The ABCs of Mutual Funds: On the Introduction of Multiple Share Classes

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Abstract

We study a significant innovation with widespread consequences for the mutual fund industry: the introduction of multiple-class funds that give investors a choice among alternative load and fee structures. The transition to a multiple-class structure represents an important step in the evolution of the mutual fund industry. It also provides a well-controlled setting for research on the structure of funds, on investor clienteles and their impact on fund performance and, more generally, about the manner in which financial innovations tend to be adopted. We develop a simple model of a fund's decision on whether and when to introduce new classes and empirically investigate the model's predictions that: (a) Funds with more skilled management, less sensitivity of flows to performance, smaller size, higher existing loads and membership in larger families are better positioned to benefit and, therefore, more likely to switch to a multiple-class structure earlier; (b) The new classes increase the level and volatility of fund inflow by attracting investors with short and uncertain investment horizons – which, in turn, can negatively impact fund performance. Our empirical results are generally supportive of the model's predictions.

GEL Classification: G2

Keywords: Mutual Funds; Distribution Channels; Investor Clienteles; Fund Flows; Fund Performance

1 Introduction

The mutual fund industry in the U.S. has experienced dramatic growth in the past two decades fueled, in part, by factors such as the flow of retirement savings and the popularity of the stock market. The industry has also been transformed by the introduction of new products such as no-load funds, index funds, country funds, and the emergence of direct (non-brokered) and discount distribution channels. In this paper, we study a significant innovation in the 1990s – the introduction of multiple classes by (brokered) funds that gave retail investors a choice among alternative load and fee structures. The multiple-class structure was widely adopted and, by the end of 2002, about 50 percent of U.S. equity funds in our sample, with over 600 billion dollars under management, offered more than one share class.

Mutual funds are sold to retail investors through various distribution channels. The traditional and still important distribution channel is the so-called 'advisor' or 'broker' intermediated channel in which financial planners and brokers play a primary role in selling a fund and providing information and other services to investors. Broker-intermediated mutual funds have traditionally been distributed with a front-end load, where the load represents the sales charge paid to brokers. In the 1990s, broker intermediated funds expanded their menu and began to offer share classes with alternative fee structures – possibly in response to the rapid growth in directly marketed no-load funds that was taking place at the time. The three share classes commonly offered by multiple-class funds are denoted A, B and C. The A class is the traditional class in which investors pay a front-end load and an annual 12b-1 fee of 25 to 35 basis points to compensate brokers. In comparison, the B and C classes have no front-end loads but may charge a contingent deferred sales load (CDSL) upon exit and usually charge higher annual 12b-1 fees of about 1 percent.

Our objective in the paper is to understand the innovation in fund structure: the factors that led to funds switching to a multiple-class structure – wherein some funds switched early while others delayed or chose not to switch – and the consequences for fund investors and performance. The transition to a multiple-class structure is a major step in the evolution of the mutual fund industry and, hence, insight into the economic factors driving the transition is important to our understanding of mutual funds. In addition, the adoption of the multiple-class structure involves substantial changes in the nature of investor clienteles and, consequently, provides a well-controlled setting for research on fund structure, fund flow characteristics, and their impact on fund performance. A real advantage here is that while the introduction of the new classes changes fund flow characteristics – fund management and investment objectives remain virtually unchanged. At a broader level, the introduction of a multiple-class structure represents a significant financial innovation by enlarging the set of financial contracts available to retail investors.[1] By analyzing the costs and benefits of the switch in fund structure, we hope to gain a better understanding of the adoption and diffusion of financial innovations in general.

We begin by developing a simple one-period model of the decision by funds to introduce new classes. Our argument is that introducing new classes will broaden the appeal of a fund and attract new investors, increasing the management fees that fund advisors receive. There may be offsetting costs, however. One significant cost is that the new classes will tend to increase both the level and volatility of fund flows, adversely impacting fund performance and eroding the cash flow benefits of the new classes. As a consequence, while some funds may move early in terms of introducing new classes, other funds may choose to delay or to not make such a switch. We use the model to develop a number of predictions – which are tested subsequently – about the adoption and impact of the new classes.

In our model we hypothesize that a switch from a single A class fund to a multiple-class fund increases the overall cash inflow by attracting new investors with different investment preferences. Given the structure of the sales charges associated with the share classes, we expect that investors

[1] See, for instance, Allen and Gale (1988) and other that discuss the trade-offs associated with introducing new financial products that result in a more 'complete' financial market.

with relatively long investment horizons will prefer the A class with its up-front load and lower annual charges, while those with short and uncertain horizons will prefer the B or C class. Investor preferences may also be determined by the value the investor places on having flexibility to move between investments. Hence, the expectation is that, compared to the existing A class, the new share classes (especially class C) will exhibit higher cash flow volatility and greater sensitivity to fund performance.

The above discussion suggests that investors attracted to the new classes are likely to alter a fund's flow characteristics — both the level and the volatility of fund flows. In the model, we draw upon the literature (*e.g.,* Edelen 1999, Nanda et al. 2000, Berk and Green 2004) and argue that higher cash flow volatility and level will adversely affect a fund's performance on account of liquidity costs and decreasing returns to scale. Hence, in equilibrium, the introduction of new share classes is expected to be accompanied by a drop in fund performance. This represents a potential trade-off in switching to a multiple-class structure: the new classes attract additional cash flows, which in turn hurt fund performance by increasing fund size and cash flow volatility. The negative impact on fund performance will diminish the fund's ability to attract additional investors, and will thus erode part of the cash flow benefits from introducing new share classes. The benefits from switching will also be diminished by the presence of fixed costs – such as legal, marketing and other costs – associated with introducing new classes.

Funds, acting rationally, will choose to add new share classes only if the expected benefits outweigh the potential costs. There are several factors that will influence a fund's decision. In our model, funds with higher managerial ability have greater incentive to switch early. The basic notion is that funds that anticipate a strong performance are in a better position to attract investors that chase past performance and have shorter investment horizons. Moreover, skilled managers are likely to better cope with the change in fund flow characteristics. We argue that the impact of the new classes on cash flow volatility will tend to be moderated by the presence of existing investors with relatively long horizons – as indicated, for instance, by low sensitivity of flows to performance and the presence of higher front-end loads on existing classes. Further, a fund's incentive to introduce new classes may be negatively affected by its existing size. The reason is that as a fund gets larger it is likely to face declining investment opportunities. Hence, we expect funds with stronger performance, low sensitivity of flows to performance, higher load and smaller size to derive greater benefits and be more willing to make a switch. Another factor that will affect the decision to switch is the fixed costs associated with introducing new share classes. These costs are usually borne by fund families. If economies of scale are important, then larger fund families are in a better position to bear the costs and, hence, more likely to introduce new classes.

In a simple extension of the model we analyze the timing aspect of the switching decision – *i.e.,* the choice by some funds to switch early, while others switch with some delay. Our analysis suggests that the same factors that increase a fund's benefits from switching, also increase the likelihood of an early switch. An early mover has more periods over which it benefits from the increase in cash flow from switching. The downside, however, is that an early mover is subject to greater initial learning costs associated with setting up a multiple-class structure – while a late mover benefits from the experience and mistakes of early movers.

In our empirical analysis we begin by testing our model's predictions regarding fund and fund family characteristics that affect the switching decision. We find that funds are more likely to switch to a multiple-class structure when they are performing well relative to a control group of funds. Using a probit regression model, we find that early switching is associated with a stronger performance in the year of adopting the new structure, as well as in the prior three years. On the other hand, funds that switch later are associated with stronger performance only in the adoption year – suggesting that timing may be a consideration for these funds. Overall the evidence is consistent with the model's prediction that funds with higher managerial ability have greater incentive to be the first movers. Further, in line with model predictions, funds that exhibit less cash flow sensitivity to performance, have higher front-end loads and are smaller in size are more likely to introduce new classes. We also find larger fund families are more likely to introduce new classes, suggesting that economies of scale could be an important consideration in the switching process.

The model makes several predictions in terms of fund flows and performance. We first examine whether a switch from a single A class fund to a multiple-class fund is associated with an increase in overall cash inflow. Controlling for performance and other fund characteristics, we find that funds with multiple share classes attract significantly more new money in the first three years after the introduction of new share classes. The cash flow differences between multiple-class funds and the control group of no-load funds cannot be attributed to differences in cash flow prior to the switch. The increase in cash inflow in the first year after adopting a multiple-class structure, controlling for factors such as performance, expenses, and fund size, is estimated to be about 12 percent. Given the average fund size (727 million dollars) in 2002, this is of the order of 87 million dollars. The new money growth slows down in the second year and later, following the switch to a multiple-class structure. To understand differences in investor clienteles, we compare the cash flow characteristics between different share classes. The C class exhibits the highest overall cash flow volatility and the highest cash flow response to fund performance. This finding is consistent with our expectation that the new share classes appeal to investors with short or uncertain horizons.

We then investigate the change in risk-adjusted returns for the A share class of multiple-class funds. Our results indicate that, in the second and subsequent years following the introduction of new share classes, the A share classes experience a significant drop in performance. Compared to no-load funds, the four-factor adjusted return is found to decline by about 1.2 to 1.6 percent on an annual basis, both before and after controlling for expenses. The estimated impact of fund performance on cash flows suggests that the new money growth would decrease by about 2 to 3 percent on an annual basis due to the performance drop. On the basis of this figure, we estimate that four years after the switch to a multiple-class structure, over half of the 12 percent additional new money growth induced by the new classes is eroded. An interesting finding is that funds that switched relatively early suffered little drop in performance after the switch. This is consistent with the model's prediction that funds that are managed by better managers – those that may be able to cope better with the increase in cash flow volatility – will be more willing to introduce new classes. Further analysis indicates that the drop in performance is indeed related to the change in fund flow characteristics.

Our paper contributes to several strands of the extant literature. First, existing research indicates that mutual fund flows are affected by past fund performance[2] (see, for example, Gruber 1996, Chevalier and Ellison 1997, Goetzmann and Peles 1997, Sirri and Tufano 1998, Bergstresser and Poterba 2002, Del Guercio and Tkac 2002, Nanda et al. 2004), load and expense charges (see, for example, Sirri and Tufano 1998, Wilcox 2003, Barber et al. 2005), and fund advertising (see Jian and Wu 2000, Cronqvist 2003, Gallaher et al. 2004, and Reuter and Zitzewitz 2006). In the presence of search costs, Hortaçsu and Syverson (2004) show that the fees charged by competing mutual funds will tend to be significantly dispersed. Our paper suggests that mutual fund managers can also affect fund flows by offering a variety of load and fee schedules on the same underlying investment portfolio.

Second, a growing body of research has focused on the development of financial products that cater to different investor clienteles. Amihud and Mendelson (1986) develop a model based on the idea that portfolio managers tailor portfolios to fit their clients' investment horizons and liquidity objectives. The model predicts that long-term investors select assets with higher spreads and earn higher returns. Massa (2003) shows that mutual fund families strategically position themselves in terms of performance, fees, and number of funds to target investors with different investment horizons. In a study on the hedge fund industry, Aragon (2007) investigates the lockup provisions and argues that longer-term investors hold shares with greater redemption restrictions. Our paper

[2]For evidence on performance persistence see, for example, Blake et al. (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Malkiel (1995), Elton et al. (1996), Gruber (1996), and Carhart (1997).

provides evidence consistent with a possible clientele effect: the multiple-class structure of a fund is designed to attract investors with different investment preferences.

Third, several papers argue that fund performance can decline with the increase in fund size and cash flow volatility due to decreasing returns to scale and liquidity costs (see, for example, Edelen 1999, Nanda et al. 2000, Rakowski 2002, Stein 2003, Berk and Green 2004, Chen et al. 2004, and Johnson 2004). This argument plays an important role in explaining the empirical finding that performance persistence and the smart money effect (see Gruber 1996, Carhart 1997, Zheng 1999, and Bollen and Busse 2005) are short lived. Our paper focuses on the change in fund performance around the introduction of new share classes. A significant advantage to analyzing performance in this setting is that though there are substantial changes in cash flow characteristics – there is no systematic change in managerial ability and investment objectives of the fund.

Fourth, there has been increasing scrutiny from the media, regulators, and researchers on situations in which fund managers and short-term investors appear to benefit at the cost of long-term investors in mutual funds. Goetzmann et al. (2001), Boudoukh et al. (2002), and Zitzewitz (2003) show that short-term traders exploit stale prices of mutual fund shares to extract value from long-term investors. Massa (2003) presents evidence that, for mutual fund families, the degree of product differentiation negatively affects performance but positively affects fund proliferation. Johnson (2004) shows that the liquidity costs imposed on the fund by short-term investors are significantly greater than those imposed by the long-term investors. Our findings suggest that the introduction of new share classes has similar wealth transfer implications – with the drop in fund performance imposing a cost on long-term investors, while fund managers benefit from the increase in fund size.

Fifth, recent research has begun to examine the multiple share class structure of mutual funds. In an Investment Company Institute (ICI) study, Reid and Rea (2003) provide a comprehensive summary of mutual fund distribution channels and distribution costs for the past 25 years. Livingston and O'Neal (1998) compare the effect on investors of distribution fees for mutual funds with different types of sales arrangements. O'Neal (1999) points out that, in most circumstances, the multiple-class structure provides brokers monetary incentives to sell the class of shares that is least advantageous to investors and thus creates a conflict of interest situation. Lesseig et al. (2002) document that multiple share class funds have lower administrative fees but higher management fees than funds with only a single class. However, there is little empirical research on how the multiple-class structure affects fund cash flows and performance. Our study contributes to the literature by analyzing the decision and consequences of introducing multiple share classes on fund cash flows, investor clienteles, and performance.

Finally, though the context is quite different, our paper is also related to the literature on financial innovations such as Tufano (1989) that investigates the first mover advantages in the introduction of new financial securities by investment banks. It is also related to papers such as Allen and Gale (1988) and others that analyze the costs and benefits of introducing new financial products that result in a more complete set of financial securities.

The rest of the paper is organized as follows. Section 2 provides institutional details about the share class structure. Section 3 develops hypotheses. Section 4 describes data and summary statistics. Section 5 presents methodology and empirical results. We conclude in Section 6.

2 Institutional Background

In the 1990s, many broker intermediated mutual funds introduced new share classes. The different share classes of a fund obtain returns from the same underlying investment portfolio but differ in realized returns on account of fees, expenses, and sales charges. We use the criteria outlined by the ICI to identify share classes and, in our study, define a fund to be a multiple-class fund if it offers A, B, and C shares or A and B shares.[3] Among the 1,731 diversified U.S. equity funds in our sample, 48 percent have multiple share classes at the end of 2002. In this section, we provide some institutional details about various share classes based on the ICI study by Reid and Rea (2003). In particular, we focus on alternative load and fee structures. We also discuss the empirical implications with respect to investors' choice of share classes.

2.1 Basics of Share Classes

Class A shares charge investors an up-front load as a percentage of total investment at the time of purchase. This was the standard form of the mutual fund contract offered by brokered funds, before the advent of the multiple-class structure. In an A class, an investor who invests, say, \$1,000 in A shares with a 5 percent front-end load, pays a \$50 load charge to the broker and has a net position of only \$950 in the fund. A typical load structure involves a maximum front-end load charged to investments below a certain threshold (*e.g.,* \$25,000) and a schedule of load reductions for larger investments. For investments above 1 million dollars, funds typically waive the load charges. Besides the front-end load, class A shares also charge an annual 12b-1 fee to compensate brokers and financial advisors. Under SEC Rule 12b-1, a fund can use its assets to pay for distribution related services. For class A shares, the annual 12b-1 fee typically ranges from 25 to 35 basis points.

Instead of a front-end load, class B investors are subject to a contingent deferred sales load (CDSL), also called a back-end load. The CDSL is contingent upon share redemptions and is based on the lesser of the original cost of shares at the time of investment and the market value of the shares at the time of redemption. A typical CDSL structure involves a maximum back-end load (about 5%) charged to investments redeemed during the first year and a schedule of load reductions

[3] Multiple-class funds offer other class types as well. For example, some share classes are specially designed for institutional investors or retirement plans. However, unlike A, B, and C classes, these share classes do not have an industry-wide standard regarding load and fee structures. Moreover, the naming of these share classes is often at the discretion of fund management, making classifications extremely difficult. For these reasons, we focus exclusively on the A, B, and C classes of multiple-class funds, which are offered to retail investors. Most multiple-class funds offer either A, B, and C shares or A and B shares. Very few funds offer the combination of A and C or B and C. Hence, we exclude them from our analysis.

for investments held longer. The pace of back-end load reductions is typically 1 percent per year. Hence, if an investor holds the class B shares for six or more years, she is not charged any back-end load in case of redemption. Class B shares usually charge an annual 12b-1 fee of 100 basis points. However, B shares are typically converted into A shares after six to eight years, resulting in a reduction of the 12b-1 fee from 100 basis points to that of A shares.

Like class B investors, shareholders of the C class pay for distribution related services through a combination of a CDSL and an annual 12b-1 fee (typically 100 basis points, referred to as the level-load). However, the load and fee structure of class C differs from that of class B along two dimensions. First, the CDSL is usually set at 1 percent and is triggered only if an investor redeems her shares during the first year of investment. For shares held for more than one year, the CDSL is normally waived. Second, unlike B shares, C shares are not converted into A shares after six to eight years. In other words, class C investors pay the 100-basis-point annual 12b-1 fee for as long as they hold the C shares.

2.2 Choice between A, B, and C Classes

As noted, the different share classes of a multiple-class fund are issued on the same underlying asset portfolio and thus have the same return before loads and expenses. The share classes typically have the same non-distribution related expenses as well and, hence, the difference in net returns (after loads and expenses) is mainly driven by the different payment arrangements for distribution costs. The net return received from the different classes depends on the holding period and, hence, an important factor in an investor's preference among a fund's classes will be her investment horizon. An investor's preferences may also be affected by the value the investor places on having flexibility to move between investments, without incurring significant costs.

Reid and Rea (2003) demonstrate how the net returns of the three share classes depend on investment horizons. For investors with short investment horizons (one to six years), class C shares deliver the highest net returns. For investors with intermediate investment horizons (seven to eight years), classes B and C perform better than class A. For long term investors with investment horizons over eight years, class A dominates the other two classes. Hence, investors with shorter horizons and greater willingness to move their investments would be expected to favor the new classes. An empirical prediction that follows from the above discussion is that the overall cash flow volatility and the cash flow response to fund performance should be higher for class C – since it attracts shorter horizon investors – than the other (A & B) classes.

2.3 No-load Funds and Single A Class Funds

In the past two decades, alternative distribution channels have emerged to compete with the traditional 'advisor' or 'broker' intermediated channel. Among the most successful ones are the 'direct' channel and the 'supermarket' channel. The majority of the funds sold through these channels are no-load funds, which usually have a single class. A typical no-load fund has no sales load and an annual 12b-1 fee of less than 25 basis points. Hence, compared to the A, B, or C share class in a multiple-class fund, no-load funds have significantly lower distribution costs. To keep distribution costs low, these funds carry out transactions with investors either directly as in the 'direct' channel or through discount brokers that offer mutual funds from a large number of fund sponsors. The latter channel is referred to as the 'supermarket' channel.

Several load funds have not adopted the multiple-class structure and only offer an A share class.[4] These funds have load and fee structures that are similar to those of the A class of multiple-class funds, and are distributed mostly through the 'advisor' or 'broker' intermediated channel.

[4] Funds that only offer a single B or C class are rarely observed.

3 Model and Hypotheses

In this section we develop a simple equilibrium model of the decision by some single-class funds to introduce new classes and use the model to develop a number of testable implications. We argue that introducing additional classes may attract new investors to a fund and, thereby, increase the fees that fund advisors receive. There may, however, be offsetting costs that cause other funds to delay or eschew a change in fund structure. The relative costs and benefits will depend on fund and managerial characteristics.

3.1 A Simple Model of Investor Clienteles and Fund Flows

We begin by analyzing an existing single-class fund i that, on account of its load and fee structure, attracts an investor clientele with a relatively long investment horizon. The existing class is denoted by A. The fund is managed by an advisor (we will interchangeably use the term 'manager') who seeks to maximize the fee revenue $\alpha_i S_{Ai}$ from managing the fund. Here S_{Ai} denotes the assets under management and α_i is the per dollar management fee. For simplicity, we assume that α_i is fixed at some level and the objective of the manager is, therefore, to maximize the size of the fund. Also, to ease exposition we will suppress the subscript i.

The model has a single period with two relevant dates, $t = 0$ and $t = 1$. The introduction of new classes and the fund's investment decisions are made on date 0 and investment returns are received and distributed to investors on date 1. Later we consider an extension of the model with additional periods in order to analyze the timing of the switching decision. To keep the model tractable we do not explicitly model investor flows between the two dates. However, we will assume, in reduced form, that the fund's performance declines with an increase in the liquidity needs of its investors and with fund size. The notion is that liquidity shocks can cause investors to withdraw funds and, in the process, impose liquidation and portfolio adjustment costs that reduce fund performance (see, for example, Nanda et al. 2000, Edelen 1999, Rakowski 2002, and Coval and Stafford 2007).[5] The increase in fund size beyond a certain level may also hurt fund performance. The notion is that as a fund grows larger, even skilled managers would face declining investment opportunities given the increasing difficulty in identifying attractive investments and the bigger price impact from trading (see Berk and Green 2004 and Chen et al. 2004). We also assume that there is no asymmetric information with regard to managerial capability, though the model can be extended to accommodate symmetric learning about managerial investment ability. The discount rate is zero and the manager is taken to be risk neutral.

We denote the NAV return (return per dollar invested) that investors expect to receive on date 1 by $R(\theta, L, S)$. Here, θ denotes the manager's investment ability, L represents the (average) liquidity needs of the fund's investors, and S refers to fund size. The expected returns are taken to be increasing in managerial ability ($\frac{\partial R}{\partial \theta} > 0$), to be decreasing in liquidity needs of its investors ($\frac{\partial R}{\partial L} < 0$), and to be decreasing in fund size ($\frac{\partial R}{\partial S} < 0$). We also assume that the cross-partials are such that $\frac{\partial^2 R}{\partial \theta \partial L} > 0$ and $\frac{\partial^2 R}{\partial \theta \partial S} > 0$, which implies that the performance consequences of increasing L and S are less severe for higher ability managers. The reason is that skilled managers may be more efficient in terms of identifying attractive investment opportunities for a larger pool of assets and/or managing more volatile fund flows — limiting the downside pressure from increased fund size and cash flow volatility on performance. Let subscript A denote the existing share class A. For tractability, we assume the following linear functional form and separable liquidity and size effects, for $R(\theta, L_A, S_A)$:

$$R(\theta, L_A, S_A) = \theta - \eta_\theta L_A - \lambda_\theta S_A, \tag{1}$$

where η_θ and λ_θ are both decreasing in θ.

In characterizing the flow of investor cash to the fund, we draw upon the existing empirical findings that investor flows are strongly affected by current and past fund performance. Specifically,

[5] The reduction in performance can be caused (*ex-post*) by unexpectedly large withdrawals and (*ex-ante*) by the fund tilting its investment portfolio toward liquid assets out of concern about such withdrawals.

we will assume that investor flows can be viewed as arising from a type of 'supply' curve, with the amount of flow increasing in the fund's anticipated performance. For simplicity we will assume a linear relation between the aggregate 'supply' of investor cash flow and the fund's anticipated 1-period performance as follows:

$$S_A = I_A[1 + \beta_A R(\theta, L_A, S_A)]. \tag{2}$$

Here, I_A is a scale parameter and β_A is the sensitivity of fund flows to anticipated fund performance.[6] Substituting equation (1) into equation (2) gives the equilibrium size for the single-class fund:

$$S_A = \frac{I_A[1 + \beta_A\theta - \beta_A\eta_\theta L_A]}{1 + I_A\beta_A\lambda_\theta}. \tag{3}$$

It is easy to verify that, under our assumptions, $\frac{\partial S_A}{\partial \theta} > 0$. Hence, in equilibrium, the size of the fund is increasing in managerial ability.

3.2 The Decision to Introduce New Classes

We now consider the possibility of the single-class fund introducing an additional class, say B, at date 0. Given our objectives, we are interested in the decision to introduce a new class that is structured – *e.g.,* by the use of annual fees in place of front-end loads – so as to attract investors with shorter horizons and greater liquidity needs than those in the fund's existing class. While the introduction of a new class can attract additional new investors, there may be costs as well. We consider two types of costs: the first are the direct legal and operational costs associated with introducing new classes. These direct costs are denoted by C and are assumed to be paid by the fund family.[7] The second are the less direct costs such as the impact of the new classes on the

[6] The connection between performance and flows is well established. Our results are unaffected if we assume that the relation between flows and performance is somewhat convex, as has been reported in the literature. The sensitivity parameter β_A would be expected to reflect investor preferences as well as the costs associated with searching and switching to another fund.

[7] While our analysis deals with a single fund, the decision to switch to a multiple-class structure is made at the family level and can involve several or all of the family's funds introducing new classes at the same time. This suggests that there are possible economies of scale that can reduce the costs as a function of family size.

characteristics and performance of the fund – which will make the fund less attractive to existing (and new) investors.

We denote the multiple-class fund with classes A and B as M. The average liquidity need of investors in M, reflecting the addition of class B with shorter horizon investors, increases to $L_M > L_A$. Investors attracted to class B also exhibit higher flow-performance sensitivity than investors in the existing A class, *i.e.,* $\beta_B > \beta_A$. As with a single-class fund, we represent the flow of funds to classes A and B as:

$$S_{AM} = I_A[1 + \beta_A R(\theta, L_M, S_M)], \tag{4}$$

and

$$S_{BM} = I_B[1 + \beta_B R(\theta, L_M, S_M)], \tag{5}$$

where the subscripts 'AM' and 'BM' indicate that these are the assets in the different classes of a multiple-class fund and $S_M (\equiv S_{AM} + S_{BM})$ is the size of the multiple-class fund. The anticipated performance of the multiple-class fund is given by

$$R(\theta, L_M, S_M) = \theta - \eta_\theta L_M - \lambda_\theta S_M. \tag{6}$$

The increase in L and S, by our assumptions, will have a negative effect on the performance of the fund. Using the above expressions, the aggregate assets under management after the introduction of a new class can be expressed as:

$$S_M = S_{AM} + S_{BM} = I_A + I_B + (I_A\beta_A + I_B\beta_B)R(\theta, L_M, S_M). \tag{7}$$

Substituting equation (6) into equation (7) gives the equilibrium size for the multiple-class fund M:

$$S_M = \frac{(I_A + I_B) + (I_A\beta_A + I_B\beta_B)(\theta - \eta_\theta L_M)}{1 + (I_A\beta_A + I_B\beta_B)\lambda_\theta}. \tag{8}$$

The size of multiple-class fund M will therefore depend on two offsetting factors: the inflow of funds due to the new share class and the outflow of funds due to the negative impact of the increase in liquidity demands and fund size on performance. The decision to introduce a new class will thus depend on the anticipated interaction of these two factors. Taking the direct costs C into account, the fund will introduce the new class only if:

$$\alpha S_M - \alpha S_A > C, \tag{9}$$

i.e., if the increase in fund fees exceeds the cost of introducing the new classes. The above condition can equivalently be expressed in terms of the assets of the classes as:

$$S_{BM} - (S_A - S_{AM}) > \frac{C}{\alpha}. \tag{10}$$

In the above condition, the increase in fund size can be viewed in terms of the size of the new class S_{BM} and the change in size of the existing class $(S_A - S_{AM})$. If the only impact of the change in fund structure on class A is on account of a decline in fund performance, we would expect the existing class to become smaller – the exact impact on class size depending on the performance sensitivity (β_A) of the existing class. This suggests potential agency problems in the process of introducing new share classes: While the fund managers may benefit from the switch, longer term investors in the existing class – reluctant to move their investments – may suffer a performance drop and/or the cost of searching and moving to another fund.

We now state and discuss several testable implications of our trade-off model. The more formal proof has been relegated to the Appendix.

Proposition 1: *Funds will be more likely to switch from a single-class structure to a multiple-class structure, ceteris paribus, when: (a) The fund advisor has higher investment ability* θ; *(b) Performance sensitivity of the existing class,* β_A, *is lower; (c) Liquidity needs of fund M investors,* L_M, *is smaller; and (d) The cost of introducing the new class,* C, *is smaller.*

Outline of Proof : The proposition follows directly from equation (9) and our assumptions about the impact of L, S, and θ on fund performance: (a) From equation (9), funds managed by higher ability managers will be more likely to switch if $\frac{\partial(S_M - S_A)}{\partial\theta} > 0$. It follows from the model assumption that the performance consequences of increasing L and S are less severe for higher ability managers, *i.e.,* $\frac{\partial^2 R}{\partial\theta\partial L} > 0$ and $\frac{\partial^2 R}{\partial\theta\partial S} > 0$. Hence, for higher ability managers, the fund outflow induced by the introduction of the new share class would be smaller. (b) This result is easily checked and follows from the fact that a smaller β_A results in a smaller flow of funds out of class A, for a given drop in performance. (c) Here, a smaller L_M implies a smaller increase in liquidity needs of investors after introducing the new class which, in turn, leads to a smaller performance drop and thus fund outflow. (d) A smaller direct cost C of changing fund structure decreases the right hand side in condition (9) and makes it more likely that the fund will switch. ■

In our discussion we have simplified the analysis by assuming a single period in which funds decide whether or not to switch at date $t = 0$. However, in a more realistic multi-period setting, we would want to recognize that funds have timing discretion – in the sense of choosing to be early or late movers in terms of adopting an innovation. As with any financial innovation, the move toward a multiple-class structure would be expected to be a gradual one – with some funds being more eager to make a switch than others.

To illustrate the issue of earlier versus later adoption, we consider a simple extension of the above model to allow for a second investment round at date $t = 1$, after the end of the first period. The returns from the second investment round are realized at a date $t = 2$. In terms of the fund's switching decision, it is assumed that the fund can choose to switch to a multiple-class structure at the start of the first investment period (at date $t = 0$) or delay the decision to the start of the second period (at date $t = 1$).

We now characterize the trade-off between switching early and switching later. Being an early-mover has the obvious advantage of attracting flows and increasing the assets under management at date $t = 0$, instead of later at $t = 1$, and, hence, receiving larger management fees in the first period. The incremental management fee from switching in the first period versus the second is $\alpha(S_M - S_A)$. On the other hand, being an early mover entails costs as well. There are presumably greater initial learning costs associated with setting up a multiple-class structure – such as determining the loads and 12b-1 fees for the new classes, dealing with legal contracting issues, deciding on the appropriate incentives for brokers, adjusting investment strategies to deal with the more volatile cash flow and so forth. There are also the costs associated with educating brokers and potential investors about the new classes. Many of these learning costs could reasonably be expected to decline over time – with a late mover benefiting from the experience and mistakes of the early movers. For our purposes, we will capture the benefits from delaying a switch to the second period by simply assuming that the costs of adoption C_2 are lower when the switch is made at $t = 1$ instead of $t = 0$, *i.e.,* $C > C_2$.

Hence, a fund's decision of whether to switch in period 1 or in period 2 involves a comparison of the benefits from such a delay — which is a lowering in fixed costs $(C - C_2)$ — to the loss of incremental management fees from such a delay, $\alpha(S_M - S_A)$. Hence, factors that make a fund more likely to switch, *i.e.,* a larger value for $(S_M - S_A)$, are also the factors that make an early switch more likely. We can state:[8]

Corollary 1: *In a two-period setting, an increase in the value of* $(S_M - S_A)$ *makes it more likely that the fund will switch its structure in the first period. A fund will switch to a multiple-class structure:*

1. *In the first period if:* $C - C_2 \leq \alpha(S_M - S_A)$ *and* $C \leq 2\alpha(S_M - S_A)$,
2. *In the second period if:* $C - C_2 > \alpha(S_M - S_A)$ *and* $C_2 \leq \alpha(S_M - S_A)$.

A fund will not switch to a multiple-class structure if $C_2 > \alpha(S_M - S_A)$.

Proof: The larger the magnitude of $(S_M - S_A)$, the more a fund loses in fees from a delay in switching. Given the fixed benefit from delaying, $C - C_2$, making a switch in period 1 becomes more likely for funds with larger $(S_M - S_A)$. If the benefit of switching is low such that $\alpha(S_M - S_A) < C_2$,

[8] Without loss of generality, when the fund is indifferent, we have expressed the inequalities as favoring a switch in period 1.

the fund will not switch even in the second period. ■

We now draw upon the model to develop a number of specific testable hypotheses.

3.3 Hypotheses

We first consider a fund's decision to switch to a multiple-class structure. As stated in Proposition 1, we expect funds with higher ability managers to have a greater incentive to switch and, from Corollary 1, a greater incentive to switch early. The reason is that higher ability managers are expected to perform better and are, thus, in a better position to attract investors to the new share classes. Moreover, skilled managers may be more efficient in terms of identifying attractive investment opportunities for a larger pool of assets and/or managing more volatile fund flows — limiting the downside pressure from increased fund size and cash flow volatility on performance. Hence, we state that:

Hypothesis H1: *Funds with higher managerial quality benefit the most from adding the new share classes and, thus, have greater incentive to switch and to switch early.*

Other factors in the switching decision include the performance sensitivity (β_A) of the existing class and the expected liquidity needs (L_M) after adding new classes. A lower performance sensitivity implies that investors in the existing share class would respond less to a performance drop associated with the introduction of new classes and, thus, the class would suffer a smaller fund outflow. For our empirical tests, we directly estimate the performance sensitivity of funds. In addition, we use front-end loads charged by the existing share classes as a proxy for performance sensitivity since funds with higher front-end loads are likely to have attracted longer term investors – less willing to move their investments. A factor that may moderate the type and level of the cash flows attracted to the new classes is the CDSL associated with these classes. Larger CDSLs may reduce the level and volatility of fund flows into the new classes. However, CDSLs on the new classes are likely to be determined largely by the load on existing classes and funds may have little discretion in the matter.[9] Hence, front-end loads could also proxy for the expected liquidity needs and the expected size of the new classes. Finally, a fund's incentive to introduce new classes may also be negatively affected by its existing size. The reason, as we have discussed, is that as a fund gets larger even skilled managers are likely to face declining investment opportunities.

Hypothesis H2: *Funds with less sensitivity of flow to performance, higher front-end loads and smaller size are more likely to introduce new classes early.*

In terms of direct introduction costs C, we would expect the costs to vary cross-sectionally if there are certain economies of scale in introducing new classes (for instance, on account of legal and marketing costs). In particular we might expect such economies of scale to favor the switching by funds in larger families since, as appears to be the practice, families tend to introduce new classes on several of their funds at the same time. This leads to the following hypothesis.

Hypothesis H3: *Larger fund families are more likely to introduce new share classes early.*

We now turn to the model's predictions about the impact of introducing new classes on the nature of fund flows. Our presumption in the model is that funds prefer to have more assets under their management – and that, in equilibrium, they introduce new share classes to appeal to a broader class of investors and attract more money. The new classes, as we have discussed, are likely to attract investors with shorter investment horizons: those with greater liquidity needs or a tendency to chase fund performance. Hence, we can state:

Hypothesis H4: *The introduction of new classes will be associated with an increase in the level of net flows to a fund. Moreover, the new B and C classes will exhibit greater cash flow volatility and flow-performance sensitivity than the existing A class.*

Hypothesis H4 states that the introduction of new share classes will tend to increase fund size as

[9] Loads are used to compensate brokers for distributing the fund. Unless the fund is seeking to promote one class over another, we would expect the loads to provide similar compensation across the classes. We discuss this in Section 5.1.2.

well as cash flow volatility. Motivated by both theoretical and empirical evidence in the literature, a central assumption in our model is that the new classes, by changing the cash flow characteristics of the fund, will cause a decline in fund performance. This represents one of the downsides of switching to a multiple-class structure. We state the anticipated impact of a multiple-class structure on fund performance in the following hypothesis:

Hypothesis H5: *The increase in fund size and fund flow volatility, associated with the introduction of new classes, will have a negative impact on the fund's subsequent performance.*

These hypotheses are empirically investigated in Section 5.

4 Data

4.1 Definition of Variables

Our data sample is based on the mutual fund database compiled by the Center for Research in Security Prices (CRSP). This data set provides information on fund complex, monthly total net assets (TNA), monthly returns, and annual characteristics (*e.g.,* expense ratio, 12b-1 fee, load, turnover ratio) for open-end mutual funds, including defunct funds. For our study we include all diversified U.S. equity funds[10] over the period from January 1993 to December 2002 and manually identify their class information. We focus on the post-1992 period during which the bulk of multiple share classes were introduced.

The CRSP mutual fund database treats the multiple share classes offered by a fund as different entities. We identify the share classes of a fund by their names. For most share classes, the recorded names provide us with information about the nature of the classes (A, B, C, or no-load).[11] To ensure the accuracy of the class coding, we verify the distribution-related costs (sales loads and

[10] To construct a sample of diversified equity funds, we select all open-end equity funds in the CRSP data and then exclude sector funds, international funds, and balanced funds.

[11] For example, AIM Large Cap Growth Fund/A, AIM Large Cap Growth Fund/B, and AIM Large Cap Growth Fund/C are identified as the A class, B class, and C class of the AIM Large Cap Growth Fund, respectively.

12b-1 fees) for each reported share class based on the criteria discussed in Section 2. We construct the fund level variables by aggregating across the share classes. For our analyses, we use both fund level and class level information.

The new money or cash flow of a multiple-class fund is calculated as the sum of new money across all share classes. For each share class, new money is defined to be the dollar change in TNA, net of price appreciation in the class assets. Assuming that new money is invested at the end of each month, the cash flow for class i in month t is given by

$$(\text{Newmoney})_{it} = (\text{TNA})_{it} - (\text{TNA})_{i,t-1} * (1 + R_{it}), \tag{11}$$

where R_{it} is the rate of return of class i in month t. For a multiple-class fund f, the fund level new money is

$$(\text{Newmoney})_{ft} = \sum_{i=A,B,C} (\text{Newmoney})_{it}. \tag{12}$$

Normalizing the new money by the fund level TNA at the beginning of the month gives a measure for the fund level new money growth:

$$(\text{Newmoneygrowth})_{ft} = \frac{(\text{Newmoney})_{ft}}{\sum_{i=A,B,C} (\text{TNA})_{i,t-1}}. \tag{13}$$

The fund level turnover ratio, expense ratio, 12b-1 fee, non 12b-1 expense (expense ratio net of 12b-1 fee), and total load are calculated as the TNA-weighted average of the corresponding class level measures.

Finally, we calculate risk-adjusted returns to measure the performance of funds and share classes in different ways. Specifically, we calculate the CAPM one-factor and Carhart (1997) four-factor adjusted returns at both the class and fund levels.[12] For a multiple-class fund, the fund abnormal return is the TNA-weighted average of its class abnormal returns. We use the following OLS regressions to estimate factor loadings and α measures:

$$R_{it} - RF_t = \alpha_i + \beta_{iRMRF}\text{RMRF}_t + e_{it}, \tag{14}$$

[12] Results (not reported) using the Fama and French (1993) three-factor adjusted returns are similar.

$$R_{it} - RF_t = \alpha_i + \beta_{iRMRF}\mathrm{RMRF}_t + \beta_{iSMB}\mathrm{SMB}_t + \beta_{iHML}\mathrm{HML}_t + \beta_{iMOM}\mathrm{MOM}_t + e_{it}, \quad (15)$$

where R_i is the rate of return of class i, RF is the one month T-bill rate, R_m is the rate of return of the market, RMRF$\equiv R_m - RF$ is the excess market return, SMB is the rate of return on the mimicking portfolio for the size factor in stock returns, HML is the rate of return on the mimicking portfolio for the book-to-market factor in stock returns, MOM is the rate of return on the mimicking portfolio for the momentum factor in stock returns, α is the excess return of the corresponding factor model, and βs are the factor loadings of the corresponding factors. Using the estimated factor loadings (βs) and excess return α, we define the risk-adjusted return (α_{it}) as[13]

$$\alpha_{it} \equiv \alpha_i + e_{it}. \quad (16)$$

4.2 Summary Statistics

Table 1 reports summary statistics for different types of funds: multiple-class funds, no-load funds and single A class funds. As indicated, the number of multiple-class funds increased dramatically from 40 in 1993 to 838 in 2002. The number of no-load funds also increased significantly from 321 in 1993 to 768 in 2002. In contrast, the number of single A class funds decreased from 313 to 125 during the same period. As also shown in Figure 1, the difference reflects the industry trend that many funds switched to a multiple-class structure by adding B and C classes to the existing A class during the sample period. Multiple-class funds in general have higher TNAs than no-load funds and single A class funds: In 2002, the median TNA of multiple-class funds is 135 million dollars while the median TNAs of no-load funds and single A class funds are 88 and 23 million dollars, respectively. The mean fund TNA is much larger than the median, indicating that the distribution of fund size is highly skewed to the right. The multiple-class funds have higher expense ratios than no-load funds and single A class funds. The median expense ratio for multiple-class funds ranges from 1.50 percent to 1.75 percent. The difference in expense ratios is mainly driven by the annual

[13] The test results remain similar if we use a rolling window of fund returns in the previous 36 months to estimate the factor loadings and use the current month fund return to calculate α_{it}.

12b-1 fee. The median sales load for multiple-class funds and single A class funds is about 5 percent over the time period.

5 Methodology and Empirical Findings

In this section we test the empirical support for our hypotheses. We begin (Section 5.1) by investigating the decision by funds to introduce new classes and the effect of various fund and/or fund family characteristics (Hypotheses H1, H2 and H3). Next, in Section 5.2, we examine whether switching from a single to a multiple-class fund is associated with an increase in overall cash flow, attracting flows to new classes from substantially different investor clienteles in terms of horizon and sensitivity to fund performance (Hypothesis H4). Finally, we explore whether the introduction of new share classes is associated with a negative impact on fund performance (Hypothesis H5) in Section 5.3.

5.1 The Decision to Introduce New Share Classes

We investigate the empirical evidence on Hypotheses H1 through H3 relating fund and fund family characteristics to the decision of whether and when to introduce new share classes.

5.1.1 Fund Performance Prior to Switching

We begin with tests on whether higher ability funds are more likely to make an earlier switch to a multiple-class structure (Hypothesis H1). We investigate the connection between managerial ability and the switch in fund structure using the pre-switch performance as a proxy for managerial ability. Specifically, we compare the pre-switch risk-adjusted return of these funds relative to that of a control group.[14] The control group consists of single A funds that did not introduce new share

[14] Note that the issue of whether funds that switch early appear to suffer less of a performance decline from introducing new classes is investigated as part of our analysis of the fund performance (Section 5.3) subsequent to the introduction of new classes.

classes over the sample period.[15] For each year from 1993 to 2000, we identify the switching funds and compute the average monthly risk-adjusted return for the three-year period prior to the switch year. The pre-switch performance of switching funds is then compared to the performance of the control group over the same period. We exclude 2001 and 2002 from the analysis because very few funds introduced new share classes in this period. Note that these initial performance tests ignore fund and family level factors that are expected to affect the decision to switch – these factors are considered in the multivariate analysis in the next section.

Table 2 reports the mean one-factor and four-factor adjusted returns for both groups.[16] The between group differences in mean returns and the t-statistics are also reported. The results indicate that funds that switched early, especially in 1993 and 1994, significantly outperformed the control group in terms of pre-switch performance. The annualized differences in four-factor adjusted returns between the two groups for 1993 and 1994 are on average 2.24% and 3.06%, respectively. For the rest of the sample period, the pre-switch performance difference between the two groups is not generally statistically significant. The evidence is thus consistent with our hypothesis that funds with higher managerial ability are more likely to switch earlier.

5.1.2 A Multivariate Probit Regression Approach

To test our hypotheses about the timing of a fund's switching decision and the role of various fund and family characteristics in a multivariate setting, we next estimate a probit model in a panel setting. The selection of explanatory variables is motivated by our model predictions. As suggested by Hypothesis H1 and the findings in Section 5.1.1, we include past performance as a proxy for managerial ability and examine whether better performing funds are more likely to switch earlier, controlling for other fund and fund family characteristics. In choosing our proxy for managerial ability, we recognize the possibility of funds engaging in strategic timing: switching

[15] Using the pre-switch performance, which is publicly available information, as the proxy is consistent with our model assumption of symmetric information with regard to managerial ability.

[16] The results using median one-factor and four-factor adjusted returns are similar and are available upon request.

in a year in which they are lucky and perform well. Hence, we use past fund performance, over the previous three years, to assess managerial ability. We also (separately) include current year performance in the regression, recognizing that its effect on the switching decision could reflect strategic timing, in addition to ability.

Further, to test Hypothesis H2, we examine the impact of cash flow characteristics on a fund's switching decision by including the flow-performance sensitivity, the front-end load, and fund size during the pre-switch period. Funds with specific investment styles, for example small cap funds, may be more susceptible to changes in fund flow characteristics and thus more reluctant to introduce new share classes. We explicitly control for such fund types in the probit regression. To the extent that economies of scale on the cost side play a role in the switching decision, we also include the size of fund family as an additional control.

Specifically, we estimate the following probit regression:

$$\begin{aligned}&\{\text{Switch, No-Switch}\}_{ft} = \alpha + \beta_1(\text{Perf})_{ft} + \beta_2(\text{Perf})_{ft} * (\text{Early Years})_t + \beta_3(\text{Perf})_{f,[t-3,t-1]} +\\ &\beta_4(\text{Perf})_{f,[t-3,t-1]} * (\text{Early Years})_t + \beta_5(\text{Large Fund})_{f,t-1} + \beta_6(\text{SCG Fund})_{f,t-1} +\\ &\beta_7(\text{High CF Sensitivity})_{f,[t-3,t-1]} + \beta_8(\text{Front-end Load})_{f,t-1} + \beta_9(\text{Log Family TNA})_{f,t-1} +\\ &\beta_{10}(\text{Log Fund Age})_{f,t-1} + (\text{Yearly Indicators}).\end{aligned} \tag{17}$$

The discrete choice variable {Switch, No-Switch} equals one if a fund switched to a multiple-class structure in year t and zero otherwise. For funds that made the switch, we delete all observations following the switching year. The explanatory variables are defined as follows: (Perf) measures the average monthly risk-adjusted return in year t and the three-year period prior to year t; (Early Years) is an indicator variable that equals one if the current year is on or before 1995; (Large Fund) is an indicator variable that equals one if the fund TNA is above the mean TNA for all funds with the same investment style[17] at the end of year $t-1$; (SCG Fund) is an indicator variable that

[17] We use the Standard&Poor style classifications as provided in the CRSP Mutual Fund Database.

equals one if the fund is an equity USA small companies fund according to the Standard & Poor style classifications; (High CF Sensitivity) is an indicator variable that equals one if the coefficient estimate from regressing new money growth on past risk-adjusted return is above the mean for all funds with the same investment style at the end of year $t-1$; (Front-end Load) is the front-end load charged by the fund in year $t-1$; (Log Family TNA) is the logarithm of family level TNA at the end of year $t-1$; and (Log Fund Age) is the logarithm of fund age at the end of year $t-1$. We also include yearly indicator variables in the regression. The standard errors are heteroskedasticity robust and are clustered by fund. For robustness purpose, we measure risk-adjusted performance using both one-factor and four-factor adjusted returns.

The results are reported in Table 3. Consistent with the results in Table 2, funds with better past performance are more likely to make an early switch. As discussed above, past performance over the previous three years serves as our proxy for managerial ability. The coefficients for the interaction terms between past performance and early years dummy are estimated with a positive sign, as predicted, though the coefficient is statistically significant (at the 5 percent level) only when four-factor adjusted returns are used. The Chi-statistics for the joint tests of past three-year performance and the interaction terms with (Early Years) are statistically significant at the 1 percent level (P-value=0.007) when four-factor adjusted returns are used and at the 10 percent level (P-value=0.08) when one-factor adjusted returns are used, respectively. This is generally supportive of Hypothesis H1 that funds with better managers are more likely to introduce new classes early. In addition, the coefficient estimates for the current year performance, $(\text{Perf})_{ft}$, are positive and statistically significant. There is no significant difference between the early years and the rest of the sample. As we have noted, the effect of short term current performance on the switching decision raises the possibility of funds engaging in strategic timing: they launch the new classes when they are performing better and are more likely to attract cash inflows – whether they actually possess higher ability managers or not.

We also observe that funds with smaller size, lower flow-performance sensitivity, and higher front-end load are more likely to switch to the multiple-class structure. This is largely consistent with Hypothesis H2. The coefficient estimates for (Large Fund) indicator are all negative and statistically significant at the 5 percent level, regardless of performance measures. The coefficient estimates for (High CF Sensitivity) indicator are also negative and statistically significant at the 10 percent level in case of four-factor adjusted returns. On the other hand, the coefficient estimates for (Front-end Load) are positive and statistically significant at the 1 percent level. This is consistent with the main trade-off proposed in the model. The introduction of new share classes may attract new investor clienteles. However, the downside is that the increased fund size and cash flow volatility may have negative impact on future fund performance. On the margin, such costs would be more binding for funds with a larger size, higher sensitivity to fund performance and lower front-end load. There is no evidence, however, that small cap funds are more reluctant to introduce new share classes after controlling for other fund characteristics.

Another important factor affecting the introduction of new share classes is the size of the fund family. The coefficient estimates for fund family TNA are both positive and highly statistically significant, suggesting that funds belonging to larger fund families are much more likely to switch to the multiple-class structure. This supports the notion that there are economies of scale in introducing new classes on account of legal and marketing costs (Hypothesis H3) and that such costs are lower for larger fund families.

Finally, as we have noted earlier, to the extent the front-end load is a proxy for (low) performance-flow sensitivity of existing investors in the A class, the result suggests possible agency problems associated with introducing new classes. The reason is that fund managers may be more willing to introduce new classes and risk a drop in performance, if existing investors are less responsive to performance. Hence, longer term investors in higher load funds may be more likely to have their funds introduce new classes – giving them little direct benefit while possibly lowering return.

This agency concern may be somewhat mitigated by the fact that, as discussed in the hypothesis section, high front-end load funds are also likely to impose high CDSLs on their new classes and to suffer less of a performance drop. The reason is that we expect higher CDSL classes to attract a lower level – and lower volatility – of new cash flows and, thus, result in less of a negative impact on performance. Hence, the result on front-end load also suggests the impact of expected liquidity needs and expected size of the new classes in the switching decision.

To empirically investigate the determinants of the CDSL for the new share classes, we use an ordered logit regression with the (equally-weighted) average CDSL for B and C classes as the dependent variable. The explanatory variables consist of the front-end load for the existing A class and other fund and fund family characteristics similar to those included in the above hazard regression. The logit result (untabulated) suggests that the front-end load for the existing A share class stands out as the most important factor affecting the choice of CDSL for the new share classes. Other factors are in general not statistically significant. The evidence thus supports the notion that CDSLs on the new classes are largely determined by the load on existing classes and funds may have little discretion in the matter. We further examine the impact of CDSL on fund flow volatility and performance using panel specifications. The results (untabulated) suggest that, after controlling for other fund and fund family characteristics, a higher CDSL is associated with lower cash flow volatility and better fund performance following the switch to the multiple-class structure.

In summary, the empirical evidence is generally consistent with Hypotheses H1 to H3. A fund is more likely to introduce new classes if it has a higher ability manager, has smaller assets under management, experiences lower cash flow volatility, belongs to a larger fund family, and has a higher front-end load in place for the existing A class.

5.2 Fund Cash Flows and Investor Clienteles

We now examine the equilibrium relationship between the introduction of new classes by a single A class fund and the subsequent change in fund cash flows, controlling for past performance and other fund attributes. We then investigate whether the new classes attract investors with different preferences in terms of investment horizons and flow-performance sensitivity.

5.2.1 Fund Cash Flows

We use fund level information by aggregating across all share classes for multiple-class funds to estimate the following pooled regression:

$$
\begin{aligned}
&\text{Newmoneygrowth}_{ft} = \alpha + \beta_1(\text{Before})_{ft} + \beta_2(\text{After}_{yr0})_{ft} + \beta_3(\text{After}_{yr1})_{ft} + \\
&\beta_4(\text{After}_{yr2})_{ft} + \beta_5(\text{After}_{yr3})_{ft} + \beta_6(\text{After}_{yr4})_{ft} + \beta_7(\text{After}_{yr5})_{ft} + \\
&\beta_8(\text{Past Perf})_{f,[t-12,t-1]} + \beta_9(\text{Past Perf})_{f,[t-24,t-13]} + \beta_{10}(\text{Past Perf})_{f,[t-36,t-25]} + \\
&\beta_{11}(\text{Past Perf})^2_{f,[t-12,t-1]} + \beta_{12}(\text{Log Fund TNA})_{f,t-1} + \beta_{13}(\text{Log Family TNA})_{t-1} + \\
&\beta_{14}(\text{Log Fund Age})_{f,t-1} + \beta_{15}(\text{Expense})_{f,t-12} + \beta_{16}(\text{Turnover})_{f,t-12} + \\
&(\text{Time Fixed-Effects}) + \epsilon_{it}. \qquad (18)
\end{aligned}
$$

Here, f is the index for fund and t is the index for month. The variable (Newmoneygrowth) is given by equation (13). To capture the impact of a multiple-class structure on new money growth over time, we rely on several indicator variables to represent the years before and after the switch. There is no reason to expect the impact to be constant over time, since it may take time for the new classes to be marketed successfully and to attract new money. Moreover, after a period of rapid growth, the cash flow growth of the new classes may slow down. The indicator variable, (Before), equals one if a fund has a single A class in the current period but subsequently switches to a multiple-class structure and zero otherwise. The indicator variable, $(\text{After}_{[yrN,(N=0..4)]})$, equals one in the N^{th} year after a fund introduces multiple share classes and zero otherwise. The indicator variable, (After_{yr5}), equals one in the 5^{th} and later years after a fund introduces multiple share classes and zero otherwise.

The variable (Past Perf) measures past fund performance by calculating the average monthly one-factor and four-factor adjusted alphas during the corresponding 12-month intervals. As noted, the impact of performance on fund flows is well established in the literature. In addition to past performance, we control for the potential impact of fund size, fund family size, and fund age on fund cash flow. Family size may, for instance, have an impact on cash flow due to search costs, as documented in Sirri and Tufano (1998). We measure fund size by the logarithm of fund level TNA (Log Fund TNA) and measure family size by the logarithm of family level TNA (Log Family TNA). The family level TNA is the sum of the TNAs across all member funds. We measure the fund age (Log Fund Age) by the logarithm of the age for the oldest share class in the fund. Following the literature, we also control for fund level expense ratio (Expense) and turnover ratio (Turnover). We include time fixed-effects for each month to control for time trends in mutual fund flows. The standard errors are heteroskedasticity robust and are clustered by month.[18]

The data sample used in our regression analysis consists of funds that switched to the multiple-class structure as well as no-load funds. We use no-load funds as the control group because these funds, given their structure, do not introduce new share classes. Our sample excludes single A funds that never switched to the multiple share class structure. We do so to avoid a possible self selection bias: since these funds have the same structure as multiple-class funds before the switch but choose not to introduce additional classes over the sample period. Nevertheless, as a robustness check, we also estimate the regression by including single A funds that did not introduce multiple share classes, with an indicator variable for this group. The results (not reported) are similar to those obtained when these single A funds are excluded.

In Table 4 we present the regression results.[19] The coefficient estimates for ($\text{After}_{[yrN,(N=0..4)]}$)

[18] The results are similar when the standard errors are clustered by fund.

[19] As a robustness check, we estimate regression (18) using the Fama and MacBeth (1973) approach. The results

are generally positive, indicating that funds tend to attract more new money after the introduction of new classes. The coefficient estimates for (After$_{yr1}$) is the largest in magnitude (1 percent each month) and statistically significant. Thus, the cash inflow to multiple-class funds in the first year after the switch is about 12 percent higher than the inflow to no-load funds – after accounting for factors such as past performance, expenses, fund size, and fund family size. The growth of new money slows down but remains statistically significant in the second (0.70 percent each month) and the third year (0.50 percent each month). The new money growth for the fourth and fifth year beyond is no longer statistically significant. Hence, the higher cash flow and the resulting increase in fund size tend to take place mainly in the first one to three years after switching to a multiple-class structure. There is no evidence that these multiple-class funds were attracting relatively more money prior to the introduction of the new classes, as indicated by the insignificant coefficients on (Before) and (After$_{yr0}$). The results are thus consistent with Hypothesis H4. Note that, since we control for various factors such as fund performance and size, the net effect of introducing new classes will depend on whether there are significant offsetting changes in performance and size. The evidence on such changes is discussed later in the paper.

The coefficient estimates on the control variables are generally consistent with previous findings in the literature. The regression results confirm a positive and significant relationship between past performance and new money growth. The responsiveness of cash flow to past fund performance declines in magnitude and statistical significance as the time lag increases, indicating that mutual fund investors respond more to recent performance. We also find that new money growth is inversely related to fund size. Consistent with Sirri and Tufano (1998), funds belonging to larger fund families have significantly higher cash inflow, possibly due to the search costs of investors and the effect of brand names associated with larger fund families.

To check the robustness of the cash flow result, we also use an event study approach to compare

are similar and are available upon request.

the new money growth of multiple-class funds to that of no-load funds. For each month during the sample period, we estimate a cross-sectional regression with new money growth as the dependent variable. The regressors include: the average monthly 4-factor adjusted returns over the consecutive 12-month periods in the past 36 months, the square of the average monthly 4-factor adjusted returns over the last 12 months, the logarithm of fund level TNA, the logarithm of family level TNA, the logarithm of fund age, the expense ratio, and the turnover ratio. The coefficient estimates from the above regression are then used to calculate the predicted new money growth for all funds in the subsequent month. The difference between the realized and the predicted new money growth is defined as the abnormal new money growth. We then compute the average monthly abnormal new money growth for each fund on a yearly basis. In the next step, we separate all funds in the sample into two groups: multiple-class funds and no-load funds. For the no-load group, we calculate the mean of the average monthly abnormal new money growth in each year across all no-load funds and use it as a benchmark for comparison purposes. For each multiple-class fund in any given year, we subtract the no-load benchmark from its average monthly abnormal new money growth to examine the impact of multiple-class structure on fund flows.

In Table 5, we report the average difference in abnormal new money growth between multiple-class funds and no-load funds based on the years relative to the switching year: the switching year (After_{yr0}), and each of the five years following the switch ($\text{After}_{[yrN,(N=0..5)]}$). The result suggests that the impact of the multiple-class structure on fund flows decreases gradually over the five years, with much of the cash flow impact occurring in the first three years after the switch. In particular, the annual abnormal new money growth (multiplying the monthly abnormal new money growth as reported in Table 5 by 12) for multiple-class funds is on average 8.3%, 6.3%, and 4.6% higher than that of their no-load counterparts in years 1, 2, and 3, respectively. The cash flow differences are statistically significant at the 5 percent level or better. For the fourth and fifth year after the switch, the differences in abnormal new money growth are no longer statistically significant. The event study results thus largely confirm the findings from the regression analysis.

5.2.2 Investor Clienteles

As discussed, the different share classes are likely to attract investors with different investment preferences and thus display different patterns of cash flow behavior (second part of Hypothesis H4). Specifically, the C class is expected to have the highest cash flow response to fund performance and overall cash flow volatility.[20]

We begin by comparing the average new money growth and cash flow volatility between the different classes for funds that have all three share classes (A, B and C). For each multiple-class fund in our sample, we first compute the means and standard deviations of the new money growth over time for each of its individual share classes. We then calculate the cross-sectional averages of the means and the standard deviations of new money growth across all funds within each class type. Finally, we conduct paired t-tests. The average monthly new money growth for classes A, B, and C is 0.72%, 1.14%, and 1.78%, respectively. The difference is statistically significant for all three paired comparisons. In terms of cash flow volatility, class C exhibits a higher standard deviation (6.95%) in monthly new money growth than class A (4.81%) or class B (4.72%). The paired t-statistics suggest that the differences in the mean volatility are statistically significant at the 1 percent level for class A versus class C and class B versus class C.

To investigate the flow-performance sensitivity for different share classes, we again focus on the multiple-class funds with all three share classes and estimate the following pooled regression with

[20] Our paper is not the first one in the literature to examine the impact of load and fee structures on investor clienteles. Chordia (1996), for instance, develops an equilibrium model in which mutual funds optimally choose the load and fee structure to discriminating investors and to dissuade redemptions. However, the paper does not provide direct evidence linking load fees to cash flow characteristics and investor clienteles. The emprical analysis in the paper focuses on the impact of load fees on fund cash holdings and illiquid stock holdings. The argument is that, if load fees are effective in dissuading redemptions, then funds with higher load fees will be holding less cash and more willing to invest in less liquid stocks.

time fixed-effects:

$$
\begin{aligned}
&\text{Newmoneygrowth}_{it} = \alpha + \beta_1(\text{Past Perf})_{i,[t-12,t-1]} * (\text{Class B Indicator})_i + \\
&\beta_2(\text{Past Perf})_{i,[t-12,t-1]} * (\text{Class C Indicator})_i + \beta_3(\text{Past Perf})_{i,[t-12,t-1]} + \\
&\beta_4(\text{Past Perf})^2_{i,[t-12,t-1]} + \beta_5(\text{Past Perf})_{i,[t-24,t-13]} + \beta_6(\text{Past Perf})_{i,[t-36,t-25]} + \\
&\beta_7(\text{Log Class TNA})_{i,t-1} + \beta_8(\text{Log Family TNA})_{i,t-1} + \beta_9(\text{Log Class Age})_{i,t-1} + \\
&\beta_{10}(\text{Expense})_{i,t-12} + \beta_{11}(\text{Turnover})_{f,t-12} + (\text{Time Fixed-Effects}) + \epsilon_{it}. \qquad (19)
\end{aligned}
$$

All the variables in the above regression are class level measures with the exception of family size (Log Family TNA). The first two regressors are the interaction terms between performance in the previous 12-month period and the class indicator variables. The indicator variables (Class B Indicator and Class C Indicator) have a value of one if the share class is B and C, respectively, and zero otherwise. The coefficient estimates on these interaction terms capture the differences in the cash flow response to past performance for the B and C classes relative to the A class. The standard errors are heteroskedasticity robust and are clustered by month.

Table 6 presents the results for regression equation (19).[21] The coefficient estimates for the interaction of the C class indicator and the previous 12-month performance are positive and significant at the 1 percent level. The coefficient estimates for the interaction of the B class indicator and the previous 12-month performance are positive and marginally significant (at the 10 percent level) when one-factor adjusted returns are used. The results suggest that, among the three share classes, class C is most responsive to past performance. For a given increase in the monthly four-factor alpha, the cash flow response for class C is about 70 percent larger than that for class A.[22]

[21] As a robustness check, we estimate regression (19) using the Fama and MacBeth (1973) approach. The results are similar and are available upon request.

[22] One concern is whether the higher flow-performance sensitivity for B and C classes is driven by the new money effect. Johnson (2007) shows that new investors to mutual funds exhibit more sensitive flow patterns than existing investors. Note that our regression controls past performance in the previous three years and thus omits data for all share classes during the first three years following the switch. Given the previous finding (Tables 4 and 5) that the new money effect concentrates in the first three years after the switch, the results in Table 6 suggest that the B/C share class effect on flow-performance sensitivity seems to go beyond the new money effect. Nonetheless, we directly

Finally, we include in regression (19) two indicator variables, positive and negative, that equal one if the past 12-month performance is non-negative and negative, respectively. We interact these variables with the class indicators to investigate whether the B and C classes respond differently to positive/negative past performance than the A class. We also explore the possibility that the flow-performance relationships for the new classes exhibit different patterns during the early vs. later years following the switch to a multiple-class structure. For this purpose, we construct a new indicator variable (2YrLater) that equals one if two years have passed since the new classes were introduced, and interact this variable with the past performance and class indicators.

The estimation results are reported in Table 6B. We focus our discussion based on the four-factor adjusted returns since the one-factor model yields similar results. As shown in Column 3 of the table, the coefficient estimates for the interaction terms between past performance and positive/negative indicators are both positive and statistically significant at the 1% level. However, the magnitude for the positive past performance is much larger than that for the negative past performance. Specifically, for the A class, a 1% improve in four-factor adjusted return when positive leads to a 2.84% increase in cash inflow. In contrast, for a 1% decline in four-factor adjusted return when negative, the new money growth will decline by only 1.20%. The difference between the positive and the negative flow-performance responses is statistically significant at the 1% level. This is consistent with the previous finding in the literature that flow-performance response exhibits a convex pattern.

The B and C classes exhibit different flow-performance sensitivity than the A class. The interaction terms between the C class indicator and the positive/negative past performance are both positive and statistically significant at the 1% level. This suggests that, compared to the A class, class C investors are more sensitive to both positive and negative past performance. This finding

investigate the possibility of new money effect using a pooled regression approach similar to the one in Table 6 but only control for past one-year performance. The result (not reported) shows that the flow-performance sensivity for the C class is even stronger three years after switching to a multiple-class structure.

is consistent with the notion that C class attracts short-term investors who are more sensitive to fund performance. For the B class, the interaction term is negative for positive performance, but positive and statistically significant for the negative performance. Hence, compared to the A class, class B investors seem to respond somewhat less to positive performance but more to negative performance. In summary, all three share classes exhibit convex flow-performance relationships, though the magnitude differs significantly. Investors in the C class are found to be most responsive to past performance, either positive or negative.

The last column of Table 6B shows that, for B and C classes, the flow-performance sensitivity exhibits a different pattern during the first two years following the switch to a multiple-class structure. For the B class, the flow-performance relationship is negative and not statistically significant during the first two years and becomes positive and statistically significant for later years. This suggests that, compared to the A class, investors in the B class are less sensitive to negative performance during the early years of their investment, likely due to the high load charges upon redemption. They become more responsive in later years, possibly because of the reduced or exempted exit penalties for investors that have been with the fund for some time. Similar results are found for the C class. This is plausible since class C investors also incur CDSL if they withdraw money within the first year of investment.

In summary, the empirical results suggest that, consistent with Hypothesis H4: (i) The introduction of new classes is associated with an increase in cash inflow to the fund for a period of one to three years, and (ii) the new classes, especially class C, appear to attract investors with shorter investment horizons and greater flow-performance sensitivity.

5.3 Fund Performance

Given the above findings on the effect of a multiple-class structure on cash flow characteristics, we now investigate whether the introduction of new share classes is associated with a drop on fund performance, as predicted by Hypothesis H5.

5.3.1 Fund Performance and Multiple-Class Structure

We compare the risk-adjusted returns of the A share class of multiple-class funds to that of no-load funds before and after the switch by estimating the following pooled regression with time fixed-effects and clustered standard errors by month[23]:

$$\begin{aligned}
&(\text{Risk-Adjusted Return})_{ft} = \alpha + \beta_1(\text{Before})_{ft} + \beta_2(\text{After}_{yr0})_{ft} + \beta_3(\text{After}_{yr1})_{ft} + \\
&\beta_4(\text{After}_{yr2})_{ft} + \beta_5(\text{After}_{yr3})_{ft} + \beta_6(\text{After}_{yr4})_{ft} + \beta_7(\text{After}_{yr5})_{ft} + \\
&\beta_8(\text{After}_{yr2})_{ft} * (\text{Early Switchers}) + \beta_9(\text{After}_{yr3})_{ft} * (\text{Early Switchers}) + \\
&\beta_{10}(\text{After}_{yr4})_{ft} * (\text{Early Switchers}) + \beta_{11}(\text{After}_{yr5})_{ft} * (\text{Early Switchers}) + \\
&\beta_{12}(\text{Log Fund TNA})_{f,t-1} + \beta_{13}(\text{Log Family TNA})_{f,t-1} + \beta_{14}(\text{Log Fund Age})_{f,t-1} + \\
&\beta_{15}(\text{Expense})_{f,t-12} + \beta_{16}(\text{Turnover})_{f,t-12} + (\text{Time Fixed-Effects}) + \epsilon_{it}. \qquad (20)
\end{aligned}$$

We focus on the performance of the A class of multiple-class funds so that the observed performance change is not driven by the change in expenses after introducing new share classes. Note that the after-expense returns for classes B and C are lower than those for class A of the same fund due to the fact that classes B and C charge higher 12b-1 fees. Most variables are defined as in regression (18). For funds that introduced new share classes, coefficients β_1 to β_7 capture the performance differences relative to the no-load funds before and after the switch, respectively. The indicator variable, (Early Switchers), equals one if the fund switched to a multiple-class structure during or before 1995. We interact this variable with several indicator variables representing the years after switching to a multiple-class structure. The coefficients for the interaction terms, β_8 to β_{11}, shed light on whether the change in performance of early switching funds is different from that of other funds. As we have discussed (Hypothesis H1), funds may be quicker to adopt a multiple-class structure if they expect to be better able to cope with the resulting change in cash flow

[23] The results are similar when the standard errors are clustered by fund.

characteristics.

The regression results, presented in Table 7, are consistent with Hypothesis H5.[24] Before switching to a multiple-class structure, the A class funds have a performance similar to that of no-load funds. However, starting from the second year after introducing new share classes, multiple-class funds underperform their no-load counterparts by about 1.2 to 1.6 percent on an annual basis using the Carhart four-factor model. The effect is similar before and after controlling for fund expenses. The under-performance is generally significant at the 5 percent level or better in these years. Note that the drop in performance starting from year 2 coincides (roughly) with the net increase in cash inflows occurring over the first three years after the change in fund structure, as shown in Tables 4 and 5. Based on the estimated impact of fund performance on cash flow in regression (18), we infer that the new money growth decreases by about 2 to 3 percent on an annual basis due to the performance drop.[25]

The last two columns of Table 7 report the estimation results for regressions including the interaction terms. The coefficient estimates for β_8 and β_9 are positive and significant at the 5 percent level or better, with about the same magnitude as the (negative) coefficient estimates for β_4 and β_5. Hence, the evidence suggests that early switching funds exhibit a different performance pattern relative to funds that switched after 1995. The performance for these early switching funds seems to be much less affected by the multiple-class structure in the first three years after the switch. An explanation, consistent with Hypothesis H1, is that first movers are likely to be funds with better skilled managers, who are more effective in coping with the increase in fund flow volatility and fund size.

[24] As with earlier regressions, we examine the robustness of the results by also estimating regression (20) using the Fama and MacBeth (1973) approach as well as including single A funds that never introduced new share classes. The results using the different specifications are similar and are available upon request.

[25] As shown in Table 4, a 1% decrease in the average four-factor adjusted return in the previous 12 months is associated with a 23% (=0.01*195.71*12) decrease in new money growth on an annual basis. Given that the performance drop after the switch is on average between 0.10% and 0.13% (as shown in the third column of Table 7), the corresponding cash flow impact is about 2.30% to 3%.

As a robustness check, we compare the performance of the A class of multiple-class funds to that of the single-class funds using a portfolio approach. In each month, we form a portfolio of the A class of multiple-class funds and another portfolio of single-class funds. The multiple-class fund portfolio includes funds that have had new share classes for at least three years. The single-class fund portfolio includes no-load funds and funds that currently have only an A share class. We compute the TNA-weighted monthly returns for these two portfolios and calculate the monthly difference in portfolio returns. We then regress the return differences on the risk/style factors (the market, size, book to market, and momentum factors). The intercept term from the regression measures the average abnormal return difference between the A class of multiple-class funds and the single-class funds. The regression result indicates that the A class of multiple-class funds underperforms the single-class funds by 1.7 percent per year using the Carhart four-factor model — largely consistent with the magnitude of performance drop reported in Table 7. The portfolio result thus confirms the earlier finding that, after introducing new share classes, the A class of multiple-class funds performs significantly worse than the single-class funds.

Drawing on the results about the impact of new share classes on fund flows and performance, we can make some (rough) assessment of the wealth transfers during the five years following the switch to a multiple-class structure. In terms of winners and losers, the investors in class A bear significant costs: of the order of 1.2 to 1.6 percent a year. For the average sized class A fund that switched to a multiple-class structure (about $480 million in 1996), this implies an annual (aggregate) loss of about $5.76 million to $7.68 million. Given that the negative impact on fund performance kicks in from the 2nd year onward, the total loss from year 2 to year 5 ranges from $23.04 million to $30.72 million. The clear winner is the fund manager who sees the size of her fund growing quickly during the five-year period. Controlling for fund performance, the aggregate growth rate of fund assets during the first three years following the switch is about 26% (see Table 4). Taking into account the negative impact on fund performance (see Table 7), about half of the aggregate growth is eroded by the end of year 5. Hence, the net growth during the five year period is about 13%. Therefore, if the fund manger receives a fee of about 2% of TNA, she increased her management fees by about $1.25 million in the 5th year (=$480 million*2%*13%) and received about $3.12 million in additional fees over the five years (=$480 million*2%*(13%/2)*5 assuming uniform growth). It is difficult to quantify the benefits to the new investors from the availability of the new classes but these numbers suggest that – to the extent that class A investors remain in the fund – they are subject to significant costs. Since these costs appear to outweigh the benefits derived by the fund managers – this suggests that the introduction of the new classes was, at a minimum, greatly facilitated by the existence of long-term, class A investors that were unwilling to exit the fund.

5.3.2 Change in Fund Performance and Change in Cash Flow Characteristics

The evidence thus far indicates that funds experience a significant drop in performance after switching to the multiple-class structure. We now investigate whether the performance drop can be explained by the change in fund cash flow characteristics, as we have hypothesized. Specifically, we estimate the following pooled regression using a sample of multiple-class funds with all three share classes (A, B and C).

$$
\begin{aligned}
&(\text{Change in Performance})_{ft} = \alpha + \beta_1(\text{Change in Fund Flow Vol})_{f,[t-12,t-1]} + \\
&\beta_2(\text{Change in Fund TNA})_{f,t-1} + \beta_3(\text{Change in Fund Flow Vol})_{f,[t-12,t-1]} * (\text{Early Switchers}) + \\
&\beta_4(\text{Change in Fund TNA})_{f,t-1} * (\text{Early Switchers}) + \beta_5(\text{Change in Family TNA})_{f,t-1} + \\
&\beta_6(\text{Log Fund Age})_{f,t-1} + \beta_7(\text{Change in Expense})_{f,t-12} + \beta_8(\text{Change in Turnover})_{f,t-12} + \\
&(\text{Time Fixed-Effects}) + \epsilon_{it}. \qquad (21)
\end{aligned}
$$

Here, we regress the change in risk-adjusted return of share class A on the changes in several key fund characteristics that could have a significant impact on performance. All changes are defined relative to the pre-switch averages, which are calculated using the monthly data during the three-year period prior to the switch year. The change in fund performance is defined as the current month risk-adjusted return minus the pre-switch average. We compute the fund cash flow volatility on a monthly basis as the standard deviation of fund-level new money growth in the previous 12 months. The change in fund cash flow volatility after the switch is then measured as the ratio of previous 12-month fund flow volatility over the pre-switch average.[26] Hence, the change in fund flow volatility represents the percentage change in cash flow volatility in any 12-month period relative to the average cash flow volatility during the pre-switch period. The change in fund (or family) TNA is defined as the logarithm of previous month-end fund (or family) TNA minus the logarithm of pre-switch monthly average. The changes in expense and turnover ratios are defined as the previous year expense and turnover ratios minus the pre-switch averages. We also control the impact of fund age by taking the logarithm transformation. The indicator variable, (Early Switchers), is defined as in regression (20). We interact this variable with the change in fund flow volatility and the change in fund TNA to investigate whether the performance of early switching funds responds differently to the changes in cash flow characteristics. The standard errors are heteroskedasticity robust and are clustered by month.[27]

Table 8 reports the regression results for (21). The coefficients for (Change in Fund Flow Vol) are negative and significant at the 1 percent level, suggesting that a greater increase in cash flow volatility after the introduction of new share classes hurts fund performance. Univariate analysis suggests that fund-level cash flow volatility in any 12-month period increases by an average of 14% after the switch, translating into a 1 percent drop in four-factor adjusted return on an annual basis.[28] The other factor that seems to contribute to the performance drop is the change in fund size. The coefficients for (Change in Fund TNA) are negative and significant at the 1 percent level. Recall

[26] Alternatively, we measure the change in fund cash flow volatility using the standard deviation of fund-level new money growth over the entire period prior to the switch year as the benchmark. The results are robust to this alternative specification.

[27] The results are similar when the standard errors are clustered by fund.

[28] The ratio of the post-switch fund flow volatility over the pre-switch fund flow volatility is on average 1.14. Multiplying the 14% increase in volatility by the coefficient of change in fund flow volatility (0.08) results in an annual impact of roughly 1% (=1.14*0.08*12).

from Table 2 that fund TNA increases by an average of 12% during the first year after the switch. Based on the coefficient estimates, the increase in fund size accounts for an approximately 0.15 percent drop in four-factor adjusted return on an annual basis.[29] The evidence is thus consistent with Hypothesis H5 that the change in cash flow volatility and fund size – stemming from the change in fund structure – is associated with a significantly negative impact on fund performance.

Another interesting result in Table 8 is related to the impact of change in fund flow volatility on early switchers. Consistent with our results in Table 7, the coefficient estimates for the interaction term are positive and significant, with about the same magnitude as the (negative) coefficient estimates for the change in fund flow volatility. The sum of the two coefficient estimates is close to zero and is not statistically significant. Hence, the performance of early switching funds does not seem to be hurt by the increase in fund flow volatility. The evidence is consistent with Hypothesis H1 that these funds may have higher ability managers, and thus are better able to deal with the increase in cash flow volatility. There is, however, no corresponding evidence that the impact of the change in fund size on performance is different for the early switching funds.

In summary, we find a decline in fund performance about two years after introducing the new share classes – which corresponds, roughly, to the time period after which multiple-class funds no longer attract significantly higher cash flows. Further analysis indicates that the magnitude of performance drop is significantly related to the change in fund flow characteristics. Overall, the empirical evidence is consistent with Hypothesis H5 and with other findings in the literature on the impact of fund flow characteristics, specifically size and cash flow volatility, on performance. Our work differs from existing research by focusing on the change in performance around a major fund restructuring and tying it directly to the corresponding change in fund flow characteristics.

[29] Multiplying the logarithm of the 12% increase in fund TNA by the coefficient of change in fund TNA (0.108) results in an annual impact of roughly 0.15% (=log(1.12)*0.108*12).

6 Conclusion

In this paper we investigate a significant innovation with widespread consequences for the mutual fund industry: the introduction of multiple-class funds that gave investors a choice among alternative load and fee structures. The study provides an understanding of the factors driving the transition to a multiple-class structure and, at a broader level, sheds some light on the manner in which financial innovations tend to be adopted. The switch in fund structure provides a well-controlled setting for research on investor clienteles and their impact on fund performance.

We first develop a simple model of the decision by funds to introduce new classes and argue that introducing new classes with different load and fee structures broadens the appeal of a fund and attracts new investors. There are offsetting costs, however. One is that the new classes would tend to increase both the level and volatility of fund flows, adversely impacting fund performance and eroding the cash flow benefits of the new classes. Another deterrent is the fixed cost associated with introducing new share classes. As a consequence, while some funds may move early in terms of introducing new classes, other funds may choose to delay or to not make such a switch.

The model is then used to develop a number of predictions about the impact and adoption of the new classes. Specifically, funds with more skilled management, lower flow-performance sensitivity, higher front-end loads and smaller size for the existing classes, and membership in larger families are better positioned to benefit and, therefore, more likely to switch to a multiple-class structure.

Using a large sample of U.S. equity funds from 1993 to 2002, we test various predictions of our model regarding fund and fund family characteristics that affect the switching decision. We find that funds with superior past performance are more likely to make an early switch – consistent with the model's prediction that funds with higher managerial ability tend to be early movers. We also observe that funds tend to switch during the year when they are performing well, suggestive of possible strategic timing behavior as part of the funds' switching decision. Consistent with managerial concerns about the offsetting costs – in terms of decreasing returns to scale and increase in fund flow volatility – associated with introducing new share classes, we show that funds with lower flow-performance sensitivity, higher front-end load and smaller size for the existing classes are more likely to switch. We also find that larger fund families are more likely to introduce new classes, suggesting that economies of scale could be an important consideration in the switching process.

Finally, we investigate the equilibrium consequences of introducing new share classes on fund flows and performance. We show that multiple-class funds attract more new money during the first three years after introducing new share classes, controlling for performance and other fund attributes. As predicted by our hypotheses, the increase in the size and volatility of the new money is associated with a significant drop in fund performance. Based on our results about the impact of new share classes on fund flows and performance, we make some rough assessment of the wealth transfers during the five years following the switch to a multiple-class structure. We argue that, in terms of winners and losers, the investors in class A bear significant costs – while the clear winner is the fund manager who sees the size of her fund growing quickly during the five-year period.

The introduction of multiple share classes raises significant new issues for empirical studies of mutual funds. Our research demonstrates the importance of controlling for the effects of the multiple-class structure for empirical studies of mutual funds using data after 1990, during which time multiple share classes emerged and became prevalent. For studies of performance evaluation, our results indicate the importance of controlling for the change in fund performance due to the multiple share class structure, since such a change does not reflect a change in management investment ability. For studies of cash flow patterns and investor behavior, it is also important to control for the temporary shock in cash flows due to the change in investor clienteles associated with the new share classes.

Appendix: Proof of Proposition 1

Proof: From equation (9), a fund will switch to a multiple-class structure if the expected increase in fund size $(S_M - S_A)$ exceeds C/α. Substituting equations (3) and (8) into the left side of equation (9) gives:

$$S_M - S_A = \frac{(I_A + I_B) + (I_A\beta_A + I_B\beta_B)(\theta - \eta_\theta L_M)}{1 + (I_A\beta_A + I_B\beta_B)\lambda_\theta} - \frac{I_A[1 + \beta_A\theta - \beta_A\eta_\theta L_A]}{1 + I_A\beta_A\lambda_\theta}.$$

After rearranging terms, we have:

$$\begin{aligned} S_M - S_A \quad = \quad & \frac{I_B}{1 + (I_A\beta_A + I_B\beta_B)\lambda_\theta} + \\ & \frac{I_B\beta_B(\theta - \eta_\theta L_M - \lambda_\theta I_A) - I_A\beta_A\eta_\theta(L_M - L_A)[1 + (I_A\beta_A + I_B\beta_B)\lambda_\theta]}{[1 + (I_A\beta_A + I_B\beta_B)\lambda_\theta](1 + I_A\beta_A\lambda_\theta)}. \end{aligned} \tag{22}$$

(a) Funds managed by higher ability managers will be more likely to switch if $\frac{\partial(S_M - S_A)}{\partial\theta} > 0$. It would be sufficient to show that both terms on the right hand side of equation (22) are increasing in θ. Given the assumption $\frac{\partial\lambda}{\partial\theta} < 0$, it is obvious that the first term is increasing in θ. Regarding the numerator of the second term, we take the first order derivative with respect to θ:

$$I_B\beta_B(1 - \frac{\partial\eta}{\partial\theta}L_M - \frac{\partial\lambda}{\partial\theta}I_A) - I_A\beta_A(L_M - L_A)[\frac{\partial\eta}{\partial\theta} + (I_A\beta_A + I_B\beta_B)(\frac{\partial\eta}{\partial\theta}\lambda_\theta + \eta_\theta\frac{\partial\lambda}{\partial\theta})] > 0,$$

since $\frac{\partial\lambda}{\partial\theta} < 0$ and $\frac{\partial\eta}{\partial\theta} < 0$. Note that the denominator of the second term is decreasing in θ. It thus follows that the second term is increasing in θ. Hence, $\frac{\partial(S_M - S_A)}{\partial\theta} > 0$, implying that higher ability managers are more likely to switch fund structure.

(b) Regarding the impact of β_A on $(S_M - S_A)$, note first that the first term on the right hand side of equation (22) is decreasing in β_A. For the second term, the denominator is obviously increasing in β_A. We now take the first order derivative of the numerator with respect to β_A:

$$-I_A\eta_\theta(L_M - L_A)[1 + I_B\beta_B\lambda_\theta + 2I_A\beta_A\lambda_\theta] < 0,$$

since $L_M > L_A$. This implies that the second term is decreasing in β_A. Hence, $\frac{\partial(S_M - S_A)}{\partial\beta_A} < 0$, suggesting that funds are more likely to switch fund structure if investors in the existing classes have lower performance sensitivity.

(c) From equation (9), we take the first order derivative with respect to L_M:

$$\frac{\partial(S_M - S_A)}{\partial L_M} = \frac{-I_B\beta_B\eta_\theta - I_A\beta_A\eta_\theta[1 + (I_A\beta_A + I_B\beta_B)\lambda_\theta]}{[1 + (I_A\beta_A + I_B\beta_B)\lambda_\theta](1 + I_A\beta_A\lambda_\theta)} < 0.$$

Hence, a fund is more likely to introduce new share classes if L_M is small. The intuition is that a smaller L_M implies a smaller increase in liquidity needs of investors after switching to a multiple-class structure, which leads to a smaller performance drop and thus fund outflow.

(d) It follows directly from the fact that a smaller direct cost C decreases the right hand side of equation (9), and thus makes the condition more likely to be satisfied. ■

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Table 1. Summary Statistics: Multiple-Class Funds, No-load Funds, and Single A Class Funds

Year	Number of Funds	Number of Families	TNA ($ Mil.)	Expense (%)	12b-1 Fee (%)	Non 12b-1 Expense (%)	Total Load (%)
Panel A: Multiple-Class Funds							
1993	40	10	224.98	1.75	0.67	1.04	5.02
1994	100	28	221.54	1.60	0.44	1.13	5.00
1995	174	49	207.83	1.50	0.41	1.11	4.89
1996	268	63	232.32	1.53	0.47	1.08	4.87
1997	359	71	260.97	1.53	0.49	1.04	4.91
1998	470	76	221.91	1.55	0.53	1.04	4.93
1999	602	86	207.24	1.59	0.57	1.04	4.93
2000	706	103	209.77	1.57	0.57	1.04	4.92
2001	791	107	181.92	1.60	0.55	1.08	4.83
2002	838	109	135.13	1.65	0.54	1.11	4.84
Panel B: No-load Funds							
1993	321	154	77.51	1.17	0.00	1.11	0.00
1994	375	165	71.70	1.13	0.00	1.08	0.00
1995	423	171	81.18	1.14	0.00	1.10	0.00
1996	471	183	97.04	1.14	0.00	1.11	0.00
1997	544	203	103.33	1.16	0.00	1.09	0.00
1998	616	217	99.13	1.17	0.00	1.09	0.00
1999	683	230	92.95	1.18	0.00	1.09	0.00
2000	720	254	92.64	1.17	0.00	1.07	0.00
2001	770	259	86.45	1.11	0.00	1.03	0.00
2002	768	257	87.98	1.15	0.00	1.08	0.00

Our data sample is based on the mutual fund database compiled by the Center for Research in Security Prices (CRSP). For our study, we include all diversified U.S. equity funds over the period from January 1993 to December 2002 and manually identify their class information. The table reports annual summary statistics for multiple-class funds, no-load funds, and single A class funds. For each year during our sample period, we count the number of funds and the number of fund families in each group. We report the median statistics for the following measures: year-end total net assets (TNA), annual expense ratio, annual 12b-1 fee, annual non 12b-1 expense (expense ratio net of 12b-1 fee), and total load charges. For multiple-class funds, the fund level expense ratio, 12b-1 fee, non 12b-1 expense, and total load are calculated as the TNA-weighted average of the corresponding class level measures.

Table 1. (continued)

Panel C: Single A Class Funds							
Year	**Number of Funds**	**Number of Families**	**TNA ($ Mil.)**	**Expense (%)**	**12b-1 Fee (%)**	**Non 12b-1 Expense (%)**	**Total Load (%)**
1993	313	128	86.10	1.22	0.22	1.02	4.75
1994	308	122	63.03	1.20	0.25	1.02	4.50
1995	279	108	63.49	1.20	0.20	1.04	4.50
1996	227	81	59.96	1.20	0.18	1.09	4.50
1997	201	77	46.69	1.23	0.25	1.06	4.50
1998	200	77	34.51	1.25	0.25	1.10	4.75
1999	187	80	36.56	1.29	0.25	1.13	4.75
2000	163	83	24.35	1.29	0.25	1.11	4.75
2001	152	76	21.19	1.32	0.25	1.15	5.25
2002	125	70	22.67	1.32	0.25	1.11	5.25

Table 2. Performance Before Switching to a Multiple-Class Structure

	One-Factor Return (%)			Four-Factor Return (%)		
	Switcher	**Control**	**Difference**	**Switcher**	**Control**	**Difference**
1993	0.145	-0.061	0.206*** (2.86)	0.112	-0.075	0.187** (2.57)
1994	0.098	-0.109	0.207** (2.11)	0.122	-0.133	0.255*** (3.07)
1995	-0.055	-0.174	0.119* (1.74)	-0.072	-0.160	0.088 (1.45)
1996	-0.045	-0.208	0.163* (2.17)	-0.077	-0.143	0.066 (1.08)
1997	-0.147	-0.221	0.074 (1.18)	-0.171	-0.138	-0.033 (0.66)
1998	0.036	-0.392	0.428*** (3.27)	-0.101	-0.244	0.143* (1.77)
1999	-0.445	-0.474	0.029 (0.18)	-0.302	-0.262	-0.040 (0.38)
2000	-0.554	-0.533	-0.021 (0.05)	-0.326	-0.310	-0.016 (0.04)

This table compares the pre-switch performance of the funds that introduced new share classes to that of a control group on an annual basis. The control group consists of funds that never introduced new share classes during the sample period. For each year from 1993 to 2000, we identify the switching funds in that year and compute the average monthly four-factor adjusted returns for the three-year period prior to the switch year. The pre-switch performance for the switching group is then compared to the performance for the control group during the same period. We exclude 2001 and 2002 from the analysis because very few funds introduced new share classes in this period. We report both the one-factor and four-factor adjusted returns for the two groups of funds. The between group difference in mean returns are also reported. The t-statistics are reported in parentheses. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. All returns reported in the table are in percentage terms.

Table 3. Factors Affecting the Introduction of Multiple Share Classes

	One-Factor		Four-Factor	
Perf (t)	22.312*** (20.30)	21.711*** (14.87)	16.580*** (7.64)	17.390** (5.86)
Perf (t) * Early Years (t)		0.582 (0.00)		-3.728 (0.09)
Perf (t-3, t-1)	7.831 (1.18)	3.750 (0.20)	13.761 (2.62)	2.132 (0.04)
Perf(t-3,t-1) * Early Years (t)		13.346 (1.30)		25.183** (3.83)
Large Fund (t-1)	-0.265** (3.89)	-0.263** (3.85)	-0.259** (3.83)	-0.261** (3.94)
SCG Fund (t-1)	0.169 (1.87)	0.159 (1.64)	0.153 (1.49)	0.152 (1.48)
High CF Sensitivity (t-3,t-1)	-0.129 (1.98)	-0.135 (2.15)	-0.157* (2.89)	-0.163* (3.05)
Front-End Load (t-1)	16.829*** (31.92)	16.769*** (31.63)	16.397*** (31.20)	16.318*** (30.90)
Log Family TNA (t-1)	0.064*** (10.86)	0.064*** (10.69)	0.067*** (11.90)	0.068*** (12.26)
Log Fund Age (t-1)	0.066 (1.38)	0.061 (1.17)	0.050 (0.77)	0.045 (0.63)
Yearly Indicators	Included	Included	Included	Included
Observations	1,652	1,652	1,652	1,652

This table investigates the role of various fund and fund family characteristics in the decision of introducing new share classes using a Probit regression approach in a panel setting. The discrete choice variable {Switch, No-Switch} equals one if the fund switched to a multiple-class structure in year t and zero otherwise. The explanatory variables include: the average monthly one-factor or four-factor adjusted return during the switching year ($Perf_t$); the average monthly one-factor or four-factor adjusted returns during the three-year period prior to the switching year ($Perf_{[t-3,t-1]}$); the interaction terms between an indicator for Early Years (=1 if the current year is on or before 1995) and the above performance measures; an indicator variable (Large Fund) that equals one if the previous year-end fund TNA is above the mean TNA of all funds with the same investment style; an indicator variable (SCG Fund) that equals one if the fund is a small cap fund; an indicator variable (High CF Sensitivity) that equals one if the coefficient estimate from regressing new money growth on past risk-adjusted performance is above the mean for all funds with the same investment style during the previous three-year period; the front-end load fee (Front-End Load) in the previous year; the logarithm of fund family TNA (Log Family TNA) at the previous year-end; and the logarithm of fund age (Log Fund Age) at the previous year-end. The Chi-square statistics are reported in parentheses. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively.

Table 4. New Money Growth and Multiple-Class Structure: Regression Approach

	New Money Growth (t)	
	One-factor	**Four-factor**
Before (t)	0.241 (1.27)	0.145 (0.77)
After$_{yr0}$ (t)	0.300 (1.04)	0.284 (0.97)
After$_{yr1}$ (t)	1.039** (2.07)	1.076** (2.15)
After$_{yr2}$ (t)	0.728*** (2.73)	0.710*** (2.70)
After$_{yr3}$ (t)	0.474** (2.16)	0.464** (2.10)
After$_{yr4}$ (t)	0.237 (1.22)	0.171 (0.86)
After$_{yr5}$ (t)	-0.205 (-1.54)	-0.214 (-1.51)
Past Perf. (t-12, t-1)	143.501*** (14.70)	195.707*** (14.06)
Past Perf. (t-24, t-13)	43.794*** (5.75)	42.921*** (3.42)
Past Perf. (t-36, t-25)	17.474* (1.87)	13.844 (1.21)
Past Perf. (t-12, t-1) Squared	636.577** (2.13)	1346.577*** (3.51)
Log Fund TNA (t-1)	-0.518*** (-7.45)	-0.535*** (-8.16)
Log Family TNA (t-1)	0.312*** (8.28)	0.325*** (8.97)
Log Fund Age (t-1)	-0.450*** (-5.07)	-0.500*** (-5.51)
Expense (t-12)	1.909 (0.28)	2.941 (0.47)
Turnover (t-12)	0.146** (2.50)	0.140** (2.39)
Time Fixed Effects	Included	Included
Observations	75,024	75,024

This table compares the new money growth of multiple-class funds to that of no-load funds using a pooled regression approach. The data sample includes funds that switched to a multiple-class structure during the sample period and no-load funds. The dependent variable is fund-level new money growth measured as the total amount of new money flowing into all share classes normalized by the previous month-end TNA of the fund. The independent variables include: an indicator variable, (Before), that equals one if a fund has a single A class in the current period but subsequently switches to a multiple-class structure and zero otherwise; indicator variables, (After$_{yrN,(N=0\ldots4)}$), that equal one in the Nth year after a fund introduces new share classes and zero otherwise; an indicator variable, (After$_{yr5}$), that equals one in the 5th and later years after a fund introduces new share classes and zero otherwise; the average monthly risk-adjusted returns over the consecutive 12-month periods in the past 36 months (Past Perf.); the square of the average monthly risk-adjusted returns over the previous 12 months (Past Perf. Squared); the logarithm of fund-level TNA (Log Fund TNA); the logarithm of family-level TNA (Log Family TNA); the logarithm of fund age (Log Fund Age); the expense ratio (Expense); and the turnover ratio (Turnover). As a robustness check, we use one-factor and four-factor adjusted returns to measure past performance. We include time fixed-effects. The error terms are heterogeneous robust and clustered by month. T-statistics are reported in parentheses. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. All coefficients reported in the table are the actual coefficient estimates multiplied by 100.

Table 5. New Money Growth and Multiple-Class Structure: Event Study Approach

Year	Difference in Monthly Abnormal New Money Growth (%)	T-statistics
After$_{yr0}$	0.056	0.26
After$_{yr1}$	0.692***	3.05
After$_{yr2}$	0.527***	2.96
After$_{yr3}$	0.385**	2.51
After$_{yr4}$	0.170	0.97
After$_{yr5}$	0.102	0.49

This table compares the new money growth of multiple-class funds to that of no-load funds using an event study approach. The data sample includes funds that switched to a multiple-class structure during the sample period and no-load funds. For each month during the sample period, we regress new money growth on the following variables: the average monthly 4-factor adjusted returns over the consecutive 12-month periods in the past 36 months (Past Perf.); the square of the average monthly 4-factor adjusted returns over the previous 12 months (Past Perf. Squared); the logarithm of fund-level TNA (Log Fund TNA); the logarithm of family-level TNA (Log Family TNA); the logarithm of fund age (Log Fund Age); the expense ratio (Expense); and the turnover ratio (Turnover). The coefficient estimates from the above regression are then used to calculate the predicted new money growth for all funds in the subsequent month. The difference between the realized and the predicted new money growth is defined as the abnormal new money growth. We then compute the difference in average monthly abnormal new money growth between load and no-load funds based on the years relative to the switching year: the switch year (After$_{yr0}$), and each of the five years following the switch (After$_{yrN, (N=1\ldots5)}$). Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively.

Table 6. Cash Flow Sensitivity to Past Performance: Classes A, B and C

	New Money Growth (t)	
	One-factor	**Four-factor**
Past Perf. (t-12, t-1) * Class B Dummy (t)	10.258* (1.68)	13.837 (1.54)
Past Perf. (t-12, t-1) * Class C Dummy (t)	57.362*** (8.85)	68.956*** (9.56)
Past Perf. (t-12, t-1)	128.871*** (12.53)	181.428*** (13.55)
Past Perf. (t-24, t-13)	41.704*** (7.89)	57.653*** (8.26)
Past Perf. (t-36, t-25)	11.731*** (2.84)	14.341*** (2.87)
Past Perf. (t-12, t-1) Squared	-50.699 (-0.15)	2440.354*** (4.07)
Log Class TNA (t-1)	-0.166*** (-5.08)	-0.213*** (-6.25)
Log Family TNA (t-1)	0.131*** (4.34)	0.179*** (5.83)
Log Class Age (t-1)	-0.855*** (-16.16)	-0.873*** (-16.40)
Expense (t-12)	-22.413** (-2.29)	-6.379 (-0.74)
Turnover (t-12)	0.023 (0.33)	0.100 (1.40)
Time Fixed Effects	Included	Included
Observations	56,035	56,035

This table compares the cash flow-performance patterns for different share classes of the multiple-class funds using a pooled regression approach. The data sample includes multiple-class funds with all A, B, and C share classes. The dependent variable is the new money growth for class A, B, or C. The independent variables include: the interactions between the average monthly risk-adjusted returns over the previous 12 months (Past Perf. (t-12, t-1)) and the indicator variables for classes B and C; the average monthly risk-adjusted returns over the consecutive 12-month periods in the past 36 months (Past Perf.); the square of the average monthly risk-adjusted returns over the previous 12 months (Past Perf. Squared); the logarithm of class-level TNA (Log Class TNA); the logarithm of family-level TNA (Log Family TNA); the logarithm of class age (Log Class Age); the expense ratio (Expense); and the turnover ratio (Turnover). As a robustness check, we use one-factor and four-factor adjusted returns to measure past performance. We include time fixed-effects. The error terms are heterogeneous robust and clustered by month. T-statistics are reported in parentheses. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. All coefficients reported in the table are the actual coefficient estimates multiplied by 100.

Table 6B. Cash Flow Sensitivity to Past Performance: Classes A, B and C

	New Money Growth (t)			
	One-factor		Four-factor	
Past Perf. * Positive (t-12, t-1)	210.391*** (10.60)	219.420*** (10.43)	284.296*** (8.97)	292.210*** (9.06)
Past Perf. * Negative (t-12, t-1)	77.901*** (4.78)	71.474*** (4.39)	119.750*** (4.67)	111.944*** (4.41)
Past Perf. * Positive (t-12, t-1) * Class B (t)	4.961 (0.66)	125.166*** (6.91)	-14.170 (-1.21)	90.100*** (2.77)
Past Perf. * Positive (t-12, t-1) * Class B (t) * 2yrLater (t)		-135.702*** (-7.13)		-124.478*** (-3.80)
Past Perf. * Negative (t-12, t-1) *Class B (t)	28.009** (2.57)	-29.353 (-1.54)	36.026*** (3.20)	-14.093 (-0.76)
Past Perf. * Negative (t-12, t-1) *Class B (t) * 2yrLater (t)		66.290*** (3.50)		60.424*** (3.13)
Past Perf. *Positive (t-12, t-1) *Class C (t)	69.925*** (8.65)	145.144*** (7.29)	92.477*** (6.29)	97.910*** (2.78)
Past Perf. *Positive (t-12, t-1) *Class C (t) * 2yrLater (t)		-88.067*** (-4.35)		-5.59 (-0.17)
Past Perf. * Negative (t-12, t-1) *Class C (t)	43.112*** (3.85)	-27.942 (-1.51)	45.913*** (4.23)	-8.644 (-0.37)
Past Perf. * Negative (t-12, t-1) *Class C (t) * 2yrLater (t)		87.331*** (4.29)		70.671*** (2.73)
Past Perf. (t-12, t-1) Squared	-1851.510*** (-4.86)	-2143.414*** (-5.15)	-969.780 (-0.94)	-1408.552 (-1.34)
Log Class TNA (t-1)	-0.106*** (-3.30)	-0.096*** (-2.98)	-0.146*** (-4.26)	-0.140*** (-4.08)
Log Family TNA (t-1)	0.142*** (4.84)	0.140*** (4.69)	0.183*** (6.14)	0.183*** (6.07)
Log Class Age (t-1)	-1.356*** (-16.82)	-1.239*** (-16.46)	-1.328*** (-17.17)	-1.270*** (-17.36)
Expense (t-12)	-20.253** (-2.03)	-16.813* (-1.66)	-4.203 (-0.44)	-2.012 (-0.21)
Turnover (t-12)	-0.095 (-1.50)	-0.101 (-1.57)	-0.086 (-1.29)	-0.089 (-1.33)
Time Fixed Effects	Included	Included	Included	Included
Observations	73,869	73,869	73,869	73,869

This table investigates whether the A, B, and C classes respond differently to positive/negative past performance using a pooled regression approach. The data sample includes multiple-class funds with all A, B, and C share classes. We include in regression two indicator variables, positive and negative, that equal one if the past 12-month performance is non-negative and negative, respectively. We interact these variables with the class indicators to investigate whether the B and C classes respond differently to positive/negative past performance than the A class. We also explore the possibility that the flow-performance relationships for the new classes exhibit different patterns during the early vs. late years following the switch to a multiple-class structure. For this purpose, we construct a new indicator variable (2YrLater) that equals one if two years have passed since the new classes were introduced, and interact this variable with the past performance and class indicators. All other variables are defined as in Table 6. We include time fixed-effects. The error terms are heterogeneous robust and clustered by month. T-statistics are reported in parentheses. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. All coefficients reported in the table are the actual coefficient estimates multiplied by 100.

Table 7. Performance: Class A of Multiple-Class Funds vs. No-Load Funds

	Risk-Adjusted Performance			
	One-factor	**Four-factor**	**One-factor**	**Four-factor**
Before (t)	-0.030 (-0.78)	0.000 (0.01)	-0.022 (-0.55)	0.008 (0.26)
After$_{yr0}$ (t)	0.109* (1.83)	0.056 (1.32)	0.115* (1.92)	0.061 (1.44)
After$_{yr1}$ (t)	0.020 (0.33)	0.043 (0.97)	0.028 (0.44)	0.049 (1.10)
After$_{yr2}$ (t)	-0.129* (-1.79)	-0.103** (-2.13)	-0.274** (-2.33)	-0.244*** (-3.69)
After$_{yr3}$ (t)	-0.157** (-2.55)	-0.100** (-2.58)	-0.296*** (-2.68)	-0.193*** (-3.26)
After$_{yr4}$ (t)	-0.192*** (-3.29)	-0.134*** (-2.95)	-0.166* (-1.95)	-0.081 (-1.38)
After$_{yr5}$ (t)	-0.147*** (-3.01)	-0.121*** (-3.35)	-0.209** (-2.31)	-0.176** (-2.29)
After$_{yr2}$ (t) *Early Switchers			0.294** (2.05)	0.284*** (3.21)
After$_{yr3}$ (t) *Early Switchers			0.268** (2.18)	0.180** (2.38)
After$_{yr4}$ (t) *Early Switchers			-0.045 (-0.40)	-0.091 (-1.09)
After$_{yr5}$ (t) *Early Switchers			0.066 (0.77)	0.058 (0.80)
Log Fund TNA (t-1)	-0.028 (-1.54)	0.014 (1.52)	-0.028 (-1.55)	0.014 (1.52)
Log Family TNA (t-1)	0.028*** (2.92)	0.007 (0.91)	0.028*** (2.92)	0.007 (0.91)
Log Fund Age (t-1)	-0.025 (-0.61)	-0.046** (-2.36)	-0.027 (-0.65)	-0.047** (-2.42)
Expense (t-12)	-4.848 (-0.75)	-5.010 (-1.37)	-4.849 (-0.75)	-5.015 (-1.37)
Turnover (t-12)	-0.010** (-2.07)	-0.006* (-1.77)	-0.010** (-2.11)	-0.007* (-1.80)
Time Fixed Effects	Included	Included	Included	Included
Observations	86,110	86,110	86,110	86,110

This table examines the impact of a multiple-class structure on fund performance using a pooled regression approach. We focus on the A classes of multiple-class funds and compare their performance to the no-load funds. The dependent variable is the risk-adjusted return for Class A of multiple-class funds and no-load funds. The independent variables include: an indicator variable, (Before), that equals one if a fund has a single A class in the current period but subsequently switches to a multiple-class structure and zero otherwise; indicator variables, (After$_{yrN,(N=0…4)}$), that equal one in the Nth year after a fund introduces new share classes and zero otherwise; an indicator variable, (After$_{yr5}$), that equals one in the 5th and later years after a fund introduces new share classes and zero otherwise; the interactions between (After$_{yrN, (N=2…5)}$) and an indicator variable (Early Switchers) that equals one if the fund switched to a multiple-class structure in or before 1995 and zero otherwise; the logarithm of fund TNA (Log Fund TNA); the logarithm of family TNA (Log Family TNA); the logarithm of fund age (Log Fund Age); the expense ratio (Expense); and the turnover ratio (Turnover). As a robustness check, we use one-factor and four-factor adjusted returns to measure risk-adjusted performance. We include time fixed-effects. The error terms are heterogeneous robust and clustered by month. T-statistics are reported in parentheses. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. All coefficients reported in the table are the actual coefficient estimates multiplied by 100.

Table 8. Change in Performance and Change in Cash Flow Characteristics

	Change in Risk-Adjusted Performance	
	One-factor	**Four-factor**
Change in Fund Flow Volatility (t-12,t-1)	-0.103*** (-2.95)	-0.078*** (-2.77)
Change in Fund TNA (t-1)	-0.262*** (-5.86)	-0.108*** (-3.57)
Change in Fund Flow Volatility (t-12,t-1) * Early Switchers	0.106** (1.99)	0.087** (2.37)
Change in Fund TNA (t-1) * Early Switchers	-0.017 (-0.31)	-0.048 (-1.14)
Change in Family TNA (t-1)	-0.026 (-0.69)	-0.012 (-0.45)
Log Fund Age (t-1)	-0.186*** (-2.96)	-0.131** (-2.54)
Change in Expense (t-12)	48.101*** (4.26)	38.521*** (3.14)
Change in Turnover (t-12)	-0.090 (-0.75)	-0.134** (-2.12)
Time Fixed Effects	Included	Included
Observations	5,116	5,116

This table examines the impact of the change in cash flow characteristics on fund performance using a pooled regression approach. The sample used in the analysis consists of multiple-class funds with all three share classes (A, B and C). We regress the change in risk-adjusted return of share class A on the changes in several key fund characteristics around the introduction of new share classes. All changes are defined relative to the pre-switch averages, which are calculated using the monthly data during the three-year period prior to the switch year. The change in performance for share class A is defined as the current month risk-adjusted return minus the pre-switch average. We compute the fund flow volatility on a monthly basis as the standard deviation of fund-level new money growth in the previous 12 months. The change in fund flow volatility after the switch is then measured as the ratio of previous 12-month fund flow volatility over the pre-switch average. The change in fund (or family) TNA is defined as the logarithm of previous month-end fund (or family) TNA minus the logarithm of pre-switch monthly average. The changes in expense and turnover ratios are defined as the previous year expense and turnover ratios minus the pre-switch averages. The indicator variable, (Early Switchers), equals one if the fund switched to a multiple-class structure in or before 1995, and zero otherwise. We interact this indicator variable with the change in fund flow volatility and the change in fund TNA. As a robustness check, we use one-factor and four-factor adjusted returns to measure risk-adjusted performance. We include time fixed-effects. The error terms are heterogeneous robust and clustered by month. T-statistics are reported in parentheses. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. All coefficients reported in the table are the actual coefficient estimates multiplied by 100.

Figure 1
Number of Funds by Year: Multple-class Funds, No-load Funds and Single A Class Funds