

# Swing Pricing and Fragility in Open-End Mutual Funds

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How can fragility be averted in open-end mutual funds? In recent years, markets have observed an innovation that changed the way open-end funds are priced. Alternative pricing rules (known as *swing pricing*) adjust funds' net asset values to pass on funds' trading costs to transacting shareholders. Using unique data on investor-level transactions in U.K. corporate bond funds, we show that swing pricing eliminates the first-mover advantage arising from the traditional pricing rule and significantly reduces outflows during market stress. Swing pricing also reduces concavity in the flow-performance relationship and dilution in fund performance. (*JEL* G2, G23, G010)

Received March 30, 2020; editorial decision January 5, 2021 by Editor Itay Goldstein. Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web site next to the link to the final published paper online.

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We thank Itay Goldstein (the editor), two anonymous referees, Matteo Aquilina, Fang Cai, Susan Christoffersen, Chris Clifford, Mark Flannery, Paul Glasserman, Valentin Haddad, Raj Iyer, David Ng, Anna Pavlova, Lukasz Pomorski, Melissa Porras Prado, Sophie Shive, Elu von Thadden, and Russ Wermers and seminar participants at the AFA, Chicago Financial Institutions Conference, Eagle Lab Finance Conference, EFA, Hebrew University Summer Finance and Accounting Conference, Koç University Finance Day Workshop, London Empirical Asset Pricing Workshop, NYU-NY FED Conference on Financial Intermediation, Recent Advances in Mutual and Hedge Fund Research, Texas A&M Young Scholars Finance Consortium, University of Oregon Summer Finance Conference, Wharton Conference on Liquidity and Financial Fragility, ECB, FED Board, HEC Paris, IMF, Imperial College London, LBS, NY Fed, Oxford, University of Bristol, and University of Southern California for their useful suggestions. All errors and omissions are our own. The views expressed herein are those of the author and should not be attributed to the Financial Conduct Authority, IMF, its Executive Board, or its management. Supplementary data can be found on *The Review of Financial Studies* web site. Send correspondence to Bige Kahraman, bige.kahraman@sbs.ox.ac.uk.

*The Review of Financial Studies* 35 (2022) 1–50

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doi:10.1093/rfs/hhab022

Advance Access publication March 8, 2021

Fragility in financial institutions poses a significant threat to economic stability and social welfare. Academics and policy makers have long been studying runs on banking institutions (Diamond and Dybvig 1983); more recently, a rapid growth of shadow banking, including that of the asset management sector, raised concerns that similar phenomena may also be present in the nonbanking sector (Allen, Babus, and Carletti 2009; Gennaioli, Shleifer, and Vishny 2013). As experienced during the financial crisis of 2008, when market conditions unexpectedly deteriorated, investors ran on open-end funds, causing fire sales and market dislocations.<sup>1</sup>

While understanding the origins of fragility is certainly important, of equal importance is the question of how to mitigate it. In the banking sector, the presence of deposit insurance and government guarantees have long been recognized as stabilizing forces. At the same time, we know much less about equally effective mechanisms in the nonbanking sector, especially in the absence of explicit guarantees. Common approaches utilized by fund companies to manage redemption risk during market stress include cash buffers or redemption fees, but such tools are not as effective in practice (Chernenko and Sunderam 2016, 2020), or can even exacerbate fragility (Zeng 2018). In this paper, we evaluate empirically a hitherto unexplored mechanism to reduce fragility in open-end funds, *swing pricing*, using the context of corporate bond funds in the United Kingdom.

To better understand our empirical context, it is useful to outline the economic friction causing fragility, namely, the pricing mechanism used by open-end funds (Chen, Goldstein, and Jiang 2010). Under the traditional pricing rule, fund investors have the right to transact their shares at the daily fixed net asset value (NAV) of the fund portfolio. As a result, the price that a transacting shareholder receives does not take into account the corresponding transaction costs that may arise because portfolio adjustments associated with shareholder transactions typically take place over multiple business days following the redemption requests. Thus, the costs of providing liquidity to transacting shareholders are borne by the nontransacting investors who remain in the fund, which dilutes the value of their shares. Chen, Goldstein, and Jiang (2010) show that this mechanism produces a first-mover advantage and amplifies the impact of negative shocks, especially during marketwide stress when market liquidity drops, and strategic complementarities become important.

Alternative pricing rules—typically known as swing pricing, or *dual pricing*—aim to adjust funds' net asset values so as to pass on the costs stemming from transactions to the shareholders associated with that activity. In this paper, we conduct a systematic empirical analysis to evaluate the impact of swing pricing on the dynamics of fund flows and fund performance. We ask:

<sup>1</sup> Coval and Stafford (2007) and Chen, Goldstein, and Jiang (2010) study runs in equity mutual funds. Goldstein, Jiang, and Ng (2017) analyze runs in bond funds, while Schmidt, Timmermann, and Wermers (2016) analyze runs on money funds.

To what extent does swing pricing help funds retain investor capital during periods of market stress? Does it prevent the dilution of fund performance and eliminate first-mover advantage? How do individual fund investors respond to fund companies' pricing rules?

Alternative pricing rules take three different forms. The first one is *full swing pricing*, whereby a fund's net asset value (NAV) can be adjusted up or down on every trading day in the direction of net fund flows: if net flows are positive, NAV shifts up, and it shifts down if net flows are negative. The magnitude of the shift is known as the *adjustment factor*. The second form, *partial swing pricing*, is invoked only when net flows cross a predetermined threshold, namely, the *swing threshold*. For both forms, a single price applies to all transactions including both redemptions and subscriptions. The third form, referred to as dual pricing, is similar to full swing pricing in that the fund's NAV can be adjusted on every trading day without a requirement to cross the threshold. However, it differs in that a fund trades at two prices—subscribing investors purchase their shares at the NAV adjusted up (ask price) and redeeming investors sell their shares at the NAV adjusted down (bid price).

Fund companies are permitted, but not required, to use the alternative pricing structures and they have full discretion in setting the value of the adjustment factor. Fund investors can learn about their funds' pricing approach in two ways. First, information about the pricing mechanism is disclosed in the funds' prospectuses and on websites.<sup>2</sup> However, with the exception of a few funds, investors can only know if a fund applies alternative pricing rules, and the principles by which it determines the size of the price adjustment, but not the precise level of the adjustment. Still, investors can rationally anticipate that in the case of significant market stress, funds are going to act in good faith and protect the interests of nontransacting investors by transferring the costs of trading onto the transacting ones. In fact, in a repeated game, funds have strong incentives to do so, to reduce the dilution in fund performance and mitigate run risks. Second, investors can also learn about adjustment factors from ex post transaction prices, either by means of updating their beliefs based on their own past history of trading or by observing actions in other funds within their own family.

Regulation permitting swing pricing has become effective in the United States only in November 2018; however, these rules have been in use in several European jurisdictions over the past few decades. To analyze their impact, we obtain data on corporate bond open-end funds that fall under the supervisory jurisdiction of the U.K.'s Financial Conduct Authority (FCA). Choosing bond funds as a testing ground allows us to capture portfolio illiquidity, a key determinant of fund fragility. The data have a number of unique features. Importantly, we have proprietary data on the holdings of funds' end investors

<sup>2</sup> Funds using one of the alternative pricing forms are required to specify whether they are using a dual, full swing, or partial swing pricing method.

that allow us to analyze individual-specific responses to changing pricing rules and address potential identification concerns. In addition, the data cover a long period from January 2006 to December 2016, which includes a number of high-stress episodes, such as the 2008 global financial crisis, the European debt crisis, or the Taper Tantrum. Periods with marketwide stress are natural candidates to study the risk of fund fragility. In the main analysis, we measure market stress using abnormal values of option-implied volatility index (VIX), but the results are robust to other stress measures.

We first examine the determinants of the dilution adjustment factor. If the pricing rules matter, we should expect fund companies to adjust prices in times of high market stress when aggregate liquidity tends to be low. This is precisely what we find. The adjustment factor is substantially higher in periods of high portfolio illiquidity, market stress (it nearly quadruples during the 2008 crisis), and high fund outflows. The impact of market stress is amplified in funds with illiquid portfolios and those holding high-yield bonds and bonds from emerging markets.

Next, we investigate the impact of swing pricing on the level of fund flows during market stress. Conceptually, the effect is *ex ante* uncertain. On the one hand, swing pricing can mitigate fragility of funds by removing the negative externalities arising from investor flows. On the other hand, swing pricing can increase fragility if investors anticipate an increase in near-term liquidation costs and act readily.<sup>3</sup> We find that funds with traditional pricing rules experience significant outflows during market stress, which is in line with prior literature (Mitchell, Pedersen, and Pulvino 2007; Ben-David, Franzoni, and Moussawi 2012). This effect *almost completely* reverses for funds that adopt alternative pricing rules, lending support to the view that such rules reduce fragility risks. Our results are robust to including a range of fixed effects (e.g., fund family, investment style, region of sale), controlling for front and back-end loads, and using alternative definitions of market stress (e.g., based on TED spread, LIBOR rate, and Merrill Lynch's MOVE index). Moreover, evidence from quantile regressions shows that the magnitude of the effect substantially increases in the left tail of the flow distribution, as one would expect.

A potential concern with the interpretation of the results is that funds and investors with different characteristics may self-select into different pricing structures. A significant advantage of our data is their investor-level granularity and the fact that some funds switch their pricing rules during our sample period. Jointly, these two elements make our paper uniquely suited to study the impact of funds' pricing rules on individual investor's responses. Formally, we identify a subsample of funds that switch their pricing methods from traditional to alternative and examine individual investors' behavior in the same fund before and after the switch. We match the sample of switchers

<sup>3</sup> Cipriani et al. (2014) provide a theory of preemptive runs when intermediaries impose gates or redemption fees.

to a sample of nonswitchers along various fund characteristics and estimate the treatment effect at the investor level. Our matched sample exhibits several desirable properties. It is balanced across various characteristics and exhibits no significant pre-trends. The switching events are staggered over time. We also do not find that the events differentially affect various flow predictors. We estimate a triple-difference regression model in which we compare investor responses in switchers versus nonswitchers before and after the switch date, conditional on the level of stress in the aggregate market. We also include investor fixed effects, which allows us to identify economic effects at the individual investor level.

We find strong evidence that our results are not solely due to selection; pricing structures also alter investor behavior. We find that the same investor is significantly less likely to redeem their shares in a stress period when the fund uses swing pricing than when the fund uses traditional pricing. This effect is not driven by the underlying differences in sensitivity to negative shocks among investors. For a limited sample of investors who have holdings in multiple funds, we also show that the differential effect across the two structures is similar when we compare the behavior of the *same* investor in two different funds, one of which switches the structure.

We complement the baseline analysis with a series of tests that provide insights into the economic mechanism behind the results. First, we examine flow-performance sensitivity and show that alternative pricing does not have a significant impact on the sensitivity of investor inflows to good performance, but it significantly reduces the sensitivity of outflows to bad performance. The asymmetric nature of the response strongly supports the interpretation that alternative pricing mitigates fragility arising from costly asset liquidations. Moreover, consistent with alternative pricing funds being more resilient to stress events, we find that they are less likely to be terminated compared with funds that apply the traditional pricing rule.

Next, we exploit cross-sectional differences in our data. Consistent with the predictions of Chen, Goldstein, and Jiang (2010), we find that the mitigating role of alternative pricing rules is particularly important for funds with illiquid assets and dispersed ownership, that is, funds that are most fragile. When we examine the differences across investors, we find that investors with longer investment horizons alter their behavior and sell less after a fund switches to swing pricing. Moreover, it is the institutional investors who alter their behavior the most. While institutional investors sell heavily in periods of stress when funds use the traditional pricing rule (thus nontransacting retail investors bear the costs due to these transactions), they significantly reduce their redemptions if a fund switches to swing pricing. This is consistent with the idea that, being more sophisticated, institutional investors are more informed about the implications of funds' pricing practices and react to them. These findings strongly support the view that strategic complementarities, rather than mechanical rebalancing rules of unsophisticated investors, drive our findings. Consistent with the hypothesis

of investor information and learning about funds' pricing rules, we also find that investors with longer investing experience in a fund are more responsive to changes in their funds' pricing rules. Similarly, we show that investors in fund families which already had at least one fund with alternative pricing rule benefit from information spillovers inside the organization, for example, by observing the approach that the fund family has taken to swing pricing in its other funds.

We further evaluate the consequences of funds' pricing methods. The negative consequence of the traditional pricing rule is the dilution effect due to large outflows for nontransacting investors, which gives rise to the first-mover advantage. If our findings are driven by the pricing structure, we expect alternative funds to be able to remove the first-mover advantage arising from fund outflows. We find that outflows indeed negatively affect *subsequent* fund performance for funds using traditional pricing. However, the negative impact of outflows on subsequent fund performance almost completely dissipates for funds with alternative pricing. This finding suggests that, on average, funds use the alternative pricing structures effectively to eliminate the first-mover advantage arising from the traditional pricing rule.

From an industrial organization perspective, the question of interest is why we observe the coexistence of both fund structures in the market. During our sample period, about 15% of traditional funds switched to swing pricing, and by the end of our sample period, 82% of funds are using one of the alternative pricing forms.<sup>4</sup> Based on these basic patterns, one perspective that we offer is that alternative pricing rules may be an ultimately preferred structure, however, the transition may not be instantaneous. This might be due to (a) gradual learning about the merits of the alternative pricing structure and (b) diminishing marginal returns to switching to an alternative pricing form when more funds have already adopted it (Capponi, Glasserman, and Weber 2020). To the extent that trading costs arising from fund outflows decrease with the number of alternative funds in the market, the marginal benefit of switching to an alternative pricing is expected to diminish as well. Consistent with this idea, we find that, when more funds use alternative pricing forms, the differences in flows between alternative and traditional funds are in fact smaller, and traditional funds are less likely to switch to alternative pricing forms. An alternative perspective is that both structures offer benefits to different types of investors. Funds with traditional funds tend to benefit impatient investors, while funds with alternative pricing are meant to compensate the patient ones, especially in bad times. Funds that cater more to either of the two groups of investors may choose their structures accordingly. Consistent with this hypothesis, we find that funds with traditional pricing, for example, attract a greater fraction of impatient investors.

<sup>4</sup> Remarkably, all the switching events have occurred solely in one direction, from traditional to alternative.

In the final set of results, we test whether swing funds tend to treat this tool as a substitute to other means of liquidity risk management, such as cash holdings, portfolio diversification, or fund loads. We find that funds with alternative pricing rules hold less cash compared to funds with traditional pricing. The effect for portfolio diversification and fund loads is less clear. One reason front-end load fees may not be as effective is that they do not eliminate the first-mover advantage as proceeds from loads are not retained in the fund; instead, they are used to compensate brokers for their services (Chen, Goldstein, and Jiang 2010). At the same time, back-end loads which in theory would increase redemption costs are rare. In our sample, only a handful of funds apply back-end loads.

Our paper contributes to a vast literature on financial stability and runs in financial institutions. The focus of this literature has been mostly the banking sector. Recent studies acknowledge that nonbank financial institutions, such as mutual funds, can also destabilize markets. In particular, several papers document significant declines in fund performance due to *aggregate* fund outflows and suggest that the resultant dilution in fund performance can lead to fragility (e.g., Edelen 1999; Coval and Stafford 2007; Alexander, Cici, and Gibson 2007; Feroli et al. 2014; Christoffersen et al. 2018). Our focus instead is to show a mechanism that mitigates fragility using *disaggregated*, investor-level data.

Chen, Goldstein, and Jiang (2010) build a global game model and show that the traditional pricing rule used by open-end funds can lead to runs on funds because predictable declines in NAV following fund outflows generate a first-mover advantage. Consistent with the predictions of the model, they document that the flow-to-performance relationship is stronger for funds investing in less liquid stocks. Goldstein, Jiang, and Ng (2017) echo the message by showing that corporate bond funds exhibit a concave flow-to-performance relationship. Our paper supports this mechanism by showing the importance of first-mover advantage and illiquidity in the corporate bond fund sector through the lens of swing pricing.

A related literature discusses possible remedies to runs in open-end funds with cash being the natural candidate. Malik and Lindner (2017) explore the cash hoarding channel and argue that some funds sell more assets than required to cover outflows. Chernenko and Sunderam (2016, 2020) analyze the cash-cushioning approach and conclude that funds' cash holdings are not sufficiently large to eliminate fire sales. One theoretical explanation of this finding is Zeng (2018), who argues that cash management cannot prevent runs; instead, cash usage actually exacerbates runs on open-end funds. We offer an alternative tool to mitigate run risks that gets at the core of the friction, the pricing mechanism. Swing pricing, which allows for dilution adjustment of fund NAV, reduces the first-mover advantage arising from the traditional pricing and substantially reduces outflows during crisis periods. In this respect, our findings are consistent with the recent theoretical study of Capponi, Glasserman, and Weber (2020), who show the stabilizing effects of swing pricing. Our paper corroborates their

predictions empirically and provides additional cross-sectional and time-series tests of their theory.

Two recent working papers empirically study swing pricing. Malik and Lindner (2017) analyze its importance for flow stability in a case study of one fund with swinging price. Their main hypothesis is a test of the dilution effect. Lewrick and Schanz (2017) compare funds domiciled in Luxembourg, where funds are permitted to (but not always) use swing pricing, to U.S.-domiciled funds during the period when they were not allowed to use swing pricing.<sup>5</sup> They show that the Luxembourg funds experience smaller sensitivity of fund outflows to negative performance, but they do not find any stabilizing flow effect during stress periods. Relative to these studies, ours is the only one using detailed information on funds' pricing practices and individual investor behavior in a large panel setting of bond funds. We also explore a rich time-series variation in market conditions which allows us to make a clear distinction between stress and nonstress periods. Finally, we utilize the switching events to improve empirical identification, which is particularly useful in the discussion of policy effects.

## **1. Institutional Background**

Open-end funds aim to provide liquidity to their shareholders on a daily basis. On any given day, fund investors have the right to transact their shares at their funds' net asset values (NAV). The common convention in Europe is that the fund pricing happens at 2:30 p.m. CET, whereas in the United States the pricing takes place at the close of market trading activity (4 p.m. ET). If the funds' portfolio is liquid, the value of nontransacting investors' fund shares is not significantly affected by transacting investors. However, for funds with illiquid assets trading activity and portfolio adjustments stemming from investor transactions can result in significant costs and these costs may occur over multiple business days following the transaction requests. As a result, these costs would be borne by nontransacting investors in the fund. Such costs reduce fund performance and dilute the value of their shares.

Alternative pricing rules have emerged to allow open-end mutual funds to adjust their NAVs to reflect such costs. These rules exist in many European domiciles: Finland, France, Ireland, Jersey, Luxembourg, Norway, Switzerland, and the United Kingdom.<sup>6</sup> All registered open-end investment companies in these jurisdictions have been eligible for using alternative pricing rules over the past few decades.

In the United States, the Securities and Exchange Commission (SEC) adopted rules permitting funds to use swing pricing in 2016. The rules have been

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<sup>5</sup> Different from our study, Lewrick and Schanz (2017) cannot identify the swing pricing funds in their data.

<sup>6</sup> Other countries allowing swing/dual pricing are Australia, the Cayman Islands, and Hong Kong.



initially set to become effective in November 2018, but later the effective date was extended. In roundtable discussions organized by the SEC, nearly all fund companies support the idea of using swing pricing; however, they also note important operational hurdles that need to be overcome in order to implement swing pricing in the United States, and funds acknowledge that they need to make important changes in their infrastructures.<sup>7</sup> Several funds express their concerns to the SEC that the differences in the speed with which funds can switch to implementing swing pricing can distort fairness in competition among funds (e.g., some fund complexes have experience with implementing swing pricing in other jurisdictions, or are larger and may have more resources available to implement swing pricing). To this effect, the SEC provided an extended effective date to help alleviate these concerns.<sup>8</sup>

There are two main alternative pricing mechanisms: swing pricing and dual pricing. Rules permit funds to swing NAV only to address the dilution effect arising from investor flows. Fund managers typically use either of two types of swing pricing: partial swing pricing or full swing pricing. In fund prospectuses, funds are required to specify the type of pricing method that they are using. Partial swing funds move the price only when the net fund flow is greater than a predetermined threshold, the *swing threshold*. This threshold is usually set in terms of a percentage or basis point impact, and it is not publicly disclosed. Full swing funds can swing their prices every day. The direction of the swing can depend on the direction of the daily fund flow or it can be set on a long-term basis based on expected flows.<sup>9</sup> In both types of swing pricing, the final price applies to all transacting shareholders (whether they are redeeming or subscribing). Although no explicit regulation stipulates to do so, several swing funds choose to cap their swing factors (often self-impose a cap of 2% of a fund value) and the dilution adjustment is applied uniformly across all shares. Swing funds are required to disclose their final prices, but not their NAVs or the adjustment factors.

To illustrate the mechanics of the rules, we present a simple numerical example of swing pricing. We consider two funds: one trading with traditional pricing and another one applying swing pricing with a swing factor of 2%. Suppose that on day  $t = -1$  both funds have the same NAVs, equal to \$10, and that each fund has the same trading cost, 2% of the value of the redemptions, accruing in equal amounts after the redemption date. Let's assume that on day  $t = 0$ , there is a one-time redemption shock, in which investors redeem 5% of each fund's assets, prompting trading activity by fund managers. The

<sup>7</sup> For instance, the end-of-the-day pricing scheme in the United States makes it more difficult for funds to have timely information on their daily flows and predict the value of the adjustments that they should implement.

<sup>8</sup> For more information, see the SEC release 33-10234 (IC-32316; File No. S7-16-15) (<https://www.sec.gov/rules/final/2016/33-10234.pdf>).

<sup>9</sup> For full swing funds, the direction of daily swing factors lines up with the direction of daily flows 85% of the time.

redemption level is assumed to be sufficiently large, so that the example can fit both full-swing and partial-swing cases. We assume that no trading costs are incurred at date 0. We also assume that to redeem the shares, trading needs to take place over the next two periods, 1 and 2. In this situation, shareholders in the fund with traditional pricing will redeem their shares on day 0 at a NAV of 10, and the NAV will then go down to \$9.995 on day 1 and to \$9.990 on day 2, when the transaction costs occur. In contrast, the NAV value of a fund with swing pricing will be moved to \$9.80 on day 0 when the redemptions occur. On day 1, the value of NAV will swing back to \$10 plus the portion of the costs that were not incurred on date 0, equal to \$0.1, for the total value of NAV=\$10.10. In period 2, the remaining transaction costs are incurred, and the new NAV is \$10. The net change in NAV is equal to zero because the swing factor is equal to the transaction costs. In sum, the fund with swing pricing offers a better value for nontransacting shareholders as its end period NAV is equal to the NAV in the absence of the transaction. Were the swing factor greater (smaller) than the value of the cost, the end-period NAV would be greater (smaller) than \$10.

Different from swing funds, which trade at a single price, dual priced funds trade at two separate prices, bid and ask. Investors purchase fund shares at the ask price and sell them at the bid price. Depending on the net fund flows, a fund manager can adjust the spread between a fund's bid and ask prices up to the bid-ask spread of the fund's underlying assets. Proceeds from net inflows or net outflows are reinvested in the fund, which protects nontransacting shareholders from dilution.<sup>10</sup> Compared with swing funds, dual priced funds are more transparent in that both bid and ask are publicly available.<sup>11</sup>

## 2. Data

### 2.1 Sample construction and measures

We obtain our data through a request sent by the FCA to major U.K.-based asset management companies with corporate bond fund offerings.<sup>12</sup> The FCA requested data on all corporate bond mutual funds domiciled in the United Kingdom or whose investment management decisions are taken from the United Kingdom.<sup>13</sup> Through this data request, the FCA received data on 299 corporate bond mutual funds (including dead funds) from 24 asset management

<sup>10</sup> In the past, dual-priced funds retained the profits from the spread on days when inflows and outflows netted out (so-called "box profits"). In the United Kingdom, new rules, which became effective on April 1, 2019, require fund managers to return box profits to fund investors (<https://www.fca.org.uk/publication/policy/ps18-08.pdf>).

<sup>11</sup> For additional institutional details on alternative pricing, see Malik and Lindner (2017).

<sup>12</sup> This also includes U.K. subsidiaries of non-U.K. asset management companies.

<sup>13</sup> The latter condition selects funds that have a significant presence (usually an office) in the United Kingdom. Funds in our sample are domiciled in various jurisdictions, the majority of which are in the United Kingdom, Luxembourg, and Ireland, representing, 55%, 31%, and 11% of the sample, respectively.

companies.<sup>14</sup> A fund is defined to be a corporate bond fund if at least 50% of its portfolio is invested in corporate bonds; however, the majority of funds in our sample have bond holdings of more than 80%. The data include funds from leading U.S. and European multinational asset management companies, covering the period from January 2006 to December 2016.

The FCA database has several unique features. First, it includes comprehensive information on funds' dilution adjustment practices. We observe fund NAVs, prices, swing factors, and swing thresholds at daily frequency. Second, for dual funds, we also observe the daily bid and ask prices. An additional unique feature of our data is information on end investors' holdings (at a monthly frequency) and their investment type (retail vs. institution). We also observe various fund-level characteristics, such as total net assets (TNA), returns, cash, and asset holdings. We complement the FCA data with information from Morningstar on institutional class indicators, fees, and fund liquidations.

Since pricing rules are applied uniformly across all share classes, we follow the literature (e.g., Kacperczyk, Sialm, and Zheng 2005) and aggregate observations to the fund level. For qualitative attributes (e.g., year of origination and country of domicile), we use the observation of the oldest class. For fund size (total assets under management), we sum the TNAs of all share classes. We take the TNA-weighted average for the rest of the quantitative attributes (e.g., returns, alphas, and expenses).

Through the matching of the various databases, we arrive at a final sample that includes 224 open-end actively managed corporate bond mutual funds in 22 families that are open to new and existing investors. The majority of funds (77%) invest in U.K. assets. Other geographic areas include Eurozone (16%), emerging markets (5%), and the United States (2%). We observe that most funds in the U.K. market use alternative pricing schemes. For instance, as of December 2016, only 18% of the funds apply traditional pricing—the remaining 82% use one of the alternative pricing rules. Within the alternative group, 54% and 18% of sample funds use partial and full swing pricing, respectively. Dual pricing funds constitute about 10%.

Over the period 2006—2016, we identify 34 funds that switched their pricing schemes from the traditional to alternative structures, specifically to swing pricing. We do not observe any switches from alternative to traditional pricing scheme during our sample period. These patterns arguably suggest that the market favors swing pricing, but the market might be in a transition phase whereby market participants are gradually learning of its promise. We will examine these ideas later in the paper.

<sup>14</sup> Twenty funds offered by four asset management companies with combined assets under management of about £3.4 billion (as of the end of 2016) failed to respond to the data request, a relatively small portion of the overall sample.

We conduct our baseline analysis at a monthly frequency. For each fund-month observation, we define the following variables: *Flow* is the monthly change in a fund's quantity of shares outstanding multiplied by the share price, divided by the fund's TNA. Both the numerator and the denominator are measured as of time  $t$  to prevent a potential contamination in *Flow* due to fund price adjustment. Notably, our measure is based on directly observed transactions rather than on indirect measures imputed from fund size as is common in the literature.<sup>15</sup> *Return* is the fund's monthly raw return net of expenses. Following earlier studies on corporate bond mutual funds (e.g., Goldstein, Jiang, and Ng 2017; Choi and Shin 2018), we estimate fund *Alpha* using a model with 12-month rolling-window monthly excess returns regressed on excess aggregate bond market returns and aggregate stock market returns. Since the majority of assets are U.K. based, we use U.K. indexes as benchmarks, which we obtain from Barclays.<sup>16</sup> *Size* is the natural logarithm of a fund's TNA; *Age* is the natural logarithm of a fund's age, in years; *Expense* is a fund's total expense ratio; and *Inst* is the fraction of a fund's assets held by institutional investors. *Illiquidity* is the value-weighted average of bid-ask spreads of a fund's assets.<sup>17</sup> Bid-ask prices are obtained from Thomson Reuters Datastream.<sup>18</sup> To mitigate the impact of outliers, we winsorize all variables at the 1% level. Table A1 in the appendix provides details on variable definitions.

We follow the literature (e.g., Rey 2015; Kacperczyk, Perignon, and Vuillemeys 2020) and define *Stress* as an indicator variable equal to one if the average of the end-of-day Chicago Board Options Exchange Volatility Index (VIX) is above the 75th percentile of the sample in a given month. Within our sample, *Stress* covers the episodes of 2008 global financial crisis, the European debt crisis, the downgrade of the credit ratings of U.S. federal government, and the Taper Tantrum. Later in the paper, we show the robustness of our results to alternative definitions of *Stress*.

## 2.2 Descriptive statistics

Table 1 presents the descriptive statistics for the fund characteristics in our sample. In our baseline results, we categorize funds into two groups: funds that use the traditional pricing rule versus those with alternative pricing rules

<sup>15</sup> Our results are robust to using the traditional flow measure in which the denominator (fund size) would be measured in  $t - 1$ , and the numerator would be inferred from changes in the fund size from  $t - 1$  to  $t$ .

<sup>16</sup> As a robustness, we show in columns 6 and 7 of Table IA.2 that our main results are similar if we exclude all non-U.K. funds from the sample.

<sup>17</sup> Since we do not have data on intraday bond returns, we use daily bid-ask spreads. Our main variable of interest is fund flows. We mostly use *Illiquidity* as a control variable.

<sup>18</sup> When available, we use the Thomson Reuters' composite price, which is the average price from multiple pricing sources. When the composite price is missing, we use the evaluated price, which is provided daily by the Fixed Income Pricing Service team at the Thomson Reuters. This pricing service uses proprietary evaluation models and is used by many industry participants, for example, for NAV calculations. If this price is also missing, we use the prices provided by iBOXX or ICMA.

**Table 1**  
**Descriptive statistics on fund characteristics**

<i>A. Alternative pricing</i>								
	Flow	Alpha	Size	Age	Expense	Illiquidity	Inst	Adj factor
P25	−0.6052	−0.0628	17.9023	1.3863	0.5643	0.0054	0.0000	0
Mean	0.7958	0.2658	18.7737	2.0778	0.8807	0.0094	23.3599	0.34
Median	0.0590	0.1948	19.2709	2.1972	0.9218	0.0078	0.0000	0
P75	1.6364	0.5561	20.1997	2.7081	1.1912	0.0108	42.5579	0.41
SD	6.8569	0.5478	2.4715	0.8578	0.4462	0.0072	35.9562	0.68
<i>B. Traditional pricing</i>								
	Flow	Alpha	Size	Age	Expense	Illiquidity	Inst	Adj factor
P25	−0.4185	−0.0888	17.7389	1.0986	0.4214	0.0047	0.0000	0
Mean	1.3315	0.2341	18.7888	1.7591	0.7570	0.0080	34.5601	0
Median	0.1124	0.1765	18.9854	1.7918	0.7500	0.0072	1.3872	0
P75	2.1596	0.5450	19.9881	2.3026	1.0200	0.0097	73.7224	0
SD	7.1247	0.5408	1.7037	0.7749	0.3926	0.0056	40.6099	0
<i>C. Fund switching dates</i>								
Switching date	Frequency							Percent
Nov. 2006	8							23.53
Oct. 2007	3							8.82
Dec. 2007	5							14.71
Nov. 2010	2							5.88
Jan. 2011	1							2.94
Mar. 2011	2							5.88
Apr. 2012	3							8.82
May 2012	6							17.65
Feb. 2015	3							8.82
Jan. 2016	1							2.94
Total	34							100.00

Panels A and B of this table present the descriptive statistics for characteristics of corporate bond funds in our sample from January 2006 to December 2016. Except for *Adj factor*, the unit of observation is a fund-month. For *Adj factor*, the unit of observation is a fund-day. Panel A shows the descriptive statistics for funds with alternative pricing; panel B shows the descriptive statistics for funds with traditional pricing. *Flow* is the monthly capital flows into a fund divided by the fund's total net assets (in %); *Alpha* is the fund's alpha in the past 12 months (in %); *Size* is natural logarithm of the fund's total net assets; *Age* is the natural logarithm of fund age in years; *Expense* is the fund's total expense ratio (in %); *Inst* is the fraction of fund's assets held by institutional investors (in %); *Illiquidity* is the value-weighted average of bid-ask spreads of the fund's assets; and *Adj factor* is the fund-level daily adjustment factor. See Table A1 in the appendix for the variable definitions. Panel C shows the frequency table of switch dates funds that switch from being a traditionally priced fund to a fund with an alternative pricing rule.

(swing or dual). Panels A and B show the descriptive statistics for funds with alternative and traditional pricing rules, respectively.

Panels A and B of Table 1 show that funds with traditional pricing appear to be similar to those with alternative pricing in a number of ways. First, they have similar TNAs. The average size for funds with alternative pricing is £141 million, while the corresponding number for funds with traditional pricing is £143 million. Further, the two groups have similar expenses, with an average annual expense ratio of 0.88% for funds that use the traditional pricing and an average expense ratio of 0.75% for funds with alternative pricing. Funds with alternative pricing appear to be slightly older (7.92 vs. 5.75 years). In general,

along many characteristics, our sample is quite similar to the U.S. corporate bond funds analyzed by Goldstein, Jiang, and Ng (2017).

We also report the descriptive statistics on asset illiquidity and investor type for the two groups of funds. Funds with alternative pricing hold more illiquid assets. On average, the value-weighted bid-ask spread of the funds' assets is about 94 basis points (bps), while it is 80 bps for funds with traditional pricing. This finding is consistent with the hypothesis that funds with more illiquid assets are more fragile and thus are more likely to use alternative pricing to offset it. Further, ownership by retail investors in funds with alternative pricing tends to be higher (77% vs. 66%). The ownership structure is important because investors with different levels of sophistication are likely to internalize the negative externalities arising from traditional structure differently.

### 3. Empirical Results

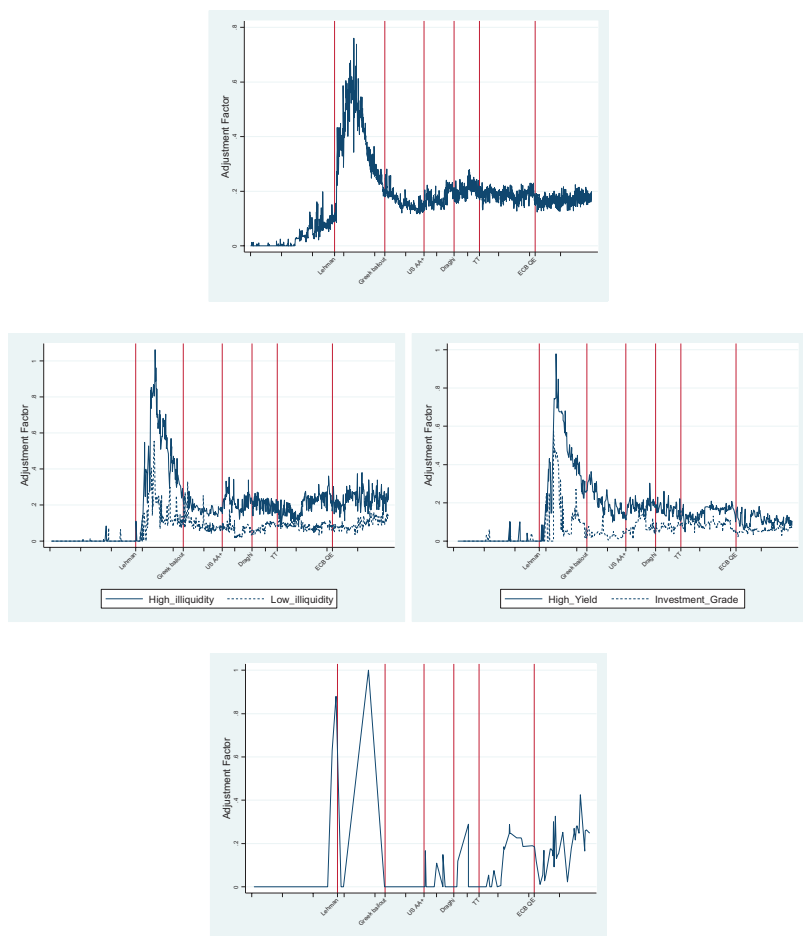
#### 3.1 Dilution adjustment factor across funds and time

We start our analysis by examining the time-series patterns in dilution adjustment factors. Alternative funds are permitted to adjust their NAVs to account for trading costs arising from price impact, bid-ask spreads, and other explicit trading costs (e.g., stamp duty, taxes). We define *Adjustment factor* as the daily *absolute value* of swing factor for swing funds. For dual funds, it is equal to the half spread of the funds' bid and ask prices,  $0.5 \times (\text{ask} - \text{bid}) / \text{mid}$ . We summarize its distribution in the last column of Table 1. During our sample period, *Adjustment factor* of funds with full swing and dual pricing is approximately 33 bps and its standard deviation is 68 bps. For partial swing funds, the median *Adjustment factor* is zero because swinging is invoked only when daily net flows cross a specific threshold. As reported in Table IA.1 of the Internet Appendix, the most commonly used thresholds (in absolute terms) are 1% and 3%.<sup>19</sup> In our sample, 90% of partial swing funds use thresholds that are less than 3%. The average dilution adjustment factor for partial swing funds is 57 bps once we restrict our sample to days with nonzero factor values.<sup>20</sup>

Figure 1 shows the time-series variation in average *Adjustment factor* of swing and dual pricing funds. The average adjustment factor is relatively small outside the crisis periods, varying from 18 bps to 25 bps, but it substantially increases during adverse market conditions. For example, it spikes up—nearly quadruples—during the 2008 global financial crisis; similarly, adjustment

<sup>19</sup> These thresholds approximately correspond to the 5% and 10% tails of the daily net flow distribution.

<sup>20</sup> To assess trading costs, funds typically rely on a measure known as implementation shortfall, which is analogous to the effective spread. Other costs, such as commission fees are often waived, and stamp duty and taxes make up about 5 bps (e.g., Busse et al. 2017). Anecdotal evidence suggests that funds often obtain trading cost estimates from third-party data providers, such as Thomson Reuters and Markit.



**Figure 1**  
**Dilution adjustment factor**

A fund's dilution adjustment factor, *Adjustment factor*, is the factor by which the fund NAV is adjusted on a given day. It equals the *absolute value* of swing factor for swing funds; for dual funds, it equals the half spread of the difference in dual funds' bid and ask prices,  $0.5 \times (ask - bid) / mid$ . The top panel shows the average adjustment factors for the overall sample of swing and dual funds during our sample period; figures at the bottom show the average adjustment factors for different types of funds. In the second row, from left to right, panels show the average adjustment factors for funds with high versus low liquid assets (defined based on *Daily illiquidity* being above or below the sample median) and high yield versus investment grade. The bottom panel shows the average adjustment factors for emerging market funds.

factors are at relatively high levels during the European debt crisis. These patterns are consistent with other studies in the literature. Among others, Biais and Declerck (2007) document that, outside the crisis periods (from 2003 to 2005), effective spreads in European corporate bonds ranged between 12 bps and 22 bps. Dick-Nielsen, Feldhutter, and Lando (2011) document dramatic

increases in corporate bond illiquidity measures (such as price impact and bid-ask spreads) during 2008.<sup>21</sup>

Next, we analyze the determinants of daily dilution adjustment factor. Since we do not observe fund managers' order and transaction data, estimating funds' trading costs is beyond the scope of this paper; instead, we exploit cross-sectional differences in fund portfolios' liquidity. We expect the degree of illiquidity of a fund's assets to be an important determinant of its adjustment factor as trading illiquid assets is more costly than trading liquid assets. Because trading costs tend to surge during market stress conditions, we also expect the adjustment factors to be asymmetric in that, they dramatically increase during such periods, and particularly so for funds with illiquid assets. Moreover, we analyze the association between adjustment factors and daily fund flows and predict that funds with more severe negative outflows should have larger adjustment factors.

Table 2 reports the results. In column 1, the main explanatory variable is *Daily Illiquidity*, which is the daily value-weighted average of the bid-ask spread of fund *i*'s assets. Our model also includes other fund characteristics, such as *Alpha*, *Size*, *Age*, *Expense*, and *Inst*, as well as day and fund fixed effects. To account for possible serial and cross-correlation in residuals, we cluster standard errors by fund and day. We find that the coefficient of *Daily illiquidity* is positive and statistically significant, indicating that asset illiquidity is an important determinant of funds' adjustment factors. A one-standard-deviation increase in *Daily illiquidity* is associated with a 33% higher adjustment factor compared to its mean value. Other fund characteristics do not appear to have an important explanatory power. In column 2, we replace day fixed effects with *Stress* to capture the business-cycle variation in adjustment factors. Consistent with countercyclical behavior of aggregate illiquidity and Figure 1, the adjustment factor significantly increases during periods of market stress. In column 3, we test the joint effect of aggregate market conditions and fund-level asset illiquidity by interacting *Stress* with *High illiquidity*, which is an indicator variable that equals one for funds with *Daily illiquidity* above the sample median in a given date. We find that the effect of fund illiquidity on adjustment factor is in fact stronger in periods of high market stress. As an alternative to *Daily illiquidity*, in columns 4 and 5, we consider interactions of *Stress* with *High yield* (an indicator variable equal to one for high-yield funds) and *Emerging market* (an indicator variable equal to one for emerging market funds). We find that both coefficients are positive, but the coefficient of *Emerging market* is statistically insignificant—possibly due to statistical power issues as these funds constitute only 5% of the overall sample.

<sup>21</sup> Figure 1 also shows the time-series variation in average adjustment factors for funds with liquid vs illiquid assets (defined based on *Daily illiquidity* being above or below the sample median), high yield versus investment grade, and for emerging market funds. Average adjustment factors for funds with liquid versus illiquid assets are 0.22 and 0.38, respectively. High-yield (investment-grade) funds have an average adjustment factor of 0.40 (0.21), and the emerging funds' average is 0.42.



Table 2  
Determinants of dilution adjustment factors

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily illiquidity	0.1642*** (0.0573)							
Stress		0.1404*** (0.0357)	0.0010 (0.0193) 0.1930** (0.0786) -0.0451 (0.0295)	0.0224* (0.0118)	0.2198*** (0.0578)			
High illiquidity × Stress								
High illiquidity								0.0028 (0.0169)
High yield × Stress								
High yield				0.1868*** (0.0634) 0.0411 (0.0365)				
Emerging market × Stress					0.0987 (0.0829) 0.1204 (0.0822)			
Emerging market								
Daily flow						0.0014 (0.0054)	0.0093 (0.0077) 0.0798*** (0.0208)	0.0031 (0.0082) 0.0525** (0.0206) 0.0637*** (0.0318) 0.0147* (0.0082)
Daily net outflow								
Daily net outflow × High illiquidity								
Daily flow × High illiquidity								
Alpha	0.0372 (0.0315)	0.0146 (0.0254)	0.0248 (0.0214)	0.0369 (0.0369)	0.0132 (0.0401)	0.0342 (0.0224)	0.0336 (0.0223)	0.0209 (0.0225)
Size	0.0058 (0.0187)	0.0150 (0.0251)	-0.0099 (0.0170)	-0.0258 (0.0243)	-0.0196 (0.0196)	0.0039 (0.0165)	0.0058 (0.0166)	-0.0141 (0.0183)
Age	0.0204 (0.1274)	-0.2311*** (0.0733)	-0.1278* (0.0751)	-0.1888* (0.1121)	0.0133 (0.0441)	-0.0456 (0.0701)	-0.0472 (0.0701)	-0.1744** (0.0864)
Expense	0.2541 (0.1843)	0.1909 (0.1527)	0.183 (0.2037)	0.0987 (0.2423)	0.2867** (0.1453)	0.2849 (0.1880)	0.2858 (0.1881)	0.3376 (0.2148)
Inst	0.0034 (0.0024)	-0.0057 (0.0037)	0.0043* (0.0025)	-0.0056 (0.0049)	-0.0014 (0.0010)	0.0036 (0.0022)	0.0038* (0.0022)	0.0047* (0.0027)
Observations	133,262	199,336	133,262	108,836	199,336	131,747	131,747	131,747
R-squared	.684	.633	.662	.617	.108	.674	.675	.653
Day FE	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Fund FE	Yes							

The dependent variable is the daily *Adj factor*, defined as the factor by which the fund NAV is adjusted on a given day. It equals the absolute value of the swing factor for swing funds and equals the half spread in the fund's bid and ask prices for dual funds. The unit of observation is a fund-day. *Stress* is an indicator variable that equals one if the monthly *VIX* is above the 75th percentile of the sample. *Daily illiquidity* is the daily value-weighted average of bid-ask spreads of a fund's assets; *High illiquidity* is an indicator variable that equals one for funds with *Daily illiquidity* above the sample median in a given date. *High yield* and *Emerging market*, respectively, are indicator variables equal to one for high-yield and emerging market funds. *Daily flow* is the daily fund net flow; *Daily net outflow* is the absolute value of *Daily flow* if it is negative, and it is set to zero otherwise. Other fund variables include lagged *Alpha*, *Size*, *Age*, *Expense*, and *Inst*. See Table A1 in the appendix for the variable definitions. Regressions use only swing pricing and dual-priced funds. We cluster standard errors by fund and day. Standard errors are reported in parentheses.  $.50 < p < .1$ ; \*  $p < .05$ ; \*\*  $p < .01$ ; \*\*\*  $p < .001$ .

In columns 6–8, we present the results of the model which links daily adjustment factor to daily flows. In column 6, we show that the association between adjustment factor and daily net flows is statistically insignificant. However, when we examine net outflows separately, we find that the effect on adjustment factor is statistically significant. Column 7 shows that a one-standard-deviation increase in daily net outflows (in absolute values) is associated with a 12% higher adjustment factor with respect to its mean value. The effect doubles when we restrict our sample to funds that have more illiquid assets (column 8). In sum, adjustment factors are higher for illiquid portfolios during stress periods, and funds with higher outflows.

### 3.2 Fund flows and alternative pricing: Cross-sectional evidence

In this section, we evaluate the impact of alternative pricing on fund flows by estimating the following regression model:

$$\begin{aligned} Flow_{i,t} = & \beta_0 + \beta_1 Alternative_{i,t} + \beta_2 Stress_t + \beta_3 Alternative_{i,t} \times Stress_t \\ & + \beta_4 Controls_{i,t} + \varepsilon_{i,t}, \end{aligned} \quad (1)$$

where *Alternative* is an indicator variable which equals one if a fund is using one of the alternative pricing mechanisms. *Flow* and *Stress* are defined as before. Control variables include lagged fund characteristics (measured previous month-end) such as *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. We cluster standard errors by fund and month.

Panel A of Table 3 reports the results of ordinary least squares (OLS) regression. In column 1, we report the results for the univariate regression model and in column 2 we report the results for the regression model with fund controls. In both specifications, the coefficient of  $\beta_3$  is positive and statistically significant. Moreover, the value of the coefficient nearly offsets the negative value of the coefficient of  $\beta_2$ . For instance, in column 1,  $\beta_2$  is  $-0.99$  and  $\beta_3$  is  $1.04$ . These results indicate that alternative pricing is effective in reducing outflows in bad times. At the same time, we also find that the coefficient of  $\beta_1$  is negative, though statistically insignificant, which indicates that alternative funds have somewhat less inflows than traditional funds in good times.

To the extent that funds with different pricing rules may have different characteristics, our test sample in columns 1 and 2 may be unbalanced. To sharpen the interpretation of our findings, in each month, we match each of our swing funds to the sample of funds that rely on traditional pricing. Following Loughran and Ritter (1997), we find the nearest bond fund using a matching algorithm which minimizes the sum of the absolute percentage differences in lagged values of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. We perform the matching with replacement. If a fund is selected as a suitable match to more than one fund, we use this observation only once.

In columns 3–7, we present the results based on the matched sample. In column 3, we repeat the same estimation as in column 2. Our results are

**Table 3**  
**Fund flows during market stress**

*A. Least squares regressions*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Alternative</i> × <i>Stress</i>	1.0410** (0.4391)	0.9934* (0.5589)	1.3711** (0.5765)	1.6676*** (0.6368)	1.6369*** (0.5876)	1.1131** (0.5191)	1.2982** (0.5489)
<i>Alternative</i>	−0.7866 (0.5297)	−0.7260 (0.5219)	−0.6895 (0.5393)	−0.0993 (0.6608)	−0.6579 (0.5413)	−0.3028 (0.7042)	−0.8621* (0.5157)
<i>Stress</i>	−0.9890*** (0.2767)	−1.0140*** (0.3688)	−1.3467*** (0.3904)	−1.7250*** (0.5021)		−1.1241*** (0.3832)	−1.3075*** (0.3884)
<i>Alpha</i>		0.3526* (0.1993)	0.3212 (0.2060)	0.7116*** (0.2190)	0.6712** (0.3234)	0.4920** (0.2040)	0.5901*** (0.2094)
<i>Size</i>		0.3001* (0.1660)	0.3164* (0.1679)	−0.6081** (0.2432)	0.3498** (0.1665)	0.0944 (0.0902)	0.2648* (0.1515)
<i>Age</i>		−1.2669*** (0.2811)	−1.3062*** (0.2884)	−1.0089* (0.5299)	−1.3192*** (0.2820)	−1.4305*** (0.2162)	−1.0009*** (0.2630)
<i>Expense</i>		0.5694 (0.4194)	0.5711 (0.4294)	−2.8110*** (0.9704)	0.5419 (0.4584)	0.3574 (0.4003)	−0.3392 (0.4365)
<i>Illiquidity</i>		12.3444 (24.6152)	11.3720 (25.9732)	52.2817** (25.3218)	−16.1868 (28.6746)	22.9051 (26.2625)	32.1082 (25.4202)
<i>Inst</i>		−0.0126*** (0.0041)	−0.0128*** (0.0040)	−0.0278** (0.0118)	−0.0133*** (0.0041)	−0.0085* (0.0046)	−0.0143*** (0.0040)
Observations	16,693	10,125	9,670	9,669	9,665	9,670	9,670
R-squared	.002	.026	.026	.164	.048	.057	.040
Fund FE				Yes			
Time FE					Yes		
Family FE						Yes	
Style FE							Yes

*B. Quantile regressions*

Variables	(1) q0.5	(2) q1	(3) q5	(4) q10	(5) q25	(6) q50	(7) q75
<i>Alternative</i> × <i>Stress</i>	11.6437*** (4.3022)	7.6198*** (2.8641)	7.8583*** (1.3784)	5.0801*** (0.7331)	2.0331*** (0.2843)	0.1766** (0.0761)	−0.2902** (0.1220)
<i>Stress</i>	−10.3889*** (2.6709)	−7.4700*** (2.0653)	−6.7904*** (1.0768)	−4.6803*** (0.6683)	−1.9531*** (0.2516)	−0.2071*** (0.0660)	0.0460 (0.0872)
<i>Alternative</i>	−6.2156** (2.5474)	−5.4366*** (1.8101)	−4.9201*** (0.9338)	−3.2272*** (0.5644)	−1.3017*** (0.2334)	−0.1058** (0.0517)	0.0293 (0.0657)
<i>Alpha</i>	4.7913*** (1.8070)	1.8043 (1.3493)	0.3221 (0.4953)	0.8600*** (0.2251)	0.5467*** (0.1017)	0.1650*** (0.0374)	0.1805*** (0.0446)
<i>Size</i>	−4.9958*** (0.3708)	−4.9824*** (0.2724)	−1.9402*** (0.1766)	−0.8382*** (0.1099)	0.0191 (0.0450)	0.0847*** (0.0158)	0.1536*** (0.0258)
<i>Age</i>	−3.5406*** (1.0434)	−3.6133*** (0.6806)	−2.2994*** (0.4492)	−1.4509*** (0.2290)	−0.6920*** (0.0862)	−0.2548*** (0.0331)	−0.5550*** (0.0336)
<i>Expense</i>	−2.8741 (2.1769)	0.5738 (1.5059)	2.5669*** (0.7234)	2.5723*** (0.3922)	0.9409*** (0.1677)	0.0716 (0.0543)	0.0869 (0.0566)
<i>Illiquidity</i>	−2.0181 (95.5381)	29.1972 (81.9912)	−44.6820 (39.5059)	−21.4796 (16.4298)	7.4657 (8.0395)	5.2756** (2.2371)	7.9140** (3.6732)
<i>Inst</i>	−0.0897*** (0.0267)	−0.0748*** (0.0192)	−0.0306*** (0.0075)	−0.0174*** (0.0038)	−0.0097*** (0.0014)	−0.0026*** (0.0004)	−0.0021*** (0.0006)
Observations	9,670	9,670	9,670	9,670	9,670	9,670	9,670

The dependent variable is *Flow*, defined as the net monthly capital flows into a fund divided by the fund's total net assets. *Alternative* is an indicator variable that equals one if the fund is using one of the alternative pricing mechanisms. *Stress* is an indicator variable that equals one if monthly *VIX* is above the 75th percentile of the sample. The unit of observation is a fund-month. Control variables include the lagged values (previous month-end) of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. Panel A presents the results of ordinary least squares regressions. In panel A, the results in columns 1 and 2 are based on the full sample, while those in columns 3 to 7 use the matched sample. The matching algorithm is described in the text. Standard errors are clustered by fund and month. Panel B presents the results of quantile regressions for the matched sample. Panel B uses bootstrapped standard errors (estimated through 331 repetitions). Standard errors are reported in parentheses. \* $p < .1$ ; \*\* $p < .05$ ; \*\*\* $p < .01$ .

both statistically and economically more significant when we use the matched sample. In column 4, we include fund fixed effects to account for time-invariant omitted fund characteristics. We also include time fixed effects (in column 5), family fixed effects (in column 6), and style fixed effects (in column 7). The findings remain similar across all the specifications.

Estimates imply that, during stress, traditional funds lose, on average, capital worth of £8.86 million in each month. The corresponding loss for funds with alternative pricing is only £0.2 million. For the matched sample, the difference is even larger (£10.32 million vs. £0.1 million). Given that the average fund has £150 million in assets under management, the average monthly effect may not seem large. However, we observe a significant variation in outflows in the cross-section of funds. To show this effect directly, we estimate quantile regression model. Panel B of Table 3 reports the results.

Results from the OLS regression are similar across different percentiles of the unconditional flow distribution, ranging from the 50<sup>th</sup> to the 0.5<sup>th</sup>, that is, the negative impact of *Stress* on fund flows is almost fully reversed for alternative funds. However, the economic magnitudes increase substantially as we move from the median fund towards the funds in the left tail of the flow distribution. For example, the estimates increase *five* times when we compare the response of the average fund to the response of a fund at the 5th percentile of the flow distribution. Overall, as one would expect, the economic significance of alternative pricing rules is particularly large in the left tail of the flow distribution.

We further ensure additional robustness to our main findings by including different fixed effects (across funds' location domicile, region of sale, or investment area), front- and back-end loads, and alternative definitions of market stress based on TED spread, LIBOR rate, and Merrill Lynch's MOVE index, all results reported in Table IA.2.<sup>22</sup> We also estimate the regression model for each fund style category separately, with results reported in Table IA.3.<sup>23</sup> Results are similar across individual styles.

### 3.3 Evidence from switching funds and individual investors' responses

A potential issue with the interpretation of the results in Section 3.2 is that the cross-sectional variation in fund flows we document may be driven by omitted variables leading to biases in our estimated coefficient of interest. In particular, the potential endogeneity may reflect underlying differences in fund characteristics predicting flows, or selection of fund investors with heterogeneous sensitivities to stress events. While including fund controls or fund fixed effects in our regressions alleviates this problem to some extent,

<sup>22</sup> We have also estimated a model with an alternative measure of stress based on the 90th percentile of VIX. The results are similar to the 75th cutoff and reported in column 11 of Table IA.2.

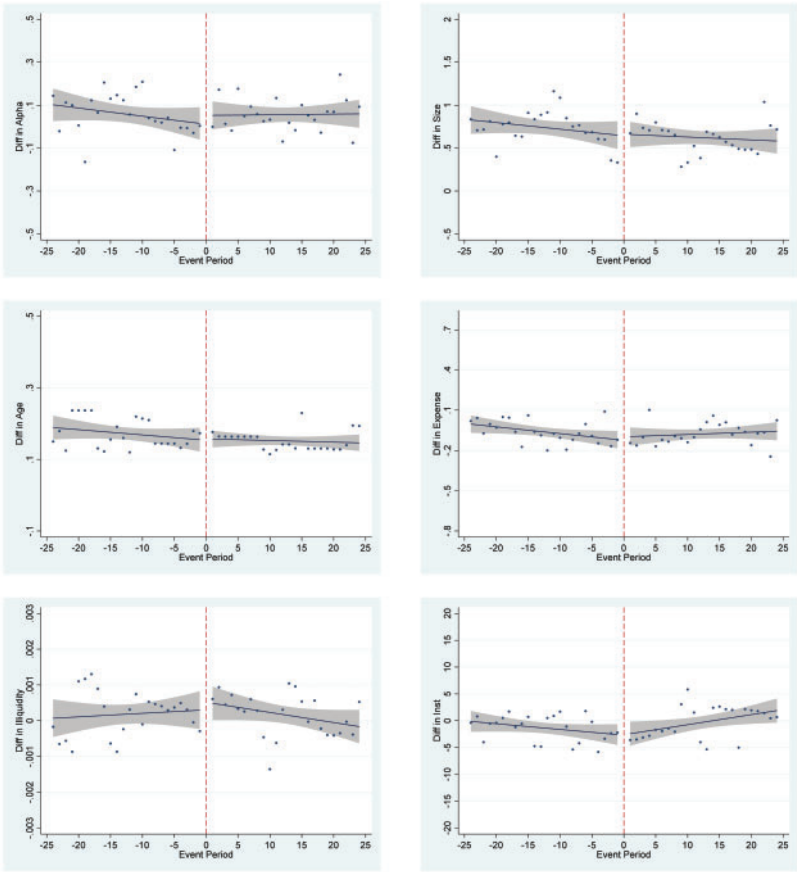
<sup>23</sup> Our style categories are motivated by the availability of the data and include corporate bond, diversified bond, high-yield bond, flexible bond, and emerging markets.

it is unlikely to solve it. In this section, we improve on this specification by using investor-level data and taking advantage of a subsample of funds that changed their pricing method during our sample period. Our combined results provide strong support for the hypothesis that alternative pricing methods reduce outflows during market stress.

**3.3.1 Sample of switching and matched control funds.** Over the period 2006–2016, 34 funds from 6 asset management companies switched their pricing schemes from traditional to alternative structures. Panel C of Table 1 lists the switching dates during our sample period. The essence of our tests is to track an individual investor in a given fund and examine their response in switching funds before and after the switch date. We then compare this with investors' responses in control funds around the same time. To balance the trade-off between the representativeness of our sample and the local nature of the switching event, we specify an event window of 48 months, with 24 months before and 24 months after the reported switch date. Because the observed effect in flows could be correlated with an unobserved time effect, ideally, we would like to observe the counterfactual fund behavior in the absence of treatment. Obviously, such counterfactual cannot be observed in the data. We instead approximate the counterfactual with a sample of control funds selected using the following algorithm: we match each fund in the treatment group, with replacement, to another one in the control group using the fund characteristics last observed before the switch date. The matched pair remains constant throughout each event period. Similar to before, we follow Loughran and Ritter (1997) and find the nearest bond fund by minimizing the sum of the absolute percentage differences in lagged values of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*.

An important assumption of our approach is that switching happens for reasons plausibly orthogonal to fund flows and their predictors. There are good reasons to believe this assumption is plausible. From the time-series perspective, the switching events are staggered over time and happen in good and bad times. Also, we do not observe any switches from alternative to traditional pricing; thus, it is unlikely that funds make their switching decisions strategically at times when the net benefit of alternative pricing is highest. Finally, since some funds within the same families do not change their structures, it is unlikely that the switches are purely familywide decisions. Formally, we compare the relative trends, between treatment and control group, in various fund characteristics around the switching dates. The existence of any differential pre-trends across the two groups could affect our inference about funds' responses to the switching events.

For our graphical presentation, in each month within the event window, we calculate the fund-level differences in average values between treated and control funds, along with the 95% confidence intervals, for the following fund characteristics: *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. Looking at



**Figure 2**  
**Fund characteristics before and after the switching event**

The panels show the average differences in fund characteristics for switchers and their matched funds over the event period [−24 months, 24 months]. The panels include linear plots with 95% confidence intervals. From the top-left corner to the bottom, respectively, panels show the differences in *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. See Table A1 in the appendix for the variable definitions.

the differences between the two groups allows us to illustrate the statistical significance of the differences on the picture. We present the plots, along with the fitted trends separately in the pre- and post-periods, for each variable in Figure 2. The plots do not indicate a statistically significant break around the switching dates for any of the six variables. All of the variables exhibit a smooth continuation from pre-period to post-period. Also, even though the slopes in the data are not perfectly flat, the time-series dynamics of the variables before the switching events do not show particularly strong pre-trends. We complement the graphical evidence with regression models in which we test for the breaks in average values of fund characteristics (dependent variables) after the switching

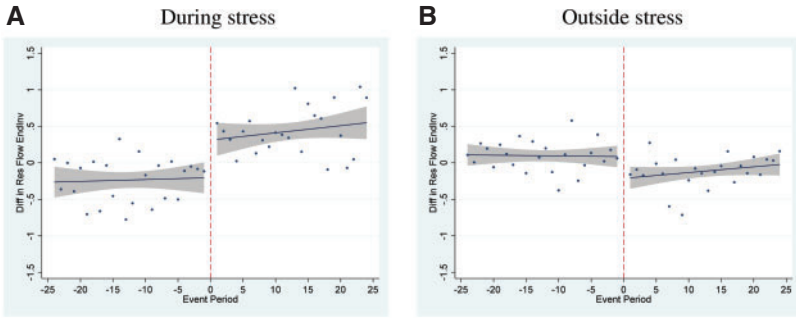
events and for the presence of any systematic differences in fund characteristics between treatment and control groups before the switching events. To assess the statistical significance of the effects, we define two additional variables. *Treated* is an indicator variable that equals one for switching funds and zero for funds in the control group. *Post* is an indicator variable equal to one for the post-event period and zero for the pre-event period. Our regressors include *Treated*, *Post*, and the interaction term between the two of them. We present the results from the regressions in Table IA.4. We note two important results. First, the coefficients of the interaction effects for all six fund characteristics are statistically insignificant, which suggests that the switching events do not induce a differential shift in potential fund predictors. Second, the coefficients of *Treated* are statistically insignificant for all the variables, which suggests that the treatment and the control samples are, on average, not significantly different from each other prior to the switching events.

**3.3.2 Evidence from individual investor flows.** Next, we assess the impact of the change in pricing structure on an individual investor's flows. Investor-level data allow us to address the second source of endogeneity concern, namely, investor selection. To restate, it is possible that the switching event itself also induces a change in the composition of investors in treated funds, and that the fund-level flow analysis captures the effects due to such compositional changes as well as the changes in a given investor's behavior. This concern generally applies to all large-sample studies of delegated asset management and has been difficult to address because of data limitations.<sup>24</sup> In this study, we are uniquely positioned to address this issue because we can observe investment decisions at the individual investor level. Consequently, we can track the behavior of *a given* investor both before and after the change in a fund's pricing rule, and can test whether the pricing rule alter investor behavior conditional on the aggregate liquidity conditions. In Table IA.5, we present basic summary statistics in the end investor data.<sup>25</sup>

We begin with a graphical presentation of possible pre-trend in investor flows, similar to our previous analysis for fund characteristics. Specifically, in each month of the event window, we calculate the average difference in residualized *Flow EndInv* between switchers and their matched funds. Residualized *Flow EndInv* (monthly change in investor's number of shares in a given fund) are obtained after controlling for fund characteristics and investor fixed effects.

<sup>24</sup> To our knowledge, the best treatment of this issue to date is to study the differences in flows of funds with the same underlying fund portfolio but different share classes catering to various investor types (e.g., Kacperczyk and Schnabl 2013; Schmidt, Timmermann, and Wermers 2016). However, these studies make the implicit assumption that each share class has either a homogenous or a stable pool of investors, which need not be true in the data.

<sup>25</sup> Detailed investor-level data are available for 230 funds in 20 families (vs. 299 in the full data); this number is reduced to 196 (vs. 224) if we constrain our sample to observations with a full record of all variables used in our tests. The average fund excluded from our analysis is not significantly different from the average fund included in the analysis. Funds provide the client classification.



**Figure 3**

**Investor-level fund flows before and after the switching event**

The panels show the average differences in end investor flows, *Res flow EndInv*, between switchers (treated) and their matched funds (control) over the event period [−24 months, 24 months]. Panel A presents the plot for stress periods, and panel B presents it for periods outside market stress. *Res flow EndInv* is obtained by regressing *Flow EndInv* on *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst* along with investor fixed effects. The panels include linear plots with 95% confidence intervals.

We present separate plots for periods of market stress and periods of no stress. Figure 3 does not indicate a pre-trend in individual investor flows. Next, we examine the change in the investor behavior before and after the switching events by estimating the following model:

$$\begin{aligned} \text{Flow EndInv}_{j,t} = & \beta_0 + \beta_1 \text{Stress}_t \times \text{Post}_t \times \text{Treated}_i + \beta_2 \text{Stress}_t \times \text{Post}_t \\ & + \beta_3 \text{Stress}_t \times \text{Treated}_i + \beta_4 \text{Treated}_i \times \text{Post}_t + \beta_5 \text{Post}_t \\ & + \beta_6 \text{Treated}_i + \beta_7 \text{Stress}_t + \beta_8 \text{Controls}_{i,t} \\ & + \beta_9 \text{Investor Fixed Effects}_j + \varepsilon_{j,t}, \end{aligned} \quad (2)$$

where the dependent variable is *Flow EndInv*, which is the monthly change in number of shares an investor *j* holds in a fund *i*. *Treated* is an indicator variable that equals one for switching funds and zero for funds in the control group. *Post* is an indicator variable equal to one for the period after the switch and zero otherwise. *Controls* is a vector of control variables that includes lagged values of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. We include investor fixed effects and cluster standard errors by investor and month. Table 4 presents the results.

As a starting point, we estimate our regression model separately for investors subjected to change (in column 1) and those being part of the control group (in column 2). The results indicate that investors in switching funds react less to stressed market conditions in terms of their withdrawals after the switch. On the other hand, the behavior of investors in the control group of funds that do not switch their pricing does not seem to change significantly during the same period. If anything, the effect is slightly negative, although statistically insignificant. In column 3, we use the combined sample with the two groups



**Table 4**  
**End investor flows during market stress for switchers and their matched funds**

Variables	(1) Treatment	(2) Control	(3)	(4)	(5) Alt. treatment
<i>Stress × Treated × Post</i>			0.6341*** (0.2230)	0.6195** (0.2517)	0.3700** (0.1620)
<i>Stress × Post</i>	0.2596* (0.1346)	−0.3205 (0.2163)	−0.3869** (0.1817)	−0.3578 (0.2261)	−0.1614 (0.1627)
<i>Stress × Treated</i>			−0.3941** (0.1929)	−0.3143 (0.2373)	−0.5964*** (0.0870)
<i>Treated × Post</i>			−0.6698*** (0.1597)	−0.4775** (0.2376)	−0.3674*** (0.0978)
<i>Post</i>	−0.2127* (0.1106)	0.5194*** (0.1376)	0.5219*** (0.1303)	0.4880** (0.2266)	0.1628* (0.0952)
<i>Treated</i>				0.0000 (0.0000)	−0.1211 (0.1307)
<i>Stress</i>	−0.1581** (0.0736)	−0.1020 (0.2131)	−0.2525 (0.1789)	0.2560 (0.2229)	—
<i>Alpha</i>	0.2757*** (0.1040)	0.4374** (0.1704)	0.3281*** (0.0856)	0.3272 (0.3049)	−0.0758*** (0.0201)
<i>Alpha × Treated × Post</i>				−0.0322 (0.3524)	
<i>Alpha × Post</i>				0.0906 (0.3226)	
<i>Alpha × Treated</i>				−0.0450 (0.3272)	
<i>Size</i>	−0.5059** (0.1919)	−0.7041*** (0.1294)	−0.6739*** (0.1157)	−0.6656*** (0.1174)	0.2505*** (0.0391)
<i>Age</i>	−1.4022* (0.7129)	−1.6378*** (0.4361)	−1.7709*** (0.3480)	−1.7936*** (0.3539)	−0.7534*** (0.0803)
<i>Expense</i>	−1.8653*** (0.6098)	−1.1982 (1.3946)	−1.6870*** (0.5755)	−1.6655*** (0.5798)	−0.8612*** (0.1518)
<i>Illiquidity</i>	−3.6082 (8.6290)	72.1860*** (25.3514)	−3.2257 (8.0409)	−0.0197** (0.0087)	0.0011 (0.0017)
<i>Inst</i>	−0.0232 (0.0139)	−0.0137 (0.0121)	−0.0199** (0.0087)	−3.1906 (8.1522)	8.1028*** (0.9325)
Observations	251,718	132,675	384,393	384,393	272,601
R-squared	.250	.363	.338	.338	.130
Investor FE	Yes	Yes	Yes	Yes	No
Investor/time FE	No	No	No	No	Yes

The dependent variable is *Flow EndInv*, which is the percentage monthly change in each investor's holding (in number of shares) [−24, 24] months. The unit of observation is an investor-month. Columns 1 and 2, respectively, show the results for treatment (switching funds) and control (matched) groups, and column 3 includes both fund groups. The matching algorithm is described in the text. The specification in column 5 mimics that in column 3, except that the control funds are chosen from the same fund family, and we include investor-time fixed effects. *Treated* is an indicator variable that equals one for switching funds; *Stress* is an indicator variable that equals one if monthly *VIX* is above the 75th percentile of the sample; and *Post* is an indicator variable that equals one for the period after the switch. Control variables include the lagged values (previous month-end) of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. See Table A1 in the appendix for the variable definitions. We cluster standard errors by investor and month. Standard errors are reported in parentheses. \*  $p < .1$ ; \*\*  $p < .05$ ; \*\*\*  $p < .01$ .

of investors and estimate the relative sensitivity of the two types of investors to change using a triple-difference regression model. The results are qualitatively similar to those obtained from our full sample fund-level estimation. Investors in funds with the alternative pricing withdraw relatively less of their money than do investors in traditional funds during periods of high market stress. Although the results are not uniformly significant, results also suggest that investors invest somewhat less money in alternative funds outside periods of stress.

One potential explanation of the last result is that funds with alternative pricing are underperforming and our results may reflect a general pre-trend in performance before the switching event. Figure 2 indicates no significant difference in performance between treatment and control group on average and it is also worth noting that our regressions control for fund alpha. To strengthen our evidence, in column 4, we additionally interact alpha with  $Treated \times Post$  (and include all the lower interaction terms). Our main variable of interest,  $Stress \times Treated \times Post$ , remains similar. Moreover, the coefficient of  $Stress \times Treated$  becomes statistically insignificant. Hence, it is unlikely that our results are driven by the underperformance of treated funds.

**3.3.3 Alternative explanations.** Even though the investor-level tests provide a clean identification of our economic hypothesis, our tests assume that investors differ only with respect to their time-invariant characteristics. The interpretation of the results could differ if some time-varying investor preferences (that happen to change around the switch dates) drive the differential responses of investors in pre- and post-periods. Given the staggered nature of switches, this is quite unlikely; moreover, the time variation in investor preferences would have to be such that investor flows are affected differently in periods of market stress versus no stress. Alternatively, investors could be affected by liquidity shocks to their entire (unobserved) wealth and rebalance their fund positions in the direction consistent with our results.

Ruling out such alternative explanations is generally challenging, but we can take advantage of a unique feature in our data. Specifically, we can design tests focusing on investors who at the same time invest in funds that do and do not undergo the pricing change. Hence, any change in investor preferences is likely to be common across the two types of funds.

Since we only observe the unique investor identifiers within the same fund management company, in this test, we select the control funds from the same management company as that of treated funds. Investors in our sample do not commonly hold simultaneously shares in both treated and control funds; still, we identify about 2,800 observations (10% of the sample) that represent investors with cross-fund holdings in a given month. The precise identification utilizes investor-time fixed effects. We report the results in column 5 of Table 4. We find that our main variable of interest remains positive and statistically significant. During market stress, investors in switching funds withdraw less money than what they withdraw from their traditional funds.<sup>26</sup>

Another alternative interpretation of our investor-level results relates to the intensive and extensive margins of investments. Since our tests utilize only the sample of investors who stay with the fund after the switching event, it is possible that these investors may be somewhat different than other investors,

<sup>26</sup> We have also repeated our tests in Equation (2) using the GBP monthly change in each investor's holdings ( $GBPFlowEndInv$ ) as a dependent variable. Our conclusions remain unchanged

especially than those in our control group. To address this point, we compare various characteristics of investors who leave our sample funds (including both switching and control funds) prior to the switching dates and those investors who stay. Specifically, our main independent variable is an indicator *InvExit*, which equals one if the investor left the fund during the 6-month period prior to the switch date, and equals zero if s/he stayed in the fund.<sup>27</sup> Our dependent variables are *Trading frequency*, *Volatility of flow EndInv*, *Inst investor*, *Investor ownership*, and *Investor-level FPS*. *Trading frequency* is the average of number of months investor traded; *Volatility of flow EndInv* is volatility of *Flow EndInv*; *Investor-level FPS* is the flow-performance sensitivity estimated for each investor at a given fund by regressing *Flow EndInv* on fund *Alpha*; *Investor ownership* is the average of investor's value of shares divided by the total fund size; *Inst investor* is an indicator variable that equals one for institutional clients. All dependent variables are calculated for each individual investor, prior to the switch date. Table 5 provides the results.

The results indicate that, on average, investors who leave their respective funds are more active as traders, their flows have greater volatility, and their flows are more sensitive to past performance. These results are consistent with the idea that investors' departures may be related to their more active trading patterns. What is more important for our purposes is whether the characteristics of departing investors differ between treated and control funds. To this end, we interact *InvExit* with *Treated*. Our results indicate no statistically significant differences in all five characteristics, which provides assurance for the interpretation of our findings.

In a final test, we explore an alternative hypothesis that investors may decide to exit the fund in anticipation of more severe redemption conditions, such as a spike in the adjustment factor. We test for this possibility by comparing fund flows *right-before-stress* periods to those in *stress* periods and remaining *nonstress* periods.<sup>28</sup> We report the results in Table IA.6. Two results emerge. First, we find no significant differences in flows in periods *right before market stress*, regardless of how close to stress periods we look. Second, the differences in flows between alternative and traditional funds during the remaining *nonstress* periods are also statistically insignificant. The flow behavior that we document in the paper is a response to realized rather than expected stress event.

In this section, we considered a number of alternative explanations and showed that they are unlikely to explain our findings. While there is generally no silver bullet to show causality in any empirical analysis, it is not clear what other alternative mechanisms—*independent of alternative pricing reducing*

<sup>27</sup> Our results are similar if we use either a shorter horizon of 3 months or a longer horizon, such as 12 or 24 months.

<sup>28</sup> We conduct this analysis using both monthly and daily flow data. In monthly regressions, we consider three versions *right before stress*, each of which use data from 1–3 months prior to the start of a “stress episode.” In daily regressions, we further zoom into data by considering 1–3 weeks prior to the start of a “stress episode.”

**Table 5**  
**Characteristics of investors who exited versus stayed prior to the switch date**

Variables	(1) <i>Trading frequency</i>	(2) <i>Volatility of flow EndInv</i>	(3) <i>Inst investor</i>	(4) <i>Investor ownership</i>	(5) <i>Investor-level FPS</i>
<i>InvExit</i> × <i>Treated</i>	0.0472 (0.1173)	7.6310 (5.8637)	0.0386 (0.0947)	0.0634 (0.0530)	0.2869 (0.9347)
<i>InvExit</i>	0.2248** (0.0921)	35.2503*** (3.9796)	0.0590 (0.0840)	−0.0655 (0.0425)	1.3193* (0.6931)
<i>Treated</i>	−0.2414** (0.0953)	5.9987* (3.1161)	0.0963 (0.1280)	0.0765 (0.0859)	−0.7544** (0.3815)
<i>Alpha</i>	−0.0974 (0.0675)	8.8064 (5.3890)	−0.0848 (0.0769)	0.0823 (0.0597)	−0.9062** (0.4572)
<i>Size</i>	−0.0780** (0.0380)	−4.8048* (2.5187)	0.1002** (0.0446)	−0.1040** (0.0409)	0.0510 (0.1989)
<i>Age</i>	0.0167 (0.0283)	−1.9901 (1.3663)	−0.3690*** (0.0605)	−0.0998** (0.0446)	0.7803*** (0.2629)
<i>Expense</i>	0.1082 (0.1172)	−14.5240** (6.4330)	−0.3586*** (0.1229)	−0.3083** (0.1419)	0.1592 (0.5261)
<i>Inst</i>	0.0064*** (0.0012)	0.1745*** (0.0569)	0.0069*** (0.0020)	0.0051*** (0.0008)	0.0190*** (0.0050)
<i>Illiquidity</i>	−3.5509 (4.8544)	370.5876 (249.8075)	−19.3927* (10.0706)	4.8040 (3.4883)	33.3383 (25.0033)
Observations	18,164	17,062	14,592	17,956	17,422
<i>R</i> -squared	.254	.587	.332	.103	.134

This table examines the differences in the key characteristics of clients who stayed versus left the fund prior to the switch date. The unit of observation is an investor. Dependent variables from columns 1 to 5 are *Trading frequency*, *Volatility of flow EndInv*, *Inst investor*, *Investor ownership*, and *Investor-level FPS*. *Trading frequency* is the average of number of months in which investor traded his/her fund shares; *Volatility of flow EndInv* is volatility of monthly *Flow EndInv*; *Investor-level FPS* is the flow-performance sensitivity estimated for each investor at a given fund by regressing *Flow EndInv* on fund *Alpha*; *Investor ownership* is the average of investor's value of shares divided by the total fund size in a given month; and *Inst investor* is an indicator variable that equals one for institutional clients. The dependent variables are calculated for each investor prior to the switch date and we use the unique observation for each individual investor. *InvExit* is an indicator variable that equals one if the client sold all of his/her shares within the 6-month period prior to the switch date. We interact *InvExit* with *Treated*, which equals one for switching funds (and zero for their matching control funds). Control variables include the lagged values (previous month-end) of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. Table A1 in the appendix defines all variables. We cluster standard errors by fund and month. Standard errors are reported in parentheses.

\*  $p < .1$ ; \*\*  $p < .05$ ; \*\*\*  $p < .01$ .

fragility—could reliably explain our findings. To strengthen the interpretation of our findings, in the next section, we test additional predictions from the economic mechanism that we offer.

### 3.4 Investment stability and alternative pricing

Our results so far suggest that open-end funds with alternative pricing structures enjoy greater flow stability, especially during market stress. In this section, we provide additional evidence to buttress this finding. To this end, we examine investors' flow-performance sensitivity and analyze fund liquidations.

**3.4.1 Flow-performance sensitivity.** A well-established finding in the equity mutual fund literature is that fund flows are strongly associated with fund performance and that the relationship between fund flows and a fund's past performance tends to be convex (e.g., Chevalier and Ellison 1999). A recent paper by Goldstein, Jiang, and Ng (2017) estimates the flow-performance

sensitivity for corporate bond funds and finds that the relationship for corporate bond funds is concave; that is, corporate bond funds' outflows appear to be more sensitive to bad performance than their inflows are to good performance. The authors interpret this finding within the theoretical model of Chen, Goldstein, and Jiang (2010), whose model predicts that the traditional pricing used by open-end funds generates strategic complementarities. If alternative pricing removes the first-mover advantage arising from the traditional pricing practice, we should expect the concavity to be lessened for swing funds. To assess this prediction, we estimate the following model:

$$\begin{aligned} Flow_{i,t+1} = & \beta_0 + \beta_1 NegAlpha \times Alternative_{i,t} + \beta_2 NegAlpha_{i,t} \\ & + \beta_3 Alpha \times Alternative_{i,t} + \beta_4 Alpha_{i,t} + \beta_5 Alternative_{i,t} \\ & + Controls_{i,t} + Time\ FE + \varepsilon_{i,t}, \end{aligned} \quad (3)$$

where *Flow* is the flow of fund *i* in month *t* + 1; *Alpha* is the average monthly fund alpha in the past 12 months; *NegAlpha* equals *Alpha* if alpha is below zero and it is set to zero, otherwise; control variables are lagged *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*, all measured at month *t*. Following past studies, we include year-month fixed effects to remove the time-series variation in flows and we focus on exploiting the cross-fund variation in alphas. We cluster standard errors by fund and time.

Panel A of Table 6 presents the results. In column 1, we only include *Alpha* and *Alpha* × *Alternative* to estimate differences in average flow-performance sensitivity. To evaluate any potential concavity, in column 2, we add *NegAlpha* and its interaction with *Alternative*. Consistent with Goldstein, Jiang, and Ng (2017), we find that flows to corporate bond funds are significantly positively related to funds' past performance and this relationship is more pronounced for funds with poor performance. Most important, the results show that concavity is significantly reduced for funds with alternative pricing. In column 2, estimated coefficients of  $\beta_1$  and  $\beta_2$  are −4.0730 and 5.8227; both are statistically significant at the 1% level. While sensitivity to negative performance is significantly lower for funds with alternative pricing, we do not find any significant difference in sensitivity to positive performance for funds with different pricing methods. Column 3 repeats the analysis for the matched sample and confirms the robustness of these findings.

We also estimate the flow-performance sensitivity at the end investor level using the sample of switching funds and their matching pairs. Specifically, we regress *Flow EndInv* on *NegAlpha* × *Treated* × *Post* and *Alpha* × *Treated* × *Post* while saturating the model with all other interaction terms. The analysis uses the 24-month period before and after the switch occurs. Regressions include end investor fixed effects. Panel B of Table 6 presents the results.

Our results are consistent with the findings obtained from the full sample. In column 1, we evaluate the overall change in the sensitivity to performance,

**Table 6**  
**Flow-performance sensitivity**

*A. Using fund flows for the full sample*

Variables	(1) <i>Fund flow</i>	(2) <i>Fund flow</i>	(3) <i>Matched sample fund flow</i>
<i>NegAlpha</i>		5.8227*** (1.4523)	7.0479*** (1.8523)
<i>NegAlpha</i> × <i>Alternative</i>		−4.0730*** (1.4817)	−5.0280*** (1.8578)
<i>Alpha</i>	1.5287*** (0.5412)	0.2767 (0.5690)	0.1114 (0.6177)
<i>Alpha</i> × <i>Alternative</i>	−0.5253 (0.4838)	0.2639 (0.5415)	0.4354 (0.5797)
<i>Alternative</i>	−0.3690 (0.5165)	−0.8427 (0.5441)	−0.9280* (0.5530)
<i>Size</i>	0.2743* (0.1459)	0.2766* (0.1465)	0.3005** (0.1494)
<i>Age</i>	−1.0158*** (0.2576)	−1.0127*** (0.2552)	−1.0070*** (0.2630)
<i>Expense</i>	−0.3771 (0.4647)	−0.2997 (0.4572)	−0.3126 (0.4695)
<i>Illiquidity</i>	12.3976 (27.0505)	22.8068 (27.5163)	20.3520 (28.2355)
<i>Inst</i>	−0.0149*** (0.0040)	−0.0138*** (0.0039)	−0.0142*** (0.0039)
Observations	10,125	10,125	9,670
<i>R</i> -squared	.060	.063	.064
Time FE	Yes	Yes	Yes

(Continued)

including both positive and negative fund alphas, and we find no significant effects. In column 2, we assess the asymmetry by including interaction terms with *NegAlpha*. Similar to the full-sample results, we find significant differences in sensitivity to *NegAlpha*. Our results show that, in a switching fund, the same investor is significantly less likely to redeem her shares in the post period (*NegAlpha* × *Treated* × *Post* is −1.5247, significant at the 10% level). In column 3, we focus on more extreme negative performance episodes by revising the definition of *NegAlpha* as being equal to *Alpha* when it is below the 25th percentile of the sample (and zero, otherwise). Results reveal the same patterns, with amplified magnitudes: in column 3, the coefficient of *NegAlpha* × *Treated* × *Post* is −4.5641, significant at the 5% level.

These results provide strong evidence that alternative pricing predominantly affects the sensitivity of flows to poor performance. The asymmetry of the results supports the interpretation that alternative pricing mitigates the run incentives arising from traditional pricing. This is because, while a *run for exit* could occur on the downside, a *run to enter* on the upside is unlikely to happen as funds with recent good performance do not continue to perform well (e.g., Carhart 1997; Chen et al. 2004). However, as we show in Section 4.6, in the absence of dilution adjustment on fund NAV, funds with poor performance experience outflows and continue performing poorly.

**Table 6**  
**(Continued)***B. Using end investor flows for switchers and their matched funds*

Variables	(1) Flow EndInv	(2) Flow EndInv	(3) Flow EndInv
<i>NegAlpha</i> × <i>Treated</i> × <i>Post</i>		−1.5247* (0.8013)	−4.5641** (1.8491)
<i>NegAlpha</i> × <i>Post</i>		1.3472* (0.7123)	4.4680** (1.8426)
<i>NegAlpha</i> × <i>Treated</i>		−0.3741 (1.6914)	0.6165 (1.8189)
<i>NegAlpha</i>		0.4240 (0.6908)	0.5432* (0.3189)
<i>Alpha</i> × <i>Treated</i> × <i>Post</i>	0.0180 (0.1364)	0.2071 (0.1588)	0.1053 (0.1477)
<i>Alpha</i> × <i>Post</i>	0.0178 (0.1268)	−0.1013 (0.1297)	−0.0392 (0.1220)
<i>Alpha</i> × <i>Treated</i>	−0.1445 (0.1138)	−0.1122 (0.1208)	−0.1750 (0.1185)
<i>Alpha</i>	0.4578*** (0.1059)	0.3965*** (0.0989)	0.4675*** (0.0977)
<i>Treated</i> × <i>Post</i>	−0.4371*** (0.1010)	−0.5233*** (0.1146)	−0.4847*** (0.1075)
<i>Post</i>	0.4163*** (0.1000)	0.4475*** (0.1000)	0.4411*** (0.0980)
<i>Size</i>	−0.6631*** (0.0683)	−0.6537*** (0.0697)	−0.6675*** (0.0696)
<i>Age</i>	−1.7081*** (0.2161)	−1.6450*** (0.2202)	−1.6804*** (0.2205)
<i>Expense</i>	−1.4161*** (0.1848)	−1.4042*** (0.1868)	−1.3883*** (0.1852)
<i>Inst</i>	−0.0187*** (0.0057)	−0.0181*** (0.0057)	−0.0186*** (0.0057)
<i>Illiquidity</i>	−1.7149 (1.6117)	−0.9046 (1.8760)	−1.7574 (1.8032)
Observations	384,393	384,393	384,393
R-squared	.338	.338	.338
Investor FE	Yes	Yes	Yes

This table shows the effect of alternative pricing rules on flow-performance sensitivity. Panel A shows the results for the full sample using fund flows. The dependent variable is *Flow*, which is the net monthly capital flows into a fund divided by the fund's total net assets. *NegAlpha* equals lagged *Alpha* if it is below zero; it is set to zero otherwise. *Alternative* is an indicator variable that equals one if the fund is using one of the alternative pricing mechanisms. Column 3 presents the results for the matched sample (all *Alternative* funds and their matching pairs). The unit of observation is a fund-month. Standard errors are clustered by fund and month. Standard errors are reported in parentheses. Panel B shows the results for the switching funds (and their matching pairs) using end investor flows. The dependent variable is *Flow EndInv*, which is percentage monthly change in each investor's holding (in number of shares). *Treated* is an indicator variable that equals one for switching funds; *Post* is an indicator variable that equals one for the period after the switch. *Alpha* is the fund's alpha in the past 12 months. The event period is [−24, 24] months. *NegAlpha* equals lagged *Alpha* if the fund's lagged *Alpha* is negative (or below the 25th percentile, in column 3); it is set to zero and otherwise. Regressions include the interaction terms of *Alpha* (and *NegAlpha*) with *Treated* and *Post*. The unit of observation is an investor-month. We cluster standard errors by investor and month. Standard errors are reported in parentheses. The matching algorithm is described in the text. Control variables include the lagged *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. See Table A1 in the appendix for the variable definitions.

**3.4.2 Fund exit.** A direct consequence of significant fund outflows and high flow volatility is the heightened probability of fund exiting the market. In this section, we test the role of alternative pricing methods on fund exits.

We obtain data on a fund's status from Morningstar. For each fund that exits the market, Morningstar reports the exit type: merged and liquidated. In total,

Table 7  
Fund exit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	<i>Fund exit</i>	<i>Merged</i>	<i>Liquidated</i>	<i>Fund exit</i>	<i>Merged</i>	<i>Liquidated</i>	<i>Liquidated matched sample</i>
<i>Alternative</i>	−0.0474 (0.0599)	0.0611* (0.0312)	−0.1081* (0.0560)	−0.1229 (0.0884)	0.0134 (0.0472)	−0.1723** (0.0836)	−0.0885* (0.0479)
<i>Alpha</i>				0.0527 (0.0567)	0.0425 (0.0508)	0.0354 (0.0441)	0.0423 (0.0453)
<i>Size</i>				−0.0422*** (0.0119)	−0.0283*** (0.0105)	−0.0256** (0.0104)	−0.0214** (0.0095)
<i>Age</i>				0.0057 (0.0256)	0.0395* (0.0211)	−0.0345 (0.0211)	−0.0269 (0.0198)
<i>Expense</i>				0.1853*** (0.0649)	0.0788 (0.0543)	0.1703*** (0.0590)	0.1492** (0.0592)
<i>Illiquidity</i>				25.7466*** (5.1310)	27.3780*** (4.3891)	4.5239 (7.6024)	4.2281 (7.7906)
<i>Inst</i>				0.0017*** (0.0006)	0.0010* (0.0006)	0.0015*** (0.0006)	0.0017*** (0.0006)
Constant	0.1739*** (0.0561)	0.0256 (0.0254)	0.1556*** (0.0542)	1.0122*** (0.2819)	0.5262** (0.2425)	0.8208*** (0.2753)	0.6486*** (0.2243)
Observations	299	281	277	174	167	163	159
R-squared	.003	.006	.026	.569	.535	.414	.416
Family FE	No	No	No	Yes	Yes	Yes	Yes

The dependent variables are *Fund exit*, which is defined as an indicator variable that equals one if the fund exits the market during our sample period, and it is set to zero if the fund remains in the sample; *Merged*, which is an indicator variable that equals one if the fund has become obsolete because of a merger event during the sample period and equals zero if the fund remains alive; and *Liquidated*, which is an indicator variable that equals one if the fund has become obsolete due to a liquidation during our sample period, and zero if the fund remains alive. *Alternative* is an indicator variable that equals one if the fund is using one of the alternative pricing mechanisms. The regression model in column 7 uses the matched sample including the control variables of lagged *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. See Table A1 in the appendix for the variable definitions and calculations of all variables in the regression. The unit of observation is a fund. We cluster standard errors by fund and month. Standard errors are reported in parentheses. \* $p < .1$ ; \*\* $p < .05$ ; \*\*\* $p < .01$ .

we observe 40 funds (out of 299) that have exited during our sample period. Of these 40 funds, 18 are liquidated and remaining 22 are merged. On average, traditional funds are more likely to exit. About 12% (32 out of 253) of alternative funds exit, whereas this is 17% for traditional funds (8 of 46).

We also evaluate the difference in fund exits between the two groups of funds using a regression framework. The dependent variable, *Fund Exit*, is an indicator variable equal to one if a fund exits the market during our sample period, and equal to zero if a fund remains alive.<sup>29</sup> The variable *Merged* (*Liquidated*) is an indicator that equals one if the fund exits due to a merger (liquidation) during our sample period, and it equals zero if the fund is still alive. The main independent variable is *Alternative*. Control variables are measured in the last month before the exit occurs. Table 7 reports the results.

Columns 1–3 report results from the univariate regression model; in columns 4–6, we control for the potential impact of fund characteristics and family fixed effects; and column 7 reports results with the matched sample. We find that, on average, alternative funds are more likely to exit but the effect is statistically

<sup>29</sup> A fund exit is defined at the fund level, that is, the level at which all of its share classes are terminated.



insignificant. However, when we condition the sample on the type of exit, we observe a visible difference between mergers and liquidations. While we observe no consistent pattern for mergers, we find that alternative funds are significantly less likely to liquidate. Overall, our results indicate that alternative funds are less likely to liquidate their portfolios, arguably because they are less subject to run risks and fund flow volatility.

### 3.5 When do alternative pricing rules matter more?

Theory of runs on open-end mutual funds is linked to the presence of strategic complementarities due to first-mover advantage in the spirit of Morris and Shin (1998), Goldstein and Pauzner (2005), and Vives (2014). In this section, we exploit the variation in the strength of such complementarities across funds and investors to provide direct evidence for the mechanism described by the theoretical studies.

**3.5.1 The role of fund characteristics.** Our first set of tests considers the differences between funds in terms of their fragility. We explore three hypotheses. First, funds' fragility should increase with the degree of their portfolios' illiquidity because illiquid portfolios take longer to liquidate, and trades are more costly. We therefore expect the pricing structure to matter more for funds with highly illiquid assets. Second, in the model of Chen, Goldstein, and Jiang (2010), when the primary source of complementarities is the price impact of future redemptions, a large investor can internalize the negative effects of their future actions, thus weakening complementarities. Hence, fragility is likely to be higher for funds with many small investors and we expect that the pricing structure should matter more for funds with more dispersed ownership structure. In a similar vein, we expect the dispersion of ownership to be higher among funds with a large fraction of retail investors who tend to hold small shares in the fund.

To test these hypotheses, we append the specification in (2) with interaction terms, each of which captures the three dimensions of strategic complementarities. For this test, we use the full sample as the analysis requires sufficient cross-sectional variation in fund characteristics (switchers' subsample is about 10% of the full sample). We present the results in Table 8. In column 1, we consider *Illiquidity*. In column 2, we characterize the dispersion in ownership. Specifically, *Ownership Concentration* is the Herfindahl-Hirschman index of end investors' ownership in a given fund. A lower value of *Ownership Concentration* indicates a more dispersed ownership. Finally, in column 3, we use  $Retail = 1 - Inst$ , defined as the fraction of a fund assets held by retail investors. All specifications are based on a matched sample of funds and include a similar set of controls as before, measured as of previous month-end. Our results support the three hypotheses we outline. The effect of alternative pricing is significantly greater for funds with more illiquid assets, funds with more dispersed ownership, and funds with more retail investors.

**Table 8**  
**Cross-fund differences**

Variables	(1)	(2)	(3)
<i>Alternative</i> × <i>Stress</i> × <i>Illiquidity</i>	26.7550* (14.5103)		
<i>Stress</i> × <i>Illiquidity</i>	−28.7799* (17.2803)		
<i>Alternative</i> × <i>Stress</i> × <i>Ownership concentration</i>		−6.0387* (3.5858)	
<i>Stress</i> × <i>Ownership concentration</i>		3.9060 (3.0725)	
<i>Alternative</i> × <i>Stress</i> × <i>Retail</i>			0.0243** (0.0114)
<i>Stress</i> × <i>Retail</i>			−0.0121 (0.0098)
<i>Alternative</i> × <i>Stress</i>	1.9128** (0.9164)	2.4103*** (0.6379)	2.2904** (0.9016)
<i>Stress</i>	−1.8045*** (0.6519)	−1.8842*** (0.6172)	−1.9369** (0.7769)
<i>Alternative</i> × <i>Illiquidity</i>	−88.0525 (61.1618)		
<i>Alternative</i> × <i>Ownership concentration</i>		6.1098*** (2.2760)	
<i>Alternative</i> × <i>Retail</i>			−0.0101 (0.0118)
<i>Alternative</i>	−0.8307* (0.4745)	−1.8383*** (0.3880)	−1.1000 (0.9592)
<i>Illiquidity</i>	78.7570 (59.6897)		
<i>Ownership concentration</i>		−6.8252*** (2.0888)	
<i>Retail</i>			0.0194* (0.0101)
Observations	9,670	8,303	9,670
Controls	Yes	Yes	Yes
R-squared	.031	.027	.026

The dependent variable is *Flow*, defined as the net monthly capital flows into a fund divided by the fund's total net assets. *Alternative* is an indicator variable that equals one if the fund is using one of the alternative pricing mechanisms. *Stress* is an indicator variable that equals one if monthly *VIX* is above the 75th percentile of the sample. Regressions use the matched sample including the control variables of lagged *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst* (*Retail* in column 3). Column 1 introduces interaction terms with lagged *Illiquidity*; column 2 with lagged *Ownership concentration*, which is the Herfindahl-Hirschman index of end investors' ownership; column 3 with *Retail* equal to  $(1 - Inst)$ . See Table A1 in the appendix for the variable definitions and calculations of all variables in the regression. The unit of observation is a fund-month. We cluster standard errors by fund and month. Standard errors are reported in parentheses. \*  $p < .1$ ; \*\*  $p < .05$ ; \*\*\*  $p < .01$ .

**3.5.2 The role of investor characteristics.** Our second set of tests exploits the variation in investor-level sensitivities to alternative pricing. We consider two measures of sensitivity: investor sophistication and investor investment horizon. Following earlier literature on fixed-income assets (e.g., Kacperczyk and Schnabl 2013; Schmidt, Timmermann, and Wermers 2016), we argue that institutional investors are likely to be better informed about the implications of funds' pricing practices. Similarly, investors with longer horizons suffer more from the dilution in fund performance due to funds' trading costs. If alternative pricing mitigates strategic complementarities, then we would expect it to matter more for institutional investors and investors with longer horizons. We test these predictions in the context of our model in Equation (2).

We present the results in Table 9. In columns 1 to 4, the investor type, *Inst Investor*, is an indicator variable that equals one if the end investor is an institutional client and zero, otherwise. Column 1 shows the results for treated funds. Consistent with the strategic complementarity hypothesis, in times of market stress, institutional investors sell more when the fund uses the traditional pricing. This indicates that, in such funds, retail investors are systematically disadvantaged. After the fund switches to swing pricing, institutional investors are more likely to alter their behavior and stay with the funds in times of stress. The behavior of institutional investors in a control sample, in column 2, suggests no change in the behavior in the post period. We perform the test of differences in the coefficients  $\beta_0$  between treated and control groups and find that the corresponding  $p$ -value equals .07.

We extend the empirical test by asking whether the type of fund's dominant investor clientele matters for the results we document above for institutional investors. In column 3, we repeat the test considering the subsample of funds predominantly held by retail investors, and in column 4, we use funds with mostly institutional investors. The results from this analysis show that institutional investors alter their behavior more in funds with broad retail ownership. This is in line with Chen, Goldstein, and Jiang (2010), who argue that funds that are held mostly by large institutional investors can be less susceptible to strategic complementarities because large institutional investors are more likely to play a cooperative game, while coordination is more difficult for a more diverse retail group. Taken together with Table 9, our analysis shows that, while the cross-fund effects are pronounced for funds with higher retail ownership, it is not driven by the retail investors that sell more in these funds, rather it is the institutional investors facing the presence of retail investors.

The investor type in columns 5 and 6 is investment horizon. Specifically, *Patient Investor* is an indicator variable that equals one if the end investor has an investment horizon above the sample median and zero otherwise, where investment horizon is the number of months investors hold their shares after an initial purchase.<sup>30</sup> In column 5, we present the results for the sample of treated funds, and in column 6 for the sample of control funds. The coefficient of the triple interaction term is positive and statistically significant for the former group, whereas it is negative, though statistically insignificant, for the latter group. The results support the hypothesis that investors with longer horizons perceive the change in pricing structure as a stabilizing force during periods of stress.

Notably, investor type may be correlated with investment horizon. In this regard, it is useful to assess the relative contribution of the two forces to the

<sup>30</sup> In calculating the investment horizon, we use purchases before December 2014. The average horizon in traditional and alternative funds is 26 versus 30 months, respectively. This is consistent with the idea that alternative pricing rules provide protection for long-term investors.

Table 9  
The role of investor characteristics

Variables	(1) <i>Treated</i>	(2) <i>Control</i>	(3) <i>Treated</i> <i>retail-oriented</i>	(4) <i>Treated</i> <i>inst-oriented</i>	(5) <i>Treated</i>	(6) <i>Control</i>	(7) <i>Treated</i>
<i>Stress</i> × <i>Post</i> × <i>Inst investor</i>	0.4409** (0.1970)	0.1051 (1.1571)	0.5693*** (0.1841)	0.0074* (0.0039)			0.4604** (0.1992)
<i>Stress</i> × <i>Post</i>	0.1275 (0.1336)	0.3316 (0.9681)	0.3425 (0.2570)	0.0009 (0.0689)	0.1711 (0.1185)	-0.2283 (0.2295)	0.0564 (0.1170)
<i>Stress</i> × <i>Inst investor</i>	-0.2614* (0.1351)	-1.9006* (1.0350)	-0.3700*** (0.1236)	-0.1270 (0.2008)			-0.2604* (0.1360)
<i>Stress</i> × <i>Post</i> × <i>Patient investor</i>					0.1249** (0.0581)	-0.1198 (0.2970)	0.0881* (0.0446)
<i>Stress</i> × <i>Patient investor</i>					-0.0899 (0.0563)	0.1691 (0.2887)	0.0091 (0.0363)
<i>Post</i>	-0.2025* (0.1101)	0.2645 (0.3958)	-0.4499** (0.2079)	0.0074 (0.0584)	-0.2160* (0.1112)	0.5246*** (0.1382)	-0.2017* (0.1091)
<i>Stress</i>	-0.0541 (0.0620)	-0.5807 (0.7479)	-0.2204 (0.1986)	-0.0178 (0.0132)	-0.0975* (0.0543)	-0.0172 (0.2004)	-0.0599 (0.0468)
Observations	231,305	64,513	145,604	85,701	251,718	132,675	231,305
R-squared	.250	.404	.284	.187	.251	.363	.250
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	<i>p</i> -value = .071		<i>p</i> -value = .066		<i>p</i> -value = .064		

The dependent variable *Flow EndInv* is percentage monthly change in each investor's holdings (number of shares). *Treated* is an indicator variable that equals one for switching funds; *Post* is an indicator variable that equals one for the period after the switch. *Inst investor* is an indicator variable that equals one if the end investor is an institutional client (set to zero otherwise). *Patient investor* is an indicator variable that equals one if the end investor has an investment horizon above the sample median (set to zero otherwise). Investment horizon is the number of months the investor holds his shares after an initial purchase. In calculating investment horizon, we use purchases before December 2014. Columns 1, 3, 4, 5, and 7 present the results for switching funds; columns 2 and 6 present the results for control funds. The unit of observation is an investor-month. We cluster standard errors by investor and month. Standard errors are reported in parentheses.  $^*p < .05$ ;  $^{**}p < .01$ ;  $^{***}p < .001$ .

total flow effect. In column 7, we jointly include  $Stress \times Post \times Inst$  investor and  $Stress \times Post \times Patient$  investor. The results indicate that both investors' sophistication and investment horizon are important interacting forces with the fund's pricing structure, though investor sophistication seems to be a statistically stronger factor.

**3.5.3 Alternative pricing rules and investor learning.** One of the basic principles of our conceptual framework is that fund investors internalize the presence of alternative pricing rules and therefore adjust their behavior if a fund switches its pricing method. For that to happen, arguably, one would expect a learning process by which such information enters the investors' domain. One way in which learning occurs is through a direct information channel between funds and their investors. Fund companies are required to report in their prospectuses what type of pricing rule they follow and inform their shareholders when they are making a change. At the same time, very few funds disclose the precise values of the adjustment factors that they apply. We argue that, while useful, full knowledge of adjustment factors may not be necessary for investors to respond to funds' switch to swing pricing. This is because investors can rationally anticipate that in the case of a significant stress and possible high illiquidity costs, the fund is going to act in the interest of nontransacting investors by transferring the trading costs onto the transacting investors. In a repeated game, funds have strong incentives to do so, to reduce the dilution in fund performance and mitigate run risks.

In Section 3.5.2, we showed that institutional investors alter their behavior more after the fund switches to swing pricing, in that they significantly reduce their redemptions during market stress. This is consistent with the idea that, being more sophisticated, institutional investors are better informed about funds' pricing practices. In this section, we design three additional tests that provide additional insights into the role of investor information and learning. In our first test, we posit that if learning happens through direct information about adjustment factors, we should expect that funds that apply dual pricing should offer a better method to stabilize flows than funds with swing pricing for which precise values of transaction costs are unknown. We decompose the effect of the alternative pricing into specific subcomponents (full swing, partial swing, and dual pricing). Our results, reported in Table 10, indicate that the type of disclosed information does not seem as relevant for flow stability. We find a similar pattern of flows for each individual component of the alternative pricing. In statistical terms, results are strongest for partial swing and weakest for dual-priced funds, arguably reflecting the differences in statistical power in each subsample, since majority of alternative funds use partial swing while dual pricing is rare.

We offer two additional predictions. First, we hypothesize that fund investors with longer history of investment with the fund might be better informed about

**Table 10**  
**Full swing versus partial swing versus dual pricing**

Variables	(1) <i>Partial swing</i>	(2) <i>Full swing</i>	(3) <i>Dual</i>	(4) <i>All</i>
<i>Partial swing</i> × <i>Stress</i>	1.3341** (0.5487)			1.3341** (0.5483)
<i>Full swing</i> × <i>Stress</i>		1.3662* (0.8062)		1.3662* (0.8032)
<i>Dual</i> × <i>Stress</i>			2.2829 (1.7599)	2.2829 (1.7505)
<i>Partial swing</i>	−0.7073 (0.5804)			−0.7073 (0.5799)
<i>Full swing</i>		−0.8312 (0.5747)		−0.8312 (0.5726)
<i>Dual</i>			−2.6175** (1.2289)	−2.6175** (1.2223)
<i>Stress</i>	−1.3154*** (0.3934)	−1.3154*** (0.3946)	−1.3154*** (0.3952)	−1.3154*** (0.3931)
Observations	6,828	3,508	2,682	9,670
R-squared	.003	.006	.014	.008
Controls	Yes	Yes	Yes	Yes

Dependent variable is *Flow*, which is the net monthly capital flows into a fund divided by the fund's total net assets; *Stress* is an indicator variable that equals one if monthly *VIX* is above the 75th percentile of the sample. Using the matched sample, Columns 1 to 3 compare traditionally priced funds to full swing, partial swing, and dual-priced funds, respectively, Column 4 uses all. *Full swing* is an indicator variable that equals one if the fund is a full swing fund; *Partial swing* is an indicator variable that equals one if the fund is a partial swing fund; and *Dual* is an indicator variable that equals one if the fund is a dual fund. The baseline category in each regression includes the matching funds that use the traditional pricing rule. Control variables include the lagged values (previous month-end) of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. The unit of observation is a fund-month. We cluster standard errors by fund and time. Standard errors are reported in parentheses. \* $p < .1$ ; \*\* $p < .05$ ; \*\*\* $p < .01$ .

the fund's pricing practices. Second, investors in fund families which have had at least one fund with an alternative pricing rule (before the switching of the fund in question) may benefit from information spillovers inside the organization, for example, by observing the approach that the fund family has taken to swing pricing in its other funds.

To test these predictions, we first measure how long a given fund investor has been investing with the fund at any point in time. To this effect, we define an indicator variable *Seasoned Investor*, which equals one if the investor's length of investment at a given point in time is above the unconditional sample median, and zero otherwise. We then estimate the difference in the response to switching a fund type for investors with long and short span of the investments in the treated sample and for investors whose funds did not change the pricing rule at the same time (the control sample). Our coefficient of interest is that of the triple interaction between *Stress*, *Post*, and *Seasoned Investor*. We present the results for the respective regression models in columns 1 and 2 of Table 11. Our results indicate that the stabilizing effect of the alternative pricing rule is more visible for investors with longer tenure inside their funds. Notably, the response for the different types of investors inside nonswitching funds shows no significant difference between investors with short and long investment history.

**Table 11**  
**The role of investor learning**

Variables	(1) <i>Treated sample</i>	(2) <i>Control sample</i>	(3) <i>Matched sample</i>	(4) <i>Matched sample</i>
<i>Stress</i> × <i>Post</i> × <i>Seasoned investor</i>	0.7301** (0.3633)	-0.4573 (0.5377)		
<i>Stress</i> × <i>Post</i>	0.3194* (0.1808)	0.0390 (0.2146)		
<i>Post</i> × <i>Seasoned investor</i>	-0.0872 (0.1003)	-0.0551 (0.0803)		
<i>Stress</i> × <i>Seasoned investor</i>	-0.5710** (0.2887)	-0.4027* (0.2165)		
<i>Stress</i> × <i>Treated</i> × <i>Post</i>			0.2885 (0.6725)	0.6050*** (0.2288)
<i>Stress</i> × <i>Post</i>			0.0945 (0.2734)	-0.3923* (0.2073)
<i>Stress</i> × <i>Treated</i>			-1.3738** (0.5921)	-0.3521* (0.2058)
<i>Treated</i> × <i>Post</i>			-0.8290 (0.9029)	-0.3846** (0.1605)
<i>Post</i>	-0.2089* (0.1126)	0.3053* (0.1644)	0.5267 (0.3458)	0.4262** (0.2067)
<i>Stress</i>	-0.1096 (0.0673)	-0.3239* (0.1818)	-0.2956 (0.1893)	-0.2697 (0.1964)
<i>Alpha</i>	0.3417*** (0.1025)	0.5777*** (0.1605)	0.3873 (0.4475)	0.3321*** (0.0712)
<i>Size</i>	-0.6046*** (0.2082)	-0.7511*** (0.1290)	-1.7294* (0.8839)	-0.6425*** (0.1207)
<i>Age</i>	-1.3311* (0.7594)	-1.7927*** (0.4326)	-0.6078 (0.6662)	-2.0332*** (0.4415)
<i>Expense</i>	-2.0189*** (0.6307)	-1.5441 (1.4116)	-1.3337 (2.2585)	-1.3938** (0.5742)
<i>Inst</i>	-0.0188 (0.0143)	-0.0123 (0.0119)	0.0244 (0.0541)	-0.0180* (0.0091)
<i>Illiquidity</i>	0.2137 (8.1144)	76.4395*** (25.2308)	11.8126 (30.4138)	-4.1253 (5.9288)
<i>Seasoned investor</i>	0.1056 (0.0871)	0.1718* (0.0928)		
Observations	251,718	132,675	58,580	327,173
R-squared	.252	.364	.216	.362
Investor FE	Yes	Yes	Yes	Yes
	<i>p</i> -value = .021		<i>p</i> -value = .034	

The dependent variable *Flow EndInv* is percentage monthly change in each investor's holdings (number of shares). *Treated* is an indicator variable that equals one for switching funds; *Post* is an indicator variable that equals one for the period after the switch. For each investor-fund-month, we calculate for how long the investor has been with the fund. *Seasoned investor* is an indicator variable that equals one if this value is above its sample median. Columns 1 and 2, respectively, present the results for treated and control samples. Columns 3 and 4 report results for the full matched sample, including both the treated and control funds. Column 3 includes switching funds (and their matching controls) which belong to fund families that have had no swing fund prior to the switch date of the fund in question. Column 4 includes switching funds (and their matching controls) that belong to fund families that have had at least one swing fund already prior to the switch of the fund in question. Control variables include the lagged values (previous month-end) of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. See Table A1 in the appendix for the variable definitions. The unit of observation is an investor-month. We cluster standard errors by investor and month. Standard errors are reported in parentheses. \**p* < .1; \*\**p* < .05; \*\*\**p* < .01.

Hence, it seems that the learning effect about the pricing rule is an important driver of the observed heterogeneity.<sup>31</sup>

<sup>31</sup> In untabulated results, we have also conducted a test of statistical significance between the two triple interactions. The difference is statistically significant with the *p*-value of .02.

In the second test, we split the sample of switching funds depending on whether the fund's family already had at least one fund with alternative pricing rule (*Prior switchers*) or the switch would be the first one ever (*First-time switchers*). Our hypothesis is that investors of switching funds that belong to families with prior history of alternative pricing may benefit from information spillovers from other funds. To test this, we estimate the regression model of Table 6 separately for the sample of *Prior switchers* and the sample of *First-time switchers*. We report the results in columns 3 and 4 of Table 11. Our results indicate that the economic effect of the triple interaction term for *Prior switchers* is at least twice as large as that for *First-time switchers*. Hence, we conclude that learning from past experiences inside the same family may be another way by which information about alternative pricing practices is transmitted to the fund investors.

### 3.6 Do alternative pricing rules affect subsequent fund performance?

A large body of empirical literature document that flow-induced trades (in particular, due to redemptions) are costly to funds and that such trades dilute fund performance (Edelen 1999; Coval and Stafford 2007; Alexander, Cici, and Gibson 2007; Christoffersen et al. 2018; Goldstein, Jiang, and Ng 2017; Feroli et al. 2014). In this section, we examine the extent to which funds with alternative pricing methods eliminate the first-mover advantage by reducing the dilution in *subsequent* fund performance due to flows.

If funds effectively use the alternative pricing rules to reduce dilution, we should expect the negative impact of investor flows on subsequent fund performance to dissipate. The effect should be stronger for funds with more illiquid portfolios, and it should be present mostly for outflows, as outflows trigger forced liquidations. In turn, inflows need not to be immediately put to force if they are to dilute fund performance significantly. To assess this hypothesis, we estimate the following regression model:

$$AbReturn_{i,t+1} = \alpha + \beta_0 Net\ flow_{i,t} \times Alternative_{i,t} + \beta_1 Net\ flow_{i,t} + \beta_2 Alternative_{i,t} + \beta_3 Controls_{i,t} + Time\ FE + \varepsilon_{i,t} \quad (4)$$

where *AbReturn* in month  $t+1$  is the abnormal fund return calculated as the difference between a fund return and a fund's exposure to bond market and stock market returns. We calculate fund returns using unadjusted prices, since our focus is on the unadjusted fund performance. Fund exposures to benchmarks are calculated as  $\beta_1_{t-11,t} \times Bond\ market\ return_{t+1}$  and  $\beta_2_{t-11,t} \times Stock\ market\ return_{t+1}$ , where  $\beta_1_{t-11,t}$  and  $\beta_2_{t-11,t}$  are obtained from the same 12-month rolling window regressions as alphas. *Net flow* includes both inflows and outflows. *Net Outflow* is the absolute value of net outflow at month  $t$ , equal to  $-Flow$  if  $Flow < 0$ , and to zero if  $Flow \geq 0$ . *Net Inflow* is the net inflow at month  $t$ , equal to  $Flow$  if  $Flow > 0$ , and to zero if  $Flow \leq 0$ . We cluster standard errors by fund and month.



**Table 12**  
**Fund flows and fund future performance**

Variables	(1) Full sample	(2) High illiquidity	(3) Full sample	(4) High illiquidity
<i>Net outflow</i>	-0.0352** (0.0170)	-0.0546* (0.0300)		
<i>Net outflow</i> × <i>Alternative</i>	0.0372** (0.0184)	0.0662** (0.0317)		
<i>Net inflow</i>			0.0028 (0.0081)	0.0079 (0.0111)
<i>Net inflow</i> × <i>Alternative</i>			-0.0019 (0.0117)	-0.0101 (0.0160)
<i>Alternative</i>	-0.0313 (0.0557)	-0.0161 (0.0589)	-0.0019 (0.0580)	0.0461 (0.0679)
<i>Size</i>	-0.0157 (0.0098)	0.0087 (0.0128)	-0.0161 (0.0100)	0.0082 (0.0128)
<i>Age</i>	0.0400 (0.0442)	0.0099 (0.0467)	0.0382 (0.0437)	0.0109 (0.0454)
<i>Expense</i>	-0.2079*** (0.0792)	-0.2039*** (0.0784)	-0.2104*** (0.0783)	-0.2122*** (0.0766)
<i>Illiquidity</i>	1.7642 (6.2322)	-0.1276 (7.3500)	1.7650 (6.2592)	-0.2475 (7.3619)
<i>Inst</i>	0.0006 (0.0007)	0.0006 (0.0008)	0.0006 (0.0007)	0.0006 (0.0008)
Observations	7,827	4,146	7,827	4,146
R-squared	.415	.480	.415	.479
Month-year FE	Yes	Yes	Yes	Yes

Dependent variable is the abnormal fund return in month  $t+1$ , calculated as the difference between the fund's return (calculated using unadjusted fund prices) and the fund's exposure to bond market and stock market returns. The fund's exposure to bond and stock market returns is calculated as  $\beta_{1t \rightarrow t-11} \times \text{Bond market return}_{t+1}$  and  $\beta_{2t \rightarrow t-11} \times \text{Stock market return}_{t+1}$ . *Net outflow* is the net monthly outflows in  $t$ , which equals  $-\text{Flow}$  if  $\text{Flow} < 0$ , and it equals zero if  $\text{Flow} \geq 0$ . *Net inflow* is the net monthly inflows in  $t$ , which equals  $\text{Flow}$  if  $\text{Flow} > 0$ , and it equals zero if  $\text{Flow} \leq 0$ . *Alternative* is an indicator variable that equals one if the fund is using one of the alternative pricing mechanisms. Control variables include year-month fixed effects, as well as *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst* measured as of timer. See Table A1 in the appendix for the variable definitions. Columns 1 and 3 report results for the full sample; columns 2 and 4 report results for the subsample of funds with more illiquid assets (*Illiquidity* above sample median). The unit of observation is a fund-month. We cluster standard errors by fund and month. Standard errors are reported in parentheses. \* $p < .1$ ; \*\* $p < .05$ ; \*\*\* $p < .01$ .

We present the results in Table 12. In column 1, we consider the full sample and the effect of increasing outflows on future performance. Consistent with the literature, we observe that higher outflows deteriorate subsequent fund performance for funds with traditional pricing. However, the negative impact of outflows on fund performance is almost fully eliminated for funds with alternative pricing. In column 2, we restrict our sample to funds with highly illiquid portfolios and show that the effect is amplified for such subsample. The magnitude of the effect is almost twice as large as that in the unconditional sample.

In columns 3 and 4, we present the respective results for the group of funds with inflows. The results are statistically insignificant, which corroborates our view that larger inflows may not be significantly distortionary because fund companies have more flexibility in deploying their new capital in ways to mitigate the associated costs. This is in line with Figure 1 and Table 2 that dilution adjustment factor is asymmetric in that, it is particularly high during

market stress, when funds experience outflows. Overall, results in this section indicate that funds seem to be able to use the alternative pricing methods effectively enough to eliminate the dilution in fund performance arising from fund outflows.

### 3.7 Why do funds with different structures coexist?

From the industrial organization perspective, the question of interest is why we observe the coexistence of both fund structures in the market. We approach this question from two perspectives. During our sample period, about 15% of traditional funds switched to swing pricing, and interestingly, all the switching events have occurred in one direction, from traditional to alternative. Moreover, by the end of our sample period, 82% of funds are using one of the alternative pricing forms, indicating that they have become the dominant pricing form over time. Based on these basic patterns, one perspective that we offer is that investors value stability and alternative pricing rules might be the preferred structure, however, the transition may not be instantaneous and exhaustive. This might be due to (a) market participants gradually learn about the merits of the alternative pricing structure and (b) positive externalities arising from a subset of funds using the alternative pricing rules reduce the incentives to switch for the remaining traditional funds. An alternative perspective is that both structures offer certain benefits to different types of investors. For example, funds with traditional pricing rules tend to benefit redeeming investors, while funds with alternative pricing are meant to protect nonredeeming investors, especially in bad times. In this section, we provide more insights on this issue. We conclude that both explanations can be partly responsible for the patterns we document in the data.

Regarding mechanism (a), our results in Section 3.5.3 provide evidence for the role of investor information and learning. With respect to mechanism (b), we argue that the more funds experience fire sales, the stronger the strategic complementarities arising from NAV-based pricing due to illiquidity costs being larger in the market. The marginal price impact on asset prices coming from fire sales of funds with traditional pricing is expected to subside as more funds transition into alternative pricing. This intuition also features in the theoretical model of Capponi, Glasserman, and Weber (2020). Hence, one would expect that the differences in flows (between traditional and alternative funds) during stressed periods is smaller as more funds adopt alternative pricing forms, which in turn reduce the incentives to change the pricing form for the remaining traditional funds. We test these predictions in two steps. First, we define a variable, *FractionAlt*, which equals the fraction of alternative funds to the total number of funds in a given month. Next, we divide the sample into two parts with the ratio below the median value of *FractionAlt* and with the ratio above the median value. We expect that the coefficient of the interaction term between *Alternative* and *Stress* to be pronounced when *FractionAlt* is below its median value. Panel A of Table 13 (columns 1 and 2) reports the results. Consistent

**Table 13**  
**Proportion of alternative funds, fund flows, and probability to switch**

**A. Proportion of alternative funds and fund flows**

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample		Higher asset liquidity		Lower asset liquidity	
	<i>FractionAlt</i> above median	<i>FractionAlt</i> below median	<i>FractionAlt</i> (within subsample) above median	<i>FractionAlt</i> (within subsample) below median	<i>FractionAlt</i> (within subsample) above median	<i>FractionAlt</i> (within subsample) below median
<i>Alternative</i>	-0.6369 (0.6338)	-0.7868 (0.5728)	-0.5766 (0.9975)	-0.3760 (0.5883)	-0.8773 (1.0821)	-0.7506 (0.5889)
<i>Alternative</i> × <i>Stress</i>	0.8860* (0.5157)	1.7820** (0.7476)	0.4948 (0.7230)	2.0141** (1.0118)	0.8318** (0.3904)	2.6027** (1.2326)
<i>Stress</i>	-1.0586** (0.5309)	-1.5820*** (0.5496)	-0.7324* (0.4273)	-1.3976*** (0.5234)	-0.9864** (0.4992)	-2.7419*** (0.9599)
<i>Alpha</i>	0.3919 (0.2873)	0.2822 (0.2740)	-0.0801 (0.2502)	0.6922* (0.3782)	0.0218 (0.2964)	1.3512*** (0.4699)
<i>Size</i>	0.3687** (0.1683)	0.2841 (0.2203)	0.3542* (0.1950)	0.2198 (0.1364)	0.5783* (0.3236)	0.1508 (0.2417)
<i>Age</i>	-1.2694*** (0.2767)	-1.3632*** (0.3964)	-1.0503*** (0.3225)	-1.0259** (0.4041)	-2.0383*** (0.5690)	-1.2754*** (0.3849)
<i>Expense</i>	0.4544 (0.5370)	0.4856 (0.5747)	-0.3453 (0.6501)	1.5431*** (0.5656)	1.2477* (0.7533)	-0.3029 (0.6302)
<i>Illiquidity</i>	-1.7293 (34.6218)	7.5809 (27.0496)	-228.5965 (141.6785)	-66.2234 (130.3757)	5.4250 (38.6590)	95.0592** (42.2586)
<i>Inst</i>	-0.0074* (0.0038)	-0.0200*** (0.0060)	-0.0041 (0.0046)	-0.0122* (0.0068)	-0.0212** (0.0089)	-0.0207*** (0.0055)
Observations	4,887	4,783	2,485	2,391	2,603	2,191
R-squared	.028	.029	.033	.039	.051	.033
	<i>p</i> -value = .046		<i>p</i> -value = .031		<i>p</i> -value = .092	

with diminishing returns to one more fund adopting an alternative pricing form, we find that the benefit of alternative pricing—that is, the stabilizing effect on flows—is in fact greater when a smaller fraction of funds is using the alternative pricing model. The difference is statistically significant at the 5% level.

Second, we examine funds' incentive to transitioning to alternative pricing over time. Motivated by the results presented in panel A of Table 13, we predict that funds will be less likely to switch to alternative pricing if a significant fraction of funds already made the move in the same direction. Formally, our dependent variable is an indicator variable *Switch*, equal to one if a fund switches its type from traditional to alternative at time  $t$ . The independent variable of interest is *FractionAlt*. Our empirical regression model also includes previously used control variables. Panel B of Table 13 presents the results from the regression. Consistent with our prediction, we find that the propensity of other funds to switch their pricing decreases with the number of funds that already made the switch.

In summary, Table 13 provides evidence that positive externalities arising from a subset of funds using the alternative pricing rules reduce the incentives to switch for the remaining traditional funds. Taken together with the results presented in Section 3.5.3 whereby we show that the merits of alternative

**Table 13**  
**Continued**  
*B. Proportion of alternative funds and probability to switch*

Variables	(1) Switch	(2) Switch	(3) Switch
		higher asset liquidity	lower asset liquidity
<i>FractionAlt</i>	−0.0135* (0.0078)		
<i>FractionAlt (within subsample)</i>		−0.0342** (0.0158)	−0.0061* (0.0037)
<i>Alpha</i>	0.0000 (0.0007)	0.0002 (0.0014)	−0.0005 (0.0008)
<i>Size</i>	0.0002 (0.0002)	0.0002 (0.0002)	0.0002 (0.0001)
<i>Age</i>	−0.0004 (0.0004)	−0.0006 (0.0008)	−0.0001 (0.0004)
<i>Expense</i>	−0.0011 (0.0015)	−0.0005 (0.0011)	−0.0015 (0.0022)
<i>Illiq</i>	−0.0078 (0.0565)	0.1192 (0.3128)	0.0357 (0.0654)
<i>Inst</i>	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
Observations	10,156	5,018	5,138
R-squared	.001	.001	.002
<i>p</i> -value = .039			

In Panel A, the dependent variable is *Flow*, which is defined as the net monthly capital flows into a fund divided by the fund's total net assets. *Alternative* is an indicator variable that equals one if the fund is using one of the alternative pricing mechanisms. *Stress* is an indicator variable that equals one if monthly *VIX* is above the 75th percentile of the sample. *FractionAlt* equals the fraction of alternative funds to the total number of funds in a given month. In columns 1 and 2, we split the full sample of matched funds into two groups: column 1 and 2, respectively, contain the subsamples of funds when *FractionAlt* is higher and below its sample median. In columns 3–6, we conduct subsample analyses. Columns 3 and 4 use the subsample of funds with higher asset liquidity (*Illiquidity* below median), and columns 5 and 6 use funds with lower asset liquidity (*Illiquidity* above median). Within each subsample (of low/high asset liquidity), we further split each subsample based on *FractionAlt (within subsample)*, which is the fraction of alternative funds to the total number of funds in each subsample of higher/lower asset liquidity in a given month. In panel B, the dependent variable is *Switch*, which is an indicator variable that equals one if a fund is switching its type from traditional to alternative at time *t*. The unit of observation is a fund-month, and the regressions use the matched sample (the matching algorithm is described in the text). Control variables include the lagged values (previous month-end) of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. Standard errors are clustered by fund and month. Standard errors are reported in parentheses. \**p* < .1; \*\**p* < .05; \*\*\**p* < .01.

pricing rules are appreciated by investors only over time, our results provide insights into why there remains a fraction of traditional funds despite the majority are using the alternative pricing form.

An alternative perspective is to consider the potential differences between the two fund structures in terms of the costs that they impose on investors. The benefit of the alternative funds is their ability to protect the interests of patient investors, especially during bad times. The downside is the higher costs imposed on impatient investors. To the extent that the fund has a large fraction of impatient investors, it might not want to use an alternative pricing form. Our conversations with fund managers tell us that some fund investors indeed fear additional costs potentially involved in swing pricing. This can be particularly important if the size of the costs is *ex ante* uncertain. We examine this conjecture

by looking at the fraction of patient investors in each fund structure. Our proxy for investor patience is *Investment Horizon*, defined as the number of months an investor holds his/her fund shares after an initial purchase. Our results in Table IA.7 indicate that funds with traditional pricing have on average investors with shorter horizons, consistent with the hypothesis that impatient investors desire the traditional pricing form. While the differences are only modest with equal-weighting (that is, each investor has an equal weight in calculating the average), differences become larger when we use value-weighted averages.

### 3.8 Do fund companies substitute away from other risk management tools?

Given that a fund's pricing structure mitigates fund flow fragility, the question is whether funds with alternative pricing are more likely to treat their pricing scheme as a partial substitute from other types of hedging. Intuitively, funds will substitute away from other hedging alternatives if swing pricing is a less costly option, either in terms of its direct implementation costs or through its effect on performance. While calibrating such costs is beyond the scope of this paper, in this section, we take the revealed preference approach to assess the degree of potential substitutability by considering three following hedging tools: cash holdings, asset concentration, and fund load fees. Under the substitution hypothesis, we should observe lower cash holdings and increased portfolio concentration. When it comes to load fees the prediction is a bit more nuanced. On the one hand, load fees are compensation to the brokerage channel and hence they cannot be used as a money transfer among fund investors in order to eliminate the negative externalities arising from outflows (Chen, Goldstein, and Jiang 2010). On the other hand, back-end loads may raise the cost of withdrawal thus still offer a useful hedging tool.

We define cash (*Cash*) as a fund's total cash holdings (including cash equivalents) divided by the fund's total assets. Asset concentration (*Asset conc*) is Herfindahl-Hirschman index of a fund's asset holdings in each month. *Front load* is the value-weighted average of (minimum) front load charges across share classes of a given fund; *Back load* is the value-weighted average of (minimum) back load charges across share classes of a given fund. We assess the relationship between pricing structure and the alternative hedging instruments in Table IA.8. Consistent with the hypothesis that cash and alternative pricing rule are substitutes for each other, we find that funds with alternative pricing hold less cash, on average. However, the coefficients for asset concentration, front load, and back load, though negative, are all statistically insignificant. While the results are overall consistent with Chen, Goldstein, and Jiang (2010), we also note that the regressions using back-end loads are unlikely to have enough statistical power as only 10 funds charge these types of loads in our sample.

#### 4. Conclusion

Open-end mutual funds globally manage tens of trillion of dollars in assets. Quite often, these assets are illiquid, making the conversion to liquid assets difficult, especially in times of market stress. Liquidity mismatch in combination with strategic complementarities arising from NAV-based pricing rules pose a significant threat to these companies and the broader financial markets. Mitigating the fragility risk is of first-order importance to financial institutions managing these companies, their investors, and policy makers concerned with financial stability and social welfare. Our results show that swing pricing can be an effective financial stability tool. Rules permitting swing pricing have been in use in European jurisdictions over the past few decades, but they are becoming effective in the rest of the globe only recently. Our results support a more widespread adoption of these alternative pricing rules. Recent guidelines published by the SEC and IMF are suggestive of a move in this direction.<sup>32</sup>

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<sup>32</sup> For instance, see chapter 1 of the IMF's (2020) Global Financial Stability Report.

## Appendix

**Table A1**  
**Variable definitions**

Label	Definition	Units
<i>Stress</i>	An indicator variable that equals one if monthly <i>VIX</i> index is above the 75th percentile of the sample	
<i>Alternative</i>	An indicator variable that equals one if a fund is using one of the alternative pricing rules	
<i>Flow</i>	Monthly net flows into a fund divided by the fund's total net assets in the same month	%
<i>Daily flow</i>	Daily net flows into a fund divided by the fund's total net assets on the same day	
<i>Flow EndInv</i>	Change in each investor's fund holdings (in number of shares) from previous month	%
<i>Return</i>	The fund's monthly raw return	%
<i>Alpha</i>	Estimated using rolling-window time-series regression for each fund using the past 12 months data. Alpha is the intercept from a regression of excess fund returns on excess bond market and stock market returns. Indexes are obtained from Barclays	%
<i>NegAlpha</i>	Equals <i>Alpha</i> if a fund's <i>Alpha</i> is negative (or below the 25th percentile) and set to zero otherwise	%
<i>Size</i>	Natural logarithm of the fund's total net assets	£
<i>Age</i>	Natural logarithm of fund age in years (using the age of the oldest class share)	
<i>Expense</i>	The fund's annual total expense ratio	%
<i>Illiquidity</i>	Value-weighted average of <i>Asset illiquidity</i> of the fund's assets in a given month. <i>Daily illiquidity</i> measures the same in daily frequency	
<i>Asset illiquidity</i>	Bid-ask spread; end-of-day bid and ask prices are obtained from Thomson Reuters Datastream and used in the following order depending on availability: Thomson Reuters composite price, Thomson Reuters Pricing Service evaluated price, iBOXX, and ICMA	
<i>Inst Ownership</i>	Fraction of a fund's total net assets held by institutional investors	%
<i>concentration</i>	Herfindahl-Hirschman index calculated using each end investors' ownership in each month	
<i>Adj factor</i>	Equals the absolute value of daily swing factor for swing funds; equals daily half spread, $(0.5 * (ask - bid) / mid)$ , for dual funds	%
<i>High yield</i>	An indicator variable that equals one if a fund invests in high yield bonds	
<i>Emerging market</i>	An indicator variable that equals one if a fund invests in emerging market bonds	
<i>Net inflow</i>	Monthly net inflows. Equals <i>Flow</i> if <i>Flow</i> > 0; equals 0 if <i>Flow</i> ≤ 0	
<i>Net outflow</i>	Monthly net outflows. Equals $-Flow$ if <i>Flow</i> < 0; equals 0 if <i>Flow</i> ≥ 0	
<i>Daily net outflow</i>	Daily net outflows. Equals $-DailyFlow$ if <i>DailyFlow</i> < 0 and equals 0 if <i>DailyFlow</i> ≥ 0	
<i>Dual</i>	An indicator variable that equals one if the fund is a dual fund	
<i>Full</i>	An indicator variable that equals one if the fund is a full swing fund	
<i>Partial</i>	An indicator variable that equals one if the fund is a partial swing fund	
<i>Cash</i>	The fund's total cash holding defined as cash plus cash equivalents including cash deposits, money market funds, Treasury Bills, commercial paper, short-term bonds, repos, and currency holdings divided by the value of total assets	%
<i>Asset conc</i>	Herfindahl-Hirschman index of a fund's asset holdings in each month	
<i>Front load</i>	Value-weighted average of (minimum) front-end load charges across share classes of a given fund	%
<i>Back load</i>	Value-weighted average of (minimum) back-end load charges across share classes of a given fund	%
<i>Investor horizon</i>	Number of months an investor holds his fund shares after an initial purchase. We use purchases before December 2014	
<i>Patient investor</i>	An indicator variable that equals one if an investor's <i>Investor horizon</i> is above its sample median	
<i>Inst investor</i>	An indicator variable that equals one if an investor is an institutional client	
<i>InvExit</i>	An indicator variable that equals one if a client sold all of his/her shares in the fund within the 6 months period prior to the switch date	

(Continued)

**Table A1**  
**(Continued)**

<i>Investor-level FPS</i>	Flow-performance sensitivity estimated for each investor at a given fund by regressing <i>Flow EndInv</i> on fund <i>Alpha</i> in the pre period	
<i>Trading frequency</i>	Average of number of months in which investor traded his/her fund shares during the pre-period	
<i>Volatility of flow EndInv</i>	Volatility of monthly <i>Flow EndInv</i> during the pre-period	%
<i>Investor ownership</i>	Average of investor's value of shares divided by the total fund size in a given month during the pre-period	
<i>Seasoned investor</i>	For each investor-fund-month, we calculate for how long the investor has been with the fund. <i>Seasoned investor</i> is an indicator variable that equals one if this value is above its sample median	
<i>Fund exit</i>	An indicator variable that equals one if the fund exits the market during our sample period, and equals zero if the fund remains alive	
<i>Merged</i>	An indicator variable that equals one if the fund has become obsolete due to a merger event during the sample period and equals zero if the fund remains alive	
<i>Liquidated</i>	An indicator variable that equals one if the fund has become obsolete due to a liquidation during our sample period, and zero if the fund remains alive	
<i>FractionAlt</i>	Equals the fraction of alternative funds to the total number of funds in a given month	
<i>FractionAlt (within subsample)</i>	Equals the fraction of alternative funds to the total number of funds in each subsample of higher/lower asset liquidity in a given month	
<i>Switch</i>	An indicator variable that equals 1 if the fund is switching (from traditional to alternative) at time <i>t</i>	



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