to find new responsibilities to replace the work previously occupied by the now-obsolete fund. All these actions are additional expenses occurred by the firm responsible for shutting the fund down.

So why do high-fee U.S.-domiciled funds stay open, controlling for all else being equal? If a fund is unsuccessful, investors can vote with their feet and exit a fund on their own. Yet, afterwards, if a high-fee fund still has enough AUM to maintain profitability, why would the firm willingly sustain the costs to shut down a fund? A high-fee fund is more likely to generate income for the fund than a low-fee fund, especially after holding growth rates and assets constant. Therefore, the lower risk of closure for a more-expensive fund makes sense. The firm may not market it, sell it, or put much effort into maintaining the investment strategy, but they will be less prone to shut it down. As a result, more high-fee funds are kept open, after all else is considered.

Exhibit 16 Fee's Effect on Fund Closure
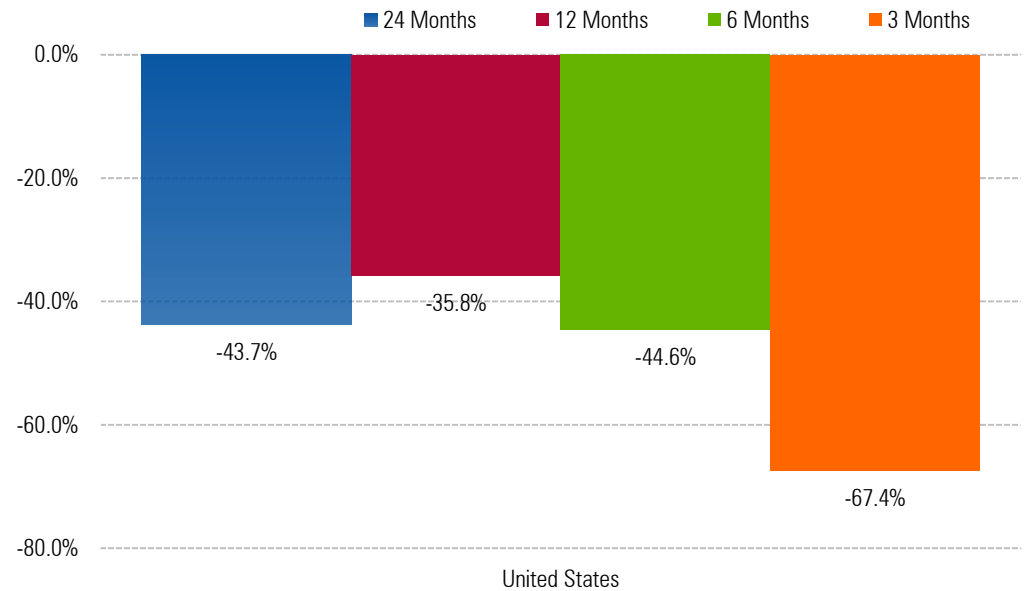
Source: Morningstar, Inc. Data as of June 30, 2016.

Model Application

As described above, the models we developed produce the relative weightings we should assign for fund, firm, and category attributes to determine a fund's probability of closure. With this information, we can see how current funds fare. We will apply the model in three applications. First, we will look at two funds with different characteristics to see how their probabilities differ when forecasting fund closure over the next 24 months. Second, we will look at one fund and how the probabilities change when forecasting over three months up to two years. Third, we will look at one fund historically and see how the probability of closing over 24 months has changed through time.

Example 1: Two Funds, Time Horizon, 24 Months

Our model decomposes the closure risks for funds into interpretable factors. Within the next 24 months, Fund A has a 20% probability of closure while Fund B has only a 1% chance. Assume that factors not listed are held constant.

For Fund A, the main sources of risk stem from the low AUM, low alpha and growth-rate interaction, and coming from a firm that has historically closed more than one third of its launched funds. Offsetting those closure risks is the fund's above-average growth rate.

Fund B is not at risk of closure, thanks to its better-than-average growth rate, large assets, and being in a popular category. Furthermore, the fund is managed by both men and women, which has been shown to reduce closure risk.

Exhibit 17 Probability of Fund Closure — Comparison of Two Funds

	Mixed-Gender	Firm Closures (%)	Category Closures (%)	Category Growth Rate (%)	Fund Assets (% Rank)	Firm Assets (% Rank)	Growth Rate (% Rank)	Alpha (% Rank)	Growth Rate and Alpha	Probability of Closure 24 Mo
Fund A	0	31	22	32	3	30	53	8	424	20
Fund B	1	12	12	72	89	72	64	39	2496	1

Source: Morningstar, Inc. Data as of June 30, 2016.

Example 2: One Fund; Time Horizon, 3 Months to 1 Year

Our model generates forecasts of fund closure over three months, six months, one year, and two years. In the short-term, Fund C has a 1% probability of closure in the next three months, and that increases over the time horizon. There is a 10% chance that the fund will close within the next two years.

The model looks at the information available today and weights factors differently based on their historical correlation to fund closures. Two main factors are increasing Fund C's risk of closure. First, the fund is domiciled in Europe and does not have a socially conscious mandate. Second, the fund experienced a management change within the past 12 months. The model tells us that neither of these two factors will cause a fund to become obsolete in the short term, as evidenced by the low three-month probability score. However, in the long term, both of these signal that this fund is at an increased risk of closure, as evidenced by the higher two-year probability score.

Exhibit 18 Probability of Fund Closure — Multiple Time Horizons

Fund C										
Region	SRI	Manager Change 12 Mo	Growth Rate (% Rank)	Firm Assets (% Rank)	Firm Closures (%)	Category Growth Rate (%)	Probability of Closure 24 Mo	Probability of Closure 12 Mo	Probability of Closure 6 Mo	Probability of Closure 3 Mo
Europe	0	1	41	69	18	46	10	4	2	0

Source: Morningstar, Inc. Data as of June 30, 2016.

Example 3: One Fund, Historical Probability Scores; Time Horizon, 24 Months

The model we developed can be recalculated each month and then applied to generate an updated forecast on a fund's likelihood of survival. In July 2006, Fund D's probability of closure was 3%, but by June 2016, this had increased to 20%.

In Exhibit 19, we see how the life cycle of Fund D is interrelated to the success of its firm. Since 2006, the firm has been downsizing, both in terms of AUM and the number of funds run, as shown by the increasing closure rate. The fund, while still growing, is being outpaced by the rest of the category. By June 2016, the fund is one of the category's smallest. During this time, it is steadily becoming more

expensive relative to its peers. While the signals point to the fund closing, the firm has a lower probability of closure than otherwise, because the firm appears to be hanging on to the fund to generate revenue.

Exhibit 19 Historical Probability Scores of Fund Closure

Fund D									
Date	Expense Ratio (% Rank)	Alpha (% Rank)	Growth Rate (% Rank)	Fund Assets (% Rank)	Firm Assets (% Rank)	Firm Closures (%)	Category Closures (%)	Category Growth Rate (%)	Probability of Closure 24 Mo
7/31/2006	41	32	47	33	72	0	0	26	3
6/30/2007	42	21	35	31	69	0	4	50	4
6/30/2008	41	30	36	29	70	3	10	64	5
6/30/2009	40	82	12	26	67	9	15	38	8
6/30/2010	38	25	22	21	62	12	17	53	10
6/30/2011	40	28	35	17	61	13	18	38	11
6/30/2012	44	78	11	18	54	14	21	39	12
6/30/2013	46	73	7	13	49	15	24	47	16
6/30/2014	47	1	40	11	51	18	24	28	18
6/30/2015	52	8	26	9	51	19	25	40	19
6/30/2016	57	31	29	7	47	20	27	26	20

Source: Morningstar, Inc. Data as of June 30, 2016.

Conclusion

Our study sought to explain factors leading to fund liquidations and mergers. By identifying characteristics forecasting fund closure, we can better recognize those funds that should be closed down but are currently still alive. In doing so, we can help investors filter out the bottom portion of the investable universe for individuals looking for long-term investment vehicles.

The main conclusion of our paper is simple. Funds become obsolete because they do not generate enough value for their investors and do not have enough assets to sustain the operational costs of running the fund. Investors should be wary of such funds currently exhibiting those characteristics. Popularity, on the firm and category level, plays an outsized role in dictating fund survival. Furthermore, we examined the role of the management team in fund closure. Any change at the management level forecasts fund closure. Globally, we find that funds run by men survive at no different rates than funds run by women, all else equal. Mixed-gender funds increase the rate of fund survival. The implication suggests that in terms of fund closures, male and female portfolio managers are held to the same standard.

The outcome of this study coalesces around one central point: The fear of closure may be misplaced. For investors, fund closure itself is not the problem. It is events preceding closure—the outflows, the liquidations, the underperformance—that harm investors. Furthermore, this paper is evidence that fund closures are forecastable. Funds leave a trail of signals that closing down the fund is inevitable. These signals start appearing six months to two years out, perhaps even longer.

Therefore, the headache an investor faces is not closure itself, but deciding whether to act on the information that a fund closure is pending. Acting means they must replace the fund. Not acting means they ride out the looming fund liquidation. Either option has unavoidable consequences. Mergers will likely alter the portfolio's investment allocation. Replacing the funds will result in due-diligence costs. Liquidations will cause a hefty tax bill and a period of sustained underperformance. By identifying that fund closures are systematic, long-term investors cannot leave their portfolio unattended. They must monitor their portfolio for these fund-closure signals.

The outcome of this study leads us to two new research topics. First, now that we have uncovered a model forecasting fund closure, can we identify a next-best alternative? By doing so, we can ease the due-diligence costs associated with replacing obsolete funds.

Second, now that we know a management change is one of the strongest signals for obsolete funds, can we forecast management change? Does manager change affect performance? If so, for how long does a manager change affect outcomes?

We expect to address these questions in the future.

Appendix

Data

Our study relied on Morningstar fund data sources. The sample period began in July 2006 and ended in June 2016. Over the entirety of the sample, 87,293 unique funds were included. Monthly fund counts ranged from 38,482 to 57,579, with recent periods having higher counts. Our sample included funds in multiple broad asset classes—balance fund counts ranged from 7,465 to 13,827; equity 21,631 to 29,434; and fixed-income from 9,455 to 14,747. In June 2016, our sample spanned a total of 57,467 funds.

Because we are interested in fund characteristics, we rolled up share-class data to the fund level. For funds providing complete asset information for all share classes, we calculated the asset-weighted variables. For those funds where complete asset information was not available, we computed equally weighted variables.

Since our study focuses on forecasting fund closure, we excluded two sets of funds. First, we omitted funds from firms with less than $1 billion in AUM. Second, we excluded funds structured to merge or liquidate at a predetermined date. Investors in such funds know when their investment will roll over into a new fund or be returned. These funds have a specific shelf life, rather than expiring due to market forces, and therefore will muddy the results. A majority of these funds are classified as cautious allocation. Therefore we excluded the cautious allocation Morningstar Category.

Our sample of funds did 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 incorporated monthly changes in fund-universe composition, providing a more holistic and realistic picture of historical performance. Each monthly snapshot captured any funds that were subsequently merged or liquidated away.

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 their Morningstar Category. Integer 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

Three-Month Survival

This is a categorical, dummy variable that indicates whether a fund survives the following three months.

Four- to Six-Month Survival

This is a categorical, dummy variable that indicates whether a fund survives the following four to six months.

Seven- to 12-Month Survival

This is a categorical, dummy variable that indicates whether a fund survives the following seven to 12 months.

13- to 24-Month Survival

This is a categorical, dummy variable that indicates whether a fund survives the following 13 to 24 months.

Independent Variables

Alpha and Beta

We run rolling 12-month CAPM regressions of a fund's return onto the category average return. All returns are in U.S. dollars, include dividends and capital gains, and are not continuously compounded.

The regression rolls monthly — providing a set of factor betas, alpha, and R-squared each month estimated from the prior 12 months' experience. The regression takes the form:

$$r_{i,t} = \alpha_i + \beta_i^{rmcatavg} RMCatAvg_t + e_{i,t}$$

To estimate a fund's alpha and beta, we require 12 months of return history. For those funds that do not have 12 months of return history, they will not have their own set of factor betas, alphas, or R-squared. In this case, we impute the Morningstar Category average value by date. Once the fund passes the 12-month mark, we stop the imputation.

All-Women Management Teams

This is a categorical, dummy variable that indicates whether the fund management team includes only women.

Category Closures

This is a numerical variable indicating the rate of fund closure within a category. The calculation is the number of funds closed within a category since 2006, divided by the number of funds alive in 2006, plus any subsequent incepted funds.

Category Growth Rate

This is a numerical variable indicating the average growth rate of assets into a category. The data is standardized into percentiles. 100 indicates the fastest-growing category in the fund universe, while 1 indicates the slowest-growing category on that date.

Firm Assets

This is a numerical variable indicating the size of fund's firm. The data is standardized into percentiles by category and date. 100 indicates the fund is from the largest firm in the asset class, while 1 indicates the fund is from the smallest firm in the asset class on that date.

Firm Closures

This is a numerical variable indicating the rate of fund closure at a firm. The calculation is the number of funds a firm has closed since 2006 divided by the number of funds alive in 2006 plus any subsequent incepted funds.

Fund Age

This is an integer variable indicating the number of months since the fund's inception.

Fund Size (AUM)

Fund size or AUM is measured as the fund's total market value of investments in U.S. dollars. The variable is placed into percentiles by date and category. Because the percentiles are left-skewed, it is necessary to square-transform it. When we refer to AUM in relation to odds, we are referring to the square odds of AUM.

Fund of Funds

This is a categorical, dummy variable that indicates whether 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).

Index Fund

This is a categorical, dummy variable that indicates whether 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.

Manager Change Zero to Six Months

This is a categorical, dummy variable that indicates whether there has been a fund management change within the previous six months.

Manager Change Six to 12 Months

This is a categorical, dummy variable that indicates whether there has been a fund management change within the previous six to 12 months.

Manager Change 12 to 24 Months

This is a categorical, dummy variable that indicates whether there has been a fund management change within the previous 12 to 24 months.

Manager Change 12-24 Months—Alpha Interaction

This is a numerical variable that interacts whether the fund had a management change within the last 12-24 months with the fund's alpha. To calculate this variable, we multiple the fund's manager change 12-24 months variable and the fund's alpha category percentile.

.

Mixed-Gender Management Team

This is a categorical, dummy variable that indicates whether the fund management team includes both men and women.

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 U.K. 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 the 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:

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

Net Expense Ratio — Alpha Interaction

This is a numerical variable that interacts the fund's expenses with the fund's alpha. To calculate this variable, we multiple the fund's net expense ratio category percentile and the fund's alpha category percentile.

Organic 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.

Organic Growth Rate — Alpha Interaction

This is a numerical variable that interacts the fund's growth rate with the fund's alpha. To calculate this variable, we multiple the fund's organic growth rate category percentile and the fund's alpha category percentile.

Socially Responsible Fund

This is a categorical, dummy variable that indicates whether 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 gambling, or in the defense industry.

Methodology

To evaluate the specific drivers of fund obsolescence, we employ a panel logistic lasso regression. We regress the four dependent variables (Three-Month Survival, Four- to Six-Month Survival, Seven- to 12-Month Survival, and 13- to 24-Month Survival) on a set of contemporaneous explanatory variables. We separate the data into four regions: Asia, Canada, cross-border EMEA, and the U.S. We purposefully re-estimate each of the four time period models for the four sets of data. The result is 16 distinct models. Separating the model has twofold benefits. First, we eliminate some of the issues resulting from regulatory differences by regions. Second, estimating the model over four different time horizons implicitly answers the question: What are the signals for fund closure and how do these signals change as the fund approaches closure? As constructed, we believe the model offers investors a glimpse at the inherent factors leading to fund closures over a two-year time horizon.

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

Panel Regression:

$$Obsolete\ Status_i = \alpha + \lambda_t X_{i,t} + \sigma_t B_{i,t} + \varepsilon_{i,t+1}$$

$Obsolete\ Status_i$ is a binary variable where 1 indicates the fund closes within the time period specified by the model. For example, in the Three-Month Survival model, 1 indicates the fund will close in the next three months and 0 indicates the fund is still open in three months. $X_{i,t}$ is a vector of explanatory characteristics at time t and $B_{i,t}$ is a set of indicator characteristics.

The contents of the vectors $X_{i,t}$ and $B_{i,t}$ are as follows:

Exhibit 20 Variables Included in Model

X_i	B_i
Fund Age	Index Fund
Net Expense Ratio	Socially Responsible Fund
Net Expense Ratio — Alpha Interaction	Fund of Funds
Organic Growth Rate	Management Change 6 Months
Organic Growth Rate — Alpha Interaction	Management Change 12 Months
Fund Size	Management Change 24 Months
Firm Size	All Female
Firm Closures	Mixed-gender
Category Closures	
Category Growth Rate	
Management Change 24 Months — Alpha Interaction	
Alpha	
Beta	

Source: Morningstar, Inc. Data as of June 30, 2016.

How to Obtain Final Estimates

The panel lasso regression, as specified above, is run for each model. As a result, we are left with16 vectors of coefficients. Coefficients not found significant in the lasso regression are purposefully left blank.

How to Convert From Log Odds to Odds

The output of a logistic regression is the change in log odds of a fund becoming obsolete given a certain characteristic. For simplicity, we covert from log odds to the change in odds. Given the below regression,

$$logit(Obsolete) = \propto_0 + \ \beta_i X_i$$

We calculate the percentage change in odds for a given variable as follows:

$$\% \ change \ in \ odds \ given \ X_j = \ e^{c\beta_j} - 1$$

Where **c** represents the multiplicative factor used to determine the maximum effect observable. A detailed table of such factors is found in Exhibit 23.

Data Tables

In the tables below, we show the panel regression results. Coefficients are expressed in percentage terms and are displayed when deemed significant by the lasso regression. Below the coefficients, t-statistics are presented in the row below. Coefficients can be interpreted as the maximum benefit a fund can obtain from the characteristic. For percentile variables, this is the change from the first percentile to the 100th percentile, for other continuous variables not in percentiles, this is the change from moving among the interquartile range or in the case of dummy variables, when the factor moves from false to true. Exhibit 23 describes the numerical distribution change for each variable.

Exhibit 21 Regression Results by Model — Asia and Canada

	Asia				Canada			
Months Until Obsolete	24	12	6	3	24	12	6	3
(Intercept)	-82.7%	-88.5%	-97.0%	-97.9%	-66.2%	-72.3%	-92.6%	-96.3%
Fund Structure								
Fund Age	-31.6%	-27.4%	-17.8%	-14.4%	—	—	4.3%	3.6%
Index Fund	-2.0%	—	—	—	—	—	—	—
Socially Responsible Fund	44.9%	29.8%	—	—	—	23.8%	3.0%	—
Fund of Funds	7.9%	10.9%	1.7%	—	—	—	—	—
Net Expense Ratio	—	—	—	—	—	—	—	—
Net Expense Ratio — Alpha Interaction	—	—	—	—	-9.6%	—	—	—
Size Characteristics								
Organic Growth Rate	-55.6%	-81.3%	-47.5%	—	-56.7%	-85.1%	-56.3%	—
Organic Growth Rate — Alpha Interaction	-27.8%	-29.7%	-2.6%	—	-52.0%	-15.5%	-49.9%	-45.8%
Fund Assets	-92.1%	-94.4%	-95.0%	-96.4%	-88.3%	-89.5%	-90.7%	-90.5%
Firm Assets	—	—	—	—	-57.0%	-65.7%	-63.3%	-53.0%
Popularity								
Firm Closures	35.2%	54.5%	59.6%	61.9%	12.3%	39.3%	53.5%	49.0%
Category Closures	2.2%	37.1%	45.8%	66.7%	—	—	—	—
Category Growth Rate	-38.4%	-36.5%	-20.1%	-14.6%	-42.9%	-42.5%	-27.3%	—
Manager Characteristics								
Management Change 6 Mo	126.8%	41.9%	21.8%	31.7%	192.5%	—	—	—
Management Change 12 Mo	71.8%	166.0%	—	3.1%	99.5%	168.0%	—	—
Management Change 24 Mo	128.7%	103.3%	217.4%	236.8%	223.0%	175.9%	273.7%	219.4%
Management Change 24 Mo — Alpha Interaction	65.9%	—	—	—	—	—	26.7%	—
All Female	—	—	—	—	—	—	—	—
Mixed-Gender	—	—	—	—	—	-3.9%	-5.7%	—
Style								
Alpha	—	—	—	—	—	-24.0%	-8.6%	—
Beta	—	—	—	—	—	—	—	—

Source: Morningstar, Inc.

Exhibit 22 Regression Results by Model — EMEA and United States

	EMEA				United States			
Months Until Obsolete	24	12	6	3	24	12	6	3
(Intercept)	-65.0%	-82.1%	-94.4%	-95.8%	-91.6%	-94.2%	-96.2%	-95.2%
Fund Structure								
Fund Age	-8.4%	-1.4%	—	—	7.0%	5.4%	3.8%	—
Index Fund	-9.5%	-7.6%	-2.7%	-2.5%	-31.8%	-11.1%	-4.0%	—
Socially Responsible Fund	-21.3%	-17.9%	-12.7%	-13.2%	—	—	—	—
Fund of Funds	—	—	—	—	-1.5%	—	—	—
Net Expense Ratio	—	—	—	—	-43.7%	-35.8%	-44.6%	-67.4%
Net Expense Ratio — Alpha Interaction	-15.2%	-0.7%	—	-5.6%	—	—	—	—
Size Characteristics								
Organic Growth Rate	-62.1%	-74.1%	-38.1%	—	-19.3%	-30.0%	-18.8%	—
Organic Growth Rate — Alpha Interaction	-39.1%	-48.4%	-53.2%	-26.6%	-58.3%	-58.3%	-54.2%	-50.5%
Fund Assets	-75.9%	-83.1%	-85.5%	-88.2%	-86.4%	-86.0%	-89.9%	-97.1%
Firm Assets	-18.0%	-10.0%	-10.2%	-9.2%	19.6%	11.1%	15.1%	23.6%
Popularity	—	—	—	—	—	—	—	—
Firm Closures	6.3%	22.0%	32.7%	42.3%	45.4%	45.9%	38.5%	10.3%
Category Closures	-10.7%	—	0.8%	3.6%	214.8%	193.5%	108.3%	—
Category Growth Rate	-46.7%	-36.6%	-25.5%	-22.5%	-26.6%	-53.7%	-63.2%	-31.4%
Manager Characteristics								
Management Change 6 Mo	57.4%	30.4%	0.0%	24.1%	27.1%	—	—	25.3%
Management Change 12 Mo	65.0%	45.9%	37.9%	11.2%	46.9%	28.7%	64.6%	—
Management Change 24 Mo	86.9%	109.4%	101.8%	113.5%	26.5%	33.0%	21.8%	143.1%
Management Change 24 Mo — Alpha Interaction	—	—	—	—	10.2%	31.2%	—	—
All Female	—	—	—	—	-21.2%	—	—	—
Mixed-gender	-13.1%	-8.6%	0.0%	—	-37.9%	-29.3%	-19.2%	—
Style								
Alpha	-0.1%	-4.9%	—	-10.9%	—	—	—	—
Beta	—	—	—	—	—	—	—	—

Source: Morningstar, Inc.

Exhibit 23 Coefficient Multiplication Factors for Chart Display

Variable	Distribution Change
Fund Age	167
Index Fund	1
Socially Responsible Fund	1
Fund of Funds	1
Net Expense Ratio	100
Net Expense Ratio — Alpha Interaction	10000
Organic Growth Rate	100
Organic Growth Rate — Alpha Interaction	10000
Fund Size	100
Firm Size	100
Firm Closures	0.18
Category Closures	0.26
Category Growth Rate	100
Management Change 6 Months	1
Management Change 12 Months	1
Management Change 24 Months	1
Management Change 24 Months — Alpha Interaction	100
All Female	1
Mixed-gender	1
Alpha	100
Beta	100

Source: Morningstar, Inc.

References

Blevins, C. & Mullen, L. "Jane, John ... Leslie? A Historical Method for Algorithmic Gender Prediction." Digital Humanities Quarterly. 2015, Vol 9:3.

Brown, S. & Goetzmann, W. "Performance Persistence." The Journal of Finance, Vol. 50, No. 2 (June, 1995), pp. 679-698.

Davidson, L., Sargis, M., & Strauts, T. 2016. The Rise and Fall of New Funds.
http://corporate1.morningstar.com/ResearchArticle.aspx?documentId=760435

Davidson, L. & Strauts, T. 2015. What Factors Drive Fund Flows?
http://corporate1.morningstar.com/ResearchArticle.aspx?documentId=721116

Liang, B. "Hedge funds: The living and the dead." Journal of Financial and Quantitative Analysis; Sep 2000; 35, 3; pg. 309

Lunde, A., Timmermann, A. & Blake, D. "The Hazards of Mutual Fund Underperformance: A Cox Regression Analysis." 1998. http://escholarship.org/uc/item/1pd3z1hm

https://www.sec.gov/about/laws/ica40.pdf page 71.

Sargis, M. & Lutton, L. 2016. Fund Managers by Gender — The Global Landscape.
http://corporate1.morningstar.com/ResearchArticle.aspx?documentId=782040

Schlanger, T. & Philips, C. 2013. The mutual fund graveyard: An analysis of dead funds.
https://personal.vanguard.com/pdf/s362.pdf M

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