Swing Pricing and Fragility in Open-end Mutual Funds*

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Abstract:

How to avert fragility 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 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 redemptions during stress market conditions. The stabilizing effect is internalized particularly by institutional investors and investors with longer investment horizons.

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1. Introduction

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 asset management companies, raised concerns that similar phenomena may also be present in the non-banking sector (Allen et al., 2009; Gennaioli et al., 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.[1]

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 non-banking 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, 2018), 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*.

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-close 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

[1] Coval and Stafford (2007) study runs in equity mutual funds. Chen et al. (2010) analyze flows in bond mutual funds, while Schmidt, Timmermann, and Wermers (2016) analyze runs on money market funds.

typically take place over multiple business days following the redemption request. Thus, the costs of providing liquidity to transacting shareholders are borne by non-transacting investors in the fund, which dilutes the value of their shares. Chen et al. (2010) show that this mechanism produces a first-mover advantage and amplifies the impact of negative shocks, especially during market-wide stress when market liquidity drops, and in environments in which strategic complementarities are 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. We ask: To what extent does swing pricing help funds to retain investor capital during periods of market stress? Are alternative funds able to prevent dilution in 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 the NAV shifts up and if net flows are negative the NAV shifts down. The magnitude of the shift is known as the *adjustment factor*. The second form, the *partial swing pricing*, is invoked only when net flows cross a pre-determined 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 a 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).

Funds are permitted, but not required, to use the alternative pricing structures and they have a full discretion for the values of adjustment factors. Investors only know if the fund applies alternative pricing rules, but they do not know the precise values of adjustments. They learn about them from the ex-post transaction prices. In this regard, the observed flow dynamics results from an interplay between managers' ability to assess illiquidity costs in the market and investors' learning about managerial pricing decisions.

Regulation permitting swing pricing has become effective in the U.S. only in November 2018; however, these rules have been used in several European jurisdictions over the past few decades. To analyze the impact of such rules, we obtain data on corporate bond open-end funds that fall under the supervisory jurisdiction of the Financial Conduct Authority (FCA). Choosing bond funds as a testing ground allows us to capture a significant component of a fund portfolio illiquidity, a key determinant of fund fragility. The data have a number of unique features. Most relevant, we observe the holdings of the funds' end-investors, which allows us to analyze individual-specific responses to pricing rules and address any identification concerns. The data cover a 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 market-wide 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 measures of stress.

We begin our empirical analysis by examining the determinants of the dilution adjustment factor. If the pricing rules matter, we should expect fund companies to implement adjustments in times of high market stress when aggregate liquidity tends to be low. This is precisely what we find. The adjustment factor is asymmetric, in that it's substantially higher (e.g., it nearly quadruples during 2008 crisis) in periods of higher portfolio illiquidity and periods of market stress.

We next investigate whether swing pricing affects the level of fund flows during market stress. While academic research on swing pricing is scarce, there is an ongoing debate about it among practitioners and supervisory authorities. One view is that swing pricing can mitigate fragility in funds by removing the negative externalities arising from investor flows.[2] An alternative view suggests that swing pricing can increase fragility. Anticipating an increase in near-term liquidation costs or fearing possible manipulation on the side of funds, investors may become more sensitive to negative shocks.[3]

We find that funds with traditional pricing rules experience significant outflows during market stress, in line with prior literature (Mitchell, Pedersen, and Pulvino, 2007; Ben-David, Franzoni, and Moussawi, 2011). Importantly, this effect *almost completely* reverses for funds that adopt alternative pricing rules, lending support to the view that such rules reduce fragility risks. 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). Furthermore, we examine each type—full swing, partial swing, and dual pricing—separately and observe largely similar patterns.

The economic magnitude of the average effect is sizable. During stress periods, an average traditional fund loses capital worth of £8.86 million every month; the corresponding loss for a fund with alternative pricing is only £0.2 million. Moreover, evidence from quantile regressions shows that the magnitude of the effect substantially increases for a group of funds with the highest flow sensitivity, supporting the view that fund fragility is heterogenous (Schmidt et al., 2016).

[2] Blackrock Viewpoint Series titled *Fund structures as systemic risk mitigants* (2014).
[3] Cipriani et al. (2014) provide a theory of pre-emptive runs when intermediaries impose gates or redemption fees.

A potential concern with the interpretation of pricing rules causing flows is that funds and investors with different characteristics may self-select into different pricing structures. A significant advantage of our data is their unique granularity that allows us to tackle this concern, and thus to uncover the economic mechanism behind our findings. These elements of the data make the paper uniquely suited to examine the impact of systematic shocks at the individual investors' level, different from the previous studies of asset management firms that exploit share-class-level data, thus assuming homogeneity within a particular group of investors (e.g., Kacperczyk and Schnabl, 2013; Schmidt et al. 2016).[4]

To this end, we first identify a subsample of funds which switch their pricing methods from traditional to alternative within our sample period, and we examine individual (same) investors' behavior before and after the switch. Empirically, we match the sample of switchers to non-switchers along various characteristics and estimate the treatment effect at the end-investor level. We estimate a triple-difference regression model in which we compare investor flows in switchers vs. non-switchers before and after the switch, conditional on the level of stress in the aggregate market. We additionally take advantage of end-investor fixed effects, which allows us to study the behavior of the same investor, in funds with different structures, before and after the change. The staggered nature of switching dates is helpful in capturing the effects due to switch.

Our findings provide strong evidence that 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 her shares in a stress period when the fund uses swing pricing than when the fund uses traditional pricing. Moreover, funds that switch to alternative pricing structures have less inflows outside the stress periods. For a limited sample of investors who have holdings in

[4] To our knowledge, the only other paper that studies runs with that level of data granularity is Iyer and Puri (2012). However, their objective is to trace a banking panic in one specific Indian bank, whereas we focus on the question of how to mitigate the threat of runs in the asset management sector.

multiple funds, we also address a possible concern due to time-varying investor-specific omitted variables by showing 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 swing 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 swing pricing mitigates fragility arising from costly asset liquidations. Moreover, consistent with these 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 zoom in on cross-sectional differences. Consistent with the predictions of Chen et al. (2010), 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, first, we find that it is the institutional investors who alter their behavior the most after the fund switches to swing pricing. Institutional investors sell heavily when the fund uses the traditional pricing rule (thus retail investors bear the costs due to their transactions), and after the switch, they significantly reduce their redemptions. This is consistent with the idea that, being more sophisticated, institutional investors better understand the implications of funds' pricing practices. Alternatively, by trading more they are able to learn more about funds' pricing policies. In a similar vein, investors with longer investment horizons also alter their behavior and sell less after the switch, as swing pricing is a tool to protect the value of their shares. These findings strongly support the view that strategic complementarities, rather than mechanical rebalancing rules of unsophisticated investors, drive our findings.

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 non-transacting 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 impact *subsequent* fund performance for funds using the traditional pricing rule. However, the negative impact of outflows on subsequent fund performance almost completely dissipates for funds with alternative pricing. This finding provides evidence that funds use the alternative pricing structures effectively to eliminate the first-mover advantage arising from the traditional pricing rule.

In the final set of results, we test whether funds with swing pricing rules 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 such funds hold less cash compared to funds with traditional pricing. The effect for portfolio diversification and fund loads is statistically insignificant. One reason why 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 et al., 2010)).

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

Chen et al. (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 most natural candidate. Morris, Shim, and Shin (2017) explore the cash hoarding channel and argue that some funds sell more assets than required to cover outflows. Chernenko and Sunderam (2016, 2018) analyze the cash-cushioning approach and conclude that funds' cash holdings are not sufficiently large to eliminate fire sales. One theoretical explanation behind this finding is Zeng (2018) who argues that cash management cannot prevent runs; instead, cash usage can actually exacerbate the 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 on fund NAV, reduces the first-mover advantage arising from the traditional pricing and substantially reduces the outflows during crisis periods. In this respect, our findings are consistent with the recent theoretical study of Capponi, Glasserman, and Weber (2018) who show the stabilizing effects of swing pricing. Our paper corroborates their predictions empirically and provides additional cross-sectional and time-series tests of the theory.[5]

2. Institutional Background

Open-end funds provide daily liquidity to their shareholders. Typically, on any given day, fund investors have the right to transact their shares at the daily-close NAV. However, trading activity and other changes in portfolio holdings associated with shareholders' transactions may occur over multiple business days following the transaction requests; hence, the costs of providing liquidity to transacting shareholders can be borne by non-transacting fund investors. Such costs reduce fund performance, thereby diluting interests of non-transacting shareholders.

To address the dilution effect arising from transacting shareholders' flows, alternative pricing rules have emerged which allow open-end mutual funds to adjust their NAVs. These rules, known as *swing* or *dual* pricing, exist in many European domiciles: Luxembourg, Finland, France, Ireland, Jersey, Norway, Switzerland, and the U.K. All registered open-end investment companies in the jurisdictions have been eligible for such pricing over the past few decades. In the U.S., the Securities and Exchange Commission (SEC) adopted rules permitting funds to use the new pricing in 2016. They have become effective in November 2018.[6]

Two main alternative pricing mechanisms are employed in European jurisdictions: swing pricing and dual pricing. When a fund uses swing pricing, its NAV is moved up or down, depending on whether the fund faces a net inflow or a net outflow: NAV swings up if a fund gets a net inflow, and swings down in case of a net outflow. The size of the swing, known as a *swing* or *adjustment factor*, while at the discretion of fund managers, aims to compensate non-transacting shareholders for the costs of trading due to capital activity by transacting

[5] Lewrick and Schanz (2018) compare funds domiciled in Luxembourg, where funds are permitted to use swing pricing, to U.S.-domiciled funds during the period when they were not allowed to use swing pricing. Their data span a short period, which does not include a major stress period. Importantly, Lewrick and Schanz (2018) do not observe the cross-sectional variation in funds' pricing rules–they simply compare all Luxembourg funds (including both swing and traditional funds) to the U.S funds (traditional funds). Perhaps not surprisingly, authors don't find important differences.
[6] Other countries allowing swing/dual pricing are Australia, Cayman Islands, and Hong Kong.

shareholders.[7] Fund managers typically use either of the two types of swing pricing: partial swing pricing or full swing pricing. Partial swing funds move the price only when the net fund flow is greater than a pre-determined threshold, the *swing threshold*. This threshold is usually set in terms of a percentage or basis point impact, and to avoid any potential gaming behavior by investors, 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.[8] In both types of swing pricing, the final price applies to all transacting shareholders (whether they are redeeming or subscribing).

Different from swing funds, which trade at a single price, dual priced funds trade at two separate prices, bid and ask. Investors purchase them at the ask price and sell 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.[9] Proceeds from net inflows or net outflows are reinvested in the fund, which protects non-transacting shareholders from dilution.[10] Compared with swing funds that do not disclose their adjustment factor, dual priced funds are more transparent as both bid and ask are publicly available.

Funds are permitted, but not required, to use dilution adjustments. 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). The pricing rule is typically determined at the start of the fund, and the dilution adjustment is applied uniformly across all shares. If a fund uses swing or dual pricing, it must disclose this information in its prospectus; however, funds are not required to report swing factors and swing threshold. Investors only observe the final price.

[7] Rules permit funds to swing NAV only to address the dilution effect arising from investor flows. To address stale prices, managers can use evaluated prices provided by third-party data providers.
[8] For full swing funds, direction of daily swing factors lines up with the direction of daily flows 85% of the time.
[9] The final price can include sales charges, if any. Sales charges are not common, and importantly, they are not retained in the fund. We calculate the spread in dual funds' bid and ask prices before any sales charges.
[10] Recently, FCA recognized that managers of dual-priced funds were retaining the profits from the spread on days when inflows and outflows net out (so called 'box profits'). The new rules, which became effective on April 1, 2019, require fund managers to return box profits to the fund investors.https://www.fca.org.uk/publication/policy/ps18-08.pdf.

Funds are required to ensure an equitable treatment of their investors. To oversee the use of dual/swing pricing, most funds set up valuation and pricing committees, either as a standalone committee or as part of the funds' boards. Moreover, depositary banks, which in the E.U. provide fiduciary and custodian services to investment funds authorized to be marketed in any E.U. jurisdiction, oversee the affairs of the funds, including those related to pricing. Depositary banks are obliged to ensure that the fund complies with the rules and its own constitutional documents. Most depository banks in the E.U. are custodian banks such as Barclays, JP Morgan, Goldman Sachs, HSBC, and State Street Corporation. Depository banks are prohibited from overseeing funds that belong to the same financial institution—that is, for instance, Goldman Sachs is not allowed to oversee the mutual funds offered by Goldman Sachs. However, it is possible for depositary banks to oversee multiple investment funds from the same financial group.

Alternative liquidity management tools are, in principle, available to fund managers; however, these alternative tools are not commonly used in practice. For instance, funds can introduce redemption gates (deferring redemptions to a future valuation point) or use redemptions in kind (returning a slice of the portfolio instead of returning cash to redeeming shareholders). Such measures are rarely used. Importantly, the potential availability of alternative tools goes against us finding significant effects due to alternative pricing rules. In addition, funds can aim to manage liquidity risk by maintaining buffers of cash and cash equivalents, such as Treasury bills and commercial papers. Holding cash and cash equivalents, however, can be associated with important opportunity costs. Moreover, a recent study by Zeng (2018) casts doubt on the effectiveness of cash and cash equivalents in mitigating fragility in funds. Whether alternative tools are substitute to alternative pricing is an empirical question that we examine in Section 4.7.

3. **Data**

3.1. Sample Construction and Measures

We obtain our data through a request sent by the FCA to major UK based asset management companies with corporate bond fund offerings.[11] The FCA requested data on all corporate bond mutual funds domiciled in the U.K. or whose investment management decisions are taken from the U.K.[12] Through this data request, the FCA received data on 299 corporate bond mutual funds (including dead funds) from 24 asset management companies.[13] 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. While funds are required to disclose the type of pricing rules that they use, they are not required to disclose swing factors and thresholds to the public. For dual funds, we also observe the daily bid and ask prices. Both features allow us to assess the degree of learning by fund investors about the costs of trading. An additional unique feature of our data is information on end-investors' holdings (at 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 fund fees (expenses) and institutional class indicators.

[11] This also includes U.K subsidiaries of non-U.K. asset management companies.
[12] The latter condition selects funds that have a significant presence (usually office) in the U.K. 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.
[13] 20 funds offered by four asset management companies with combined assets under management of about £3.4bn (as of the end of 2016) failed to respond to the data request, a relatively small portion of the overall sample.

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 (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 various databases, we arrive at the final sample that includes 224 open-end actively managed corporate bond mutual funds in 22 families that are open to new and existing investors. 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 constitutes about 10%.

Over the period 2006-2016, we detect 34 funds which 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 it is likely to be still in a transition phase whereby market participants are gradually learning of its promise. Additionally, the unobservability of all managerial actions in the alternative funds may impede the speed of the learning process.

We conduct our baseline analysis at monthly frequency. For each fund-month observation, we define a number of variables. *Flow* is the monthly change in the quantity of shares outstanding multiplied by the share price, divided by a 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 flows rather than on indirect measures imputed from fund size as is common in the literature.[14] *Return* is the fund's monthly raw return net of expenses. Following the earlier studies on corporate bond mutual funds (e.g., Goldstein et al., 2017; Choi and Shin, 2018), we estimate fund *Alpha* using a 12-month rolling-window regression model of monthly excess returns on excess aggregate bond market and aggregate stock market returns. We obtain market indexes from Barclays. *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 total expense ratio; *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.[15] Bid-ask prices are obtained from Thomson Reuters Datastream.[16] To mitigate the impact of outliers we winsorize all variables at the 1% level. We provide details on variable definitions in Appendix A.

We follow the literature 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. Figure 1 shows the time series of VIX during our sample period. Later in the paper, we show the robustness of our results to alternative definitions of *Stress*.

3.2. 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

[14] 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 fund size from *t-1* to *t*.

[15] 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.

[16] When available, we use Thomson Reuters' composite price, which is an average price from multiple pricing sources. When 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, e.g. for NAV calculations. If this price is also missing, we use prices provided by iBOXX or ICMA.

versus those with alternative pricing rules (swing or dual). Panel A and B shows the descriptive statistics for funds with alternative and traditional pricing rules, respectively.

Table 1 shows 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 et al. (2017).

In the last two columns, we 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 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. We examine this issue in Section 4.5.

4. **Empirical Results**

4.1 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*(ask-bid)/mid*. During our sample period, *Adjustment Factor* of funds with full swing and dual pricing is approximately 33 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%.[17] In our sample, 90% of partial swing funds use thresholds that are less than 3%. The average dilution adjustment factor for partial funds is 57 bps once we restrict our sample to days with non-zero factor values.

Figure 2 shows the time-series variation in average *Adjustment Factor* of swing and dual pricing funds. The adjustment factor is relatively small outside the crisis periods, varying from 18 bps to 25 bps, but it substantially increases in adverse market conditions. For example, the average factor spikes up—nearly quadruples—during the 2008 global financial crisis; similarly, adjustment factors are at relatively high levels during the European debt crisis. Overall, patterns in the average factor line up with those documented in other studies. Among others, Biais and Declerck (2013) document that, outside the crisis periods (from 2003 to 2005), effective spreads in European corporate bonds ranged between 12 bps and 22 bps. Also, Dick-Nielsen, Feldhutter, and Lando (2011) document dramatic increases in corporate bond illiquidity measures (such as price impact and bid-ask spreads) during 2008.[18]

Next, we analyze which fund characteristics are associated with dilution adjustment factor. Since we do not observe detailed order and transaction data, estimating funds' trading costs is difficult, instead we examine the illiquidity of fund's assets. Because trading illiquid assets is more costly than trading liquid assets, we expect the degree of illiquidity of a fund's

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[17] These thresholds approximately correspond to 5% and 10% tails of the daily net flow distribution.
[18] To assess trading costs, funds typically rely on a measure known as implementation shortfall, which is analogous to 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, Markit, and others.

assets to be an important determinant of its adjustment factor. Moreover, because trading costs tend to surge during market stress conditions, we expect the adjustment factors to be asymmetric in that, they dramatically increase during such periods. To test these predictions, we estimate the following regression model:

$$AdjustmentFactor_{i,d} = \propto + \beta_0 Illiquidity_{i,d} + \ Day\ FE + Fund\ FE + \\ Other\ Fund\ Characteristics_{i,d} + \ \varepsilon_{i,d} \quad (1)$$

where *Illiquidity* is the daily value-weighted average of the bid-ask spread of fund *i*'s assets, *Day (Fund) FE* are day (fund) fixed effects. To assess the role of other fund characteristics, we extend the model to include *Size*, *Age*, *Expense*, and *Inst*, all measured at the end of the previous month. Further, in the latter specification, we remove day-fixed effects and include *Stress (VIX* is above the 75^{th} percentile of the sample) to capture the time-series variation. To account for possible serial and cross-correlation in residuals, we cluster standard errors by fund and day.

We report the results in Table 2. In column (1), we present results from estimating the univariate regression model with *Illiquidity* as the main explanatory variable. In columns (2)-(3), we sequentially add other fund characteristics and fund-fixed effects. Across all specifications, we find that the coefficient of *Illiquidity* is positive and statistically significant, indicating that asset illiquidity is an important determinant of funds' adjustment factors. Other fund characteristics do not appear to have an important explanatory power. In columns (4) and (5), we show the results with *Stress* as the main explanatory variable. Consistent with patterns observed in Figure 2, the adjustment factor significantly increases during periods of market stress. Finally, in column (6), we present the results from the model in which we interact *Illiquidity* and *Stress*. The results indicate that the adjustment factor is particularly high for illiquid portfolios during stress periods, as one would expect.

4.2. Fund Flows and Alternative Pricing: Cross-sectional Evidence

Under the traditional pricing, fund investors have the right to redeem their shares at the fund's daily-close NAV. Following substantial outflows, a fund needs to adjust its portfolio and consequently it may conduct costly and unprofitable trades. Since most of the resulting trades are likely to be executed *after* the day of redemptions, such costs are not reflected in the NAV paid out to redeeming investors but are rather borne by those who stay in the fund. Chen et al. (2010) show that this mechanism produces a first-mover advantage and amplifies the impact of negative shocks, especially during market-wide stress when market liquidity dries up. The expectation that some investors may redeem their shares boosts the incentives of other investors to redeem as well, leading to the amplification of negative shocks. To the extent that alternative pricing rules protect the interests of non-transacting investors in the fund by passing on the trading costs to redeeming investors, such fragility can be mitigated. However, because the degree of price adjustment is ex ante unknown, the efficiency of the rules remains an empirical question.

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

$$Flow_{i,t} = \propto + \beta_0\, Alternative_{i,t} + \beta_1\, Stress_t + \beta_2\, Alternative_{i,t}\, x\, Stress_t + \beta_3\, Controls_{i,t} + \varepsilon_{i,d} \qquad (2)$$

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.

In Table 3, Panel A, we report the results of 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 *Alternative x Stress* is positive and statistically significant. Moreover, the value of the coefficient nearly offsets the negative value of the coefficient of *Stress.* For instance, in column (1), the coefficient is 1.04 and that of *Stress* is -0.99. 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 *Alternative* is negative, though statistically insignificant, which suggests that alternative funds have somewhat less inflows than traditional funds in good times. This result is consistent with the existence of some costs that are relatively more pronounced outside the stress period.

To the extent that funds with different pricing rules may have different characteristics, our test sample in columns (1)-(2) may be unbalanced. To sharpen the interpretation of our findings, we match each of our swing funds to the sample of funds which 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). In column (4), we include fund fixed effects to account for time-invariant omitted fund characteristics. In column (5), we include time-fixed effects. In column (6), we include family-fixed effects; in column (7), style-fixed effects. The findings reported across the specifications appear robust. Results are both statistically and economically more significant when we use the matched sample.

In Table IA.2 of the Internet Appendix, we provide additional robustness tests using alternative fixed effects (such as fund's location domicile, region of sale, investment area), front and back-end loads, and alternative definitions of market stress, which are defined based on TED spread, LIBOR rate, and Merrill Lynch's MOVE index. Results are similar throughout.

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 effects may not seem large. However, we observe a significant variation in outflows in the cross-section of funds. To show this effect directly, we resort to estimating quantile regression models. We present the results in Panel B of Table 3.

Results obtained from the OLS regression are similar across different percentiles of the flow distribution, ranging from the 50^{th} to the 0.5^{th}, that is, the negative impact of *Stress* on fund flows is almost fully reversed for alternative funds. Importantly, 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 mean response to the response of a fund in the 5^{th} percentile. Overall, results show that the economic significance of alternative pricing rules is particularly large in the tails of the flow distribution.

In Table 4, we decompose the effect of the alternative pricing into specific sub-components (full swing, partial swing, and dual pricing). This decomposition allows us to understand better the information content of alternative pricing rules. While dual pricing is generally known to investors, the magnitude of the swing factor is unobserved. Given that we observe funds with different structures, we can empirically assess how important such unobservability is for investors in the funds. The results indicate that the issue does not seem as relevant. We find a similar pattern of the flow reversal 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.

4.3. Fund Flows and Alternative Pricing: Evidence from Switching Funds

One potential concern with interpreting the results in Section 4.2 is that cross-sectional differences in flows to funds with different characteristics may reflect underlying differences across funds with different structures or they may reflect self-selection of funds into different structures. While including fund controls alleviates this issue, it is unlikely to solve it fully.

In this section, we address this issue by taking advantage of a subsample of funds which change their pricing method. Over the period 2006-2016, 34 funds from six asset management companies switched their pricing schemes from the traditional to alternative structures.[19] Panel A of Table IA.2 lists the dates when the switch took place.

Although we cannot fully ensure the switches are entirely exogenous, anecdotal evidence from interviews with the companies suggests that the switches were unlikely to be related to fund performance, flows, or other characteristics correlated with flows. Since some funds within the same families did not change their structures, it is also unlikely that the switches were purely family-wide decisions. Finally, the staggered nature of the switches makes it unlikely that the change in structure reflected a structural change in the market.

4.3.1 Evidence from Funds' Responses

In order to assess the impact of the change in fund structure on fund flows, we first look at the results at the fund level. Our empirical strategy involves comparing the flows of funds that change their structures to alternative pricing—treated funds—before and after the change. For our analysis, we specify a 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 control fund defined as a close match using the algorithm in Section 4.2.

We examine the potential pre-trends that may determine any differential response to the shock of our interest. The presence of such pre-trends cannot be tested directly; however, we can inspect their plausibility using graphical presentation and regression evidence. In Figure 3, we present the time-series dynamics of average values for various fund characteristics

[19] We do not observe any switches from alternative to traditional pricing scheme during our sample period.

around the event time. We do not observe significant differences. In Panel B of Table IA.3, we formally examine this by testing the differences in fund characteristics for treated funds relative to control funds before and after the event. We estimate a difference-in-differences regression model of the following form:

$$Characteristic_{i,t} = \propto + \beta_0\ Treated_i\ x\ Post_t + \beta_1\ Post_t + \beta_2\ Treated_i + \varepsilon_{i,d} \quad (3)$$

We define an indicator variable *Post* that equals one for the period after the change and equals zero before the change. *Treated* is an indicator variable that equals one for all funds that have changed their structure, and zero for the funds in the control group. Columns (1) to (7) of Panel B in Table IA.3 show the results for *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, *Inst*, and *# Inv*, respectively. Across all characteristics, we find that both β_2 and β_0 coefficients are statistically insignificant, which indicates no significant differences between the treatment and the control group during the event window. The switch itself, on average, does not induce significant differential responses in fund characteristics that could predict any heterogeneous effects for fund flows after the switch.

We next evaluate the impact of change in fund's pricing structure on fund flows conditional on the level of stress in the market, similar to our specification in (2). Specifically, we estimate:

$$\begin{aligned} Flow_{i,t} = \propto &+ \beta_0\ Stress\ _t x\ Post_t\ x\ Treated_i + \beta_1\ Stress_t\ x\ Post_t + \beta_2\ Stress_t\ x\ Treated_i \\ &+ \beta_3\ Treated_i x\ Post_t + \beta_4\ Post_t + \beta_5\ Treated_i \\ &+ \beta_6\ Stress_t + \beta_7\ Controls_{i,t} + \varepsilon_{i,d} \quad (4) \end{aligned}$$

Our coefficient of interest is β_0. We present the results in Table 5. In column (1), we report the results for the specification that does not include any controls or fixed effects. We find a strong positive and statistically significant differential effect, β_0, on treated funds during market stress. Moreover, in the absence of stress, the difference in flows between treated and control group, β_3, is negative. In column (2), we add the same control variables as in Section 4.2. In column (3), we further include fund-fixed effects to account for any time-invariant fund characteristics, while in column (4) we include time-fixed effects. In all cases, the coefficient β_3 remains positive and statistically significant.

4.3.2 Evidence from Individual Investors' Responses

Our fund-level analysis based on switchers helps to trace down the effect of pricing schemes on fund flows; however, one remaining identification concern is related to investor heterogeneity. Thus far, we have assumed that the investor base in the treated funds remains unchanged following the treatment and any estimated differences reflect the change due to pricing rule only. However, it is quite possible that the shock itself also induces a change in the composition of investors in treated funds, and funds before and after the treatment are owned by investors with different preferences for risk or investment horizon. This concern generally applies to all large-sample studies of delegated asset management and has been difficult to address due to data limitations.[20] 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, conditional on the overall market stress.

We first present the overall patterns in the end-investor data.[21] The average (median) fund in our sample has 596 (85) investors, 13% of which are institutional clients. An individual investor's participation in a given fund (defined as the investor's value of holding divided by total fund size) is typically small. For retail clients, the mean and median values are 0.005 and 0.003, respectively. For institutional clients, these values are larger, with the mean equal to 0.17 and median is 0.006. The maximum investor ownership in the sample is 2.3%.

[20] To our knowledge, the best treatment of this issue to date was to study 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 et al. (2016)). However, these studies make an implicit assumption that each share class has either homogenous or stable pool of investors, which need not be true in the data.

[21] 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 full record of all variables used in our tests. The average fund excluded from investor-level analysis does not appear significantly different from the average fund included in the analysis. The client classification is provided by funds. Potential measurement error in the classification would likely go against finding significant differences between different groups.

In total, we observe about 120K investor trades taking place in our event window. We calculate the frequency of trading by each investor during the event period. We first define an indicator variable *trade* which equals one if the investor is trading in a given month. We then define *trading frequency,* which is the average of *trade* for a given investor during the event period. Cross-sectional average (median) of *trading frequency* is 0.33 (0.16).

The 25th and the 75th percentiles for *trading frequency* are 0 and 0.5, indicating a significant cross-sectional variation in trading frequency. We observe that institutional investors tend to be more active traders. Mean (median) frequency of trading for institutional investors is 0.44 (0.3). In a similar vein, the average flow volatility (standard deviation of investor-level flows during the event period) for institutional versus retail clients is 3.9 and 0.78, respectively.

Even though investors in our sample do not trade too often, when they do, their trades, in relative terms, can be large. For instance, conditional on selling, the mean and median end-investors' outflows are 50% and 38% of their total positions, respectively. About 40% of sales are full-position sales. Among purchases, 10% of purchases are new positions. The median (mean) value of purchases that are adjustments on existing positions is 0.7% (5%). Analogous numbers for exits are 5% and 16%. Although purchases tend to be smaller than sales, they are more frequent (18% versus 82%). Overall, patterns indicate that purchases are more frequent but smaller. Sales occur less frequently but when investors sell, they sell large amounts.

Next, we assess the impact of the change in pricing structure on an individual investor's flows. To this end, we estimate the regression model in (4) at the investor level. Relative to equation (4), our new dependent variable is *Flow EndInv*, which is the monthly change in number of shares an investor holds in a given fund. We include investor fixed effects, which allows us to control for any permanent differences among investors and measure the differential effects due to pricing change for a given investor. We present the results in Table 6.

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 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. At the same time, they invest less money in alternative funds in periods of no stress.[22]

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

[22] Figure 4 shows the average differences in *Flow EndInv* between switchers (treated) and their matched funds (control) after controlling for investor fixed effects. We show differences for each event month during the [-24, 24] month period. We report separate plots for periods of market stress and no stress.

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 shares in both treated and control funds at the same time, however, we identify about 2,800 (about 10% of the sample) observations that correspond to investors with cross-fund holdings in a given month. Including investor *x* time-fixed effects, we focus on such cases and find that the coefficient of the triple interaction term remains to be positive and statistically significant (Table IA.4 of the Internet Appendix). During market stress, investors in switching funds withdraw less money than when they withdraw from traditional funds.[23]

Overall, our investor-level analysis indicates a meaningful response of the same investor within the local event window around the pricing change and provides strong evidence that alternative pricing structures affect investors' decisions and mitigate fragility in funds. The same investor is significantly less likely to redeem her shares during a stress period if the fund uses alternative pricing than if the fund uses traditional pricing.

4.4. 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. First, we examine investors' flow-performance sensitivity. Second, we look at the volatility of individual investors' flows. Finally, we analyze funds' decisions to exit the market.

4.4.1 Flow-Performance Sensitivity

[23] An additional robustness test (reported in Table IA.4) is that we repeat the tests using an alternative dependent variable, *GBPFlowEndInv*, the GBP monthly change in each investor's holding. Our conclusions remain similar.

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 et al. (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 et al. (2010), which 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:

$$\begin{aligned} Flow_{i,t+1} = \propto &+ \beta_0 NegAlpha\ x\ Alternative_{i,t} \\ &+ \beta_1 NegAlpha_{i,t} + \beta_2 Alpha\ x\ Alternative_{i,t} + \beta_3 Alpha_{i,t} + \beta_4 Alternative_{i,t} \\ &+ Controls_{i,t} + Time\ FE + \varepsilon_{i,d} \quad (5) \end{aligned}$$

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 7 presents the results. In column (1), we only include *Alpha* and *Alpha x 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 et al. (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 for *NegAlpha* and *NegAlpha x Alternative* are 5.8227 and -4.0730; 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.

Moreover, we 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 x Treated x Post* and *Alpha x Treated x 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. Results are in Panel B of Table 7.

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, 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 x Treated x Post* is *-1.5247*, significant at 10%). 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 x Treated x Post* is -4.5641, significant at 5%.

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 there can be a *run for exit* on the downside, there is unlikely to be a *run to enter* on the upside as funds with recent good performance do not continue to perform well (e.g., Carhart, 1997; Chen at 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.

4.4.2 Volatility of End-Investor Flows

Another way through which fund stability may manifest is volatility of individual investors' flows. To the extent that alternative pricing reduces outflows in stress times and decreases inflows in other times, individual investors' flow volatility is expected to be lowered. To assess this, for each investor, we calculate *Vol of Flow EndInv* (volatility of *Flow EndInv)* before and after the switch date, and estimate:

$$VolFlowEndInv_{i,t} = \propto + \beta_0 Treated_i x\ Post_t + \beta_1 Post_t + \beta_2 Treated_i + \beta_3 Controls_{i,t} + \varepsilon_{i,d} \quad (7)$$

We present the results in Table IA.5 of the Internet Appendix. The results show that, following the change in a fund's pricing, fund investors in the treatment group, in fact, have less volatile flows than investors in funds that do not undergo a change in their pricing method.

4.4.3 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, 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 out of 46).

We also evaluate the difference in fund exits between the two group of funds using a regression framework. The dependent variable, *Exit,* is an indicator variable that equals one if the fund exits the market during our sample period, and it equals zero if the fund is still alive.[24] 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. We present the results from the estimation in Table 8.

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 in column (7), we report results with the matched sample. We find that, on average, alternative funds are more likely to exit but the effect is statistically 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.

4.5. 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 that allows us to provide direct evidence for the mechanism described by the theoretical studies.

4.5.1 The Role of Fund Characteristics

[24] A fund exit is defined at the fund level, that is, when all of its share classes are terminated.

Our first set of tests considers the differences between funds in terms of their fragility. We explore three hypotheses. First, the fund fragility should increase with the degree of their portfolios' illiquidity because such portfolios take longer to liquidate, and trades are more costly. We therefore expect the impact of pricing structure to matter more for funds with highly illiquid assets. Second, in the model of Chen et al. (2010), when the primary source of complementarities is the price impact of future redemptions, a large investor can internalize the negative effects of his 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 9. 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.

4.5.2 The Role of Investor Characteristics

Our second set of tests exploits the variation in investor-level sensitivities. We start by examining the differences between institutional and retail investors. Being more sophisticated (e.g., Kacperczyk and Schnabl, 2013, and Schmidt et al., 2016) institutional investors are like to be better informed about the implications of funds' pricing practices and act accordingly. Moreover, 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. To test this prediction, we estimate the regression model based on the switching experiment at the investor level. We cluster standard errors by investor and month.

$$Flow\ EndInv_{i,t} = \propto + \beta_0\ Stress\ _t x\ Post_t\ x\ Inv\ Type_i + \beta_1\ Stress_t\ x\ Post_t + \beta_2\ Stress_t\ x\ Inv\ Type_i + \beta_3\ Inv\ Type_i x\ Post_t + \beta_4\ Post_t + \beta_5 Inv\ Type_i + \beta_6\ Stress_t + \beta_7\ Controls_{i,t} + \varepsilon_{i,d} \quad (8)$$

Inv Type is a generic variable for two measures of investor types. 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. We present the results in Table 10. 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 β_0 between treated and control groups and find that the corresponding p-value equals 0.07.

We extend the empirical test by asking whether a dominant type of a fund investment 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 et al. (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 harder 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 investing horizon above the sample median and zero, otherwise, where investing horizon is the number of months the investor holds his shares after an initial purchase.[25] 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, the 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 total flow effect. In column (7), we jointly include *Stress x Post x Inst Investor* and *Stress x Post x Patient Investor.* The results indicate that both investor sophistication and investment horizon of investors in a fund are important interacting forces with the fund's pricing structure, though investor sophistication seems to be a statistically stronger factor.

[25] In calculating investing horizon, we use purchases before December 2014. 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.

4.6. Do Alternative Pricing Rules Affect Subsequent Fund Performance?

A central tenet of fragility in open-end funds is that the traditional NAV-based pricing induces the dilution effect of large flows for non-transacting investors and this gives rise to first-mover advantage. 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 et al., 2007; Christoffersen et al., 2018; Goldstein et al., 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 investor 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. Moreover, 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 create undesired consequences. To assess this hypothesis, we estimate the following regression model:

$$AbReturn_{i,t+1} = \propto + \beta_0 Net\ flow_{i,t}\ x\ Alternative_{i,t} + \beta_1 Net\ flow_{i,t} + \beta_2 Alternative_{i,t} + \beta_5 Controls_{i,t} + Time\ FE + \varepsilon_{i,d} \quad (9)$$

where *AbReturn* in month *t+1* is calculated as the difference between a fund return and a fund's exposure to global bond market and global 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 $\beta 1_{t-11,t}\ x\ Bond\ market\ return_{t+1}$ and $\beta 2_{t-11,t}\ x\ \ Stock\ market\ return_{t+1}$, 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 net outflow at month *t*, equal to *Flow* if *Flow<0*, and to zero if *Flow>=0*. *Net Inflow* is the net inflow at month *t*, equal to *Flow* if *Flow>0*, and to zero if *Flow<=0*. We cluster standard errors by fund and month.

We present the results in Table 11. 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 unconditional 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 distortionary because fund companies have more flexibility in deploying their new capital which mitigates the associated costs. This is in line with Figure 2 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.

4.7 Do Fund Companies Internalize their Investors' Decisions?

Given that a fund's pricing structure is a way to address a problem of possible fund fragility, in this section, we examine whether funds treat their pricing scheme as a substitute for other hedging instruments. Based on the literature, we examine three options: increased cash holdings, reduced asset concentration, and fund load fees.

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 H*erfindahl–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 by estimating the following regression model:

$$Hedging\ Instrument_{i,t+1} = \propto + \beta_0 Alternative_{i,t} + \beta_1 Controls_{i,t} + Time\ FE + \varepsilon_{i,d} \quad (10)$$

where *Hedging Instrument* is a generic name for different instruments. We present the results in Table 12. We find that funds with alternative pricing rules hold less cash, on average, consistent with the hypothesis that cash and alternative pricing rule are substitutes for each other. On the other hand, the coefficients for asset concentration, front load, and back load, though negative, are all statistically insignificant. The results are consistent with those of Chen et al. (2010) who argue that loads cannot eliminate dilution in fund value due to flows, therefore they cannot address strategic complementarities. This is because proceeds from loads are not retained in the fund; rather loads are usually paid out to the distribution channel.

5. 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 at times of significant market stress. Such liquidity mismatch in combination with strategic complementarities arising from NAV-based pricing rule pose a significant threat to these companies and the broad market. 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.

In this paper, we empirically evaluate the effectiveness of one tool, *swing pricing*, that allows for dilution adjustment of funds' net asset values. Through the FCA, we obtain detailed data on U.K-based corporate bond mutual funds with different pricing practices and investors' base. Using a combination of micro-level identification strategies that alleviate endogeneity concerns, we show that alternative pricing rules change open-end funds' operations in a way that enables funds to more effectively manage their liquidity risk. They reduce the degree of redemptions during periods of high market stress. The stabilizing effect is particularly visible for institutional investors and investors with long investment horizons, which supports the presence of strategic complementarities in the data. Moreover, these funds eliminate the first-mover advantage by removing the dilution in fund performance arising from fund outflows.

These results indicate that swing pricing is a useful financial stability tool. This is consistent with the facts that majority of U.K. funds are now using alternative pricing schemes (82% as of December 2016), and that several funds have abandoned the traditional scheme for swing pricing over the past decade, suggesting a gradual transitioning in the market. Although the results are not as consistently strong, we also document that swing funds tend to have less inflows outside the crisis periods, suggesting that there might be also some costs, arguably, due to reduction in liquidity for investors who wish to redeem, and potential concerns about manipulation in pricing. The clear dominance of alternative pricing structure is therefore difficult to establish. Future research can aim to further evaluate swing pricing relative to its potential alternatives.

Our results offer important policy implications. Recently, policy makers have expressed concerns with the growing illiquidity mismatch in various parts of the asset management industry. For example, in his policy speech on June 26, 2019, the Governor of the Bank of England, Mark Carney, called for actions preventing possible systemic runs on the industry arising from significant illiquidity mismatch. This risk has partly materialized during the recent Coronavirus crisis and has only been muted through the very costly intervention of various Central Banks globally. However, such mitigation may be les costly if managers efficiently use available pricing rules. Simultaneously, regulation permitting alternative pricing rules has become effective in the U.S. only recently, in November 2018. Given similarity in investor types and general development of European and U.S. markets, our results may help to understand the expected effects of the new regulation for the U.S. market.

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Appendix A. Variable Definitions

Label	Definition	Units
Stress	An indicator variable that equals one if monthly *VIX* index is above the 75th percentile of the sample	
Alternative	An indicator variable that equals one if the fund is using one of the alternative pricing rules	
Flow	Monthly capital flows into a fund divided by fund's total net assets in *t*	%
Flow EndInv	Change in each investor's holding (in number of shares) from previous month	%
Return	Fund's monthly raw return	%
Alpha	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 global bond market and global stock market returns. Indices obtained from Barclays	%
NegAlpha	Equals *Alpha* if the fund's *Alpha* is negative (or below the 25th percentile); set to zero otherwise	%
Size	Natural logarithm of fund's total net assets	£
Age	Natural logarithm of fund age in years (using the age of the oldest class share)	
Expense	Fund's annual total expense ratio	%
N of Inv	Natural logarithm of total number of investors in a given fund	
Illiquidity	Value-weighted average of *Asset Illiquidity* of fund's assets	
Asset Illiquidity	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.	
Inst	Fraction of fund's total net assets held by institutional investors	%
Ownership Concentration	*H*erfindahl–Hirschman Index calculated using each end-investors' ownership in each month	
Adjustment Factor	Equals the absolute value of swing factor for swing funds; equals half-spread, (*0.5*(ask-bid)/mid,* for dual funds	%
Net Inflow	Net monthly inflows. Equal to *Flow* if *Flow*>0; equal to 0 if *Flow*<=0	
Net Outflow	Net monthly outflows. Equal to *Flow* if *Flow*<0; equal to 0 if *Flow*>=0	
Dual	An indicator variable that equals one if the fund is a dual fund	
Full	An indicator variable that equals one if the fund is a full swing fund	
Partial	An indicator variable that equals one if the fund is a partial swing fund	
Cash	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	%
Tracking Error	*-1* times R-squared from the alpha regression described above	
Asset Conc	*H*erfindahl–Hirschman Index of fund's asset holdings in each month	
Front Load	Value-weighted average of (minimum) front-end load charges across share classes of a given fund	%
Back Load	Value-weighted average of (minimum) back-end load charges across share classes of a given fund	%
New Investor	Number of new investors divided by the fund's total number of investors in each month	%
Investor Horizon	Number of months the investor holds his shares after an initial purchase. We use purchases before December 2014	

Table 1: Descriptive Statistics on Fund Characteristics

This table presents the descriptive statistics for characteristics of corporate bond funds in our sample from January 2006 to December 2016. The unit of observation is fund-month. 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 fund's total net assets (in %); *Alpha* is the fund's alpha in the past 12 months (in %); *Size* is natural logarithm of fund's total net assets; *Age* is the natural logarithm of fund age in years; *Expense* is funds' 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 fund's assets. Details on the definitions of the variables are provided in Appendix A.

Panel A. Alternative Pricing

	Flow	Alpha	Size	Age	Expense	Illiquidity	Inst
P25	-0.6052	-0.0628	17.9023	1.3863	0.5643	0.0054	0.0000
Mean	0.7958	0.2658	18.7737	2.0778	0.8807	0.0094	23.3599
Median	0.0590	0.1948	19.2709	2.1972	0.9218	0.0078	0.0000
P75	1.6364	0.5561	20.1997	2.7081	1.1912	0.0108	42.5579
Std	6.8569	0.5478	2.4715	0.8578	0.4462	0.0072	35.9562

Panel B. Traditional Pricing

	Flow	Alpha	Size	Age	Expense	Illiquidity	Inst
P25	-0.4185	-0.0888	17.7389	1.0986	0.4214	0.0047	0.0000
Mean	1.3315	0.2341	18.7888	1.7591	0.7570	0.0080	34.5601
Median	0.1124	0.1765	18.9854	1.7918	0.7500	0.0072	1.3872
P75	2.1596	0.5450	19.9881	2.3026	1.0200	0.0097	73.7224
Std	7.1247	0.5408	1.7037	0.7749	0.3926	0.0056	40.6099

Table 2: Determinants of Dilution Adjustment Factors

Dependent variable is the daily *Adjustment Factor*, defined as the factor by which the fund NAV is adjusted on a given day. It equals the absolute value of swing factor for swing funds, and equals the half spread in funds' bid and ask prices for dual funds. The unit of observation is fund-day. *Stress* is an indicator variable that equals one if monthly *VIX* is above the 75th percentile of the sample. *Daily Illiquidity* is the daily value-weighted average of bid-ask spreads of 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. Other fund variables include lagged *Alpha*, *Size*, *Age*, *Expense*, and *Inst*. Appendix A lists the detailed definitions and calculations of all variables in the regression. Regressions use only swing pricing and dual priced funds. We cluster standard errors by fund and day. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Daily Illiquidity	0.2449***	0.2164***	0.1642***			
	(0.0805)	(0.0798)	(0.0573)			
Stress				0.2411***	0.1404***	0.0010
				(0.0581)	(0.0357)	(0.0193)
High Illiquidity x Stress						0.1930**
						(0.0786)
High Illiquidity						-0.0451
						(0.0295)
Alpha		0.0903*	0.0372		0.0146	0.0248
		(0.0475)	(0.0315)		(0.0254)	(0.0214)
Size		-0.0293*	0.0058		0.0150	-0.0099
		(0.0168)	(0.0187)		(0.0251)	(0.0170)
Age		0.0470	0.0204		-0.2311***	-0.1278*
		(0.0509)	(0.1274)		(0.0733)	(0.0751)
Expense		0.0391	0.2541		0.1909	0.3183
		(0.1058)	(0.1843)		(0.1527)	(0.2037)
Inst		-0.0016	0.0034		-0.0057	0.0043*
		(0.0011)	(0.0024)		(0.0037)	(0.0025)
Observations	172,007	133,262	133,262	270,793	199,336	133,262
R-squared	0.077	0.136	0.684	0.022	0.633	0.662
Day FE	Y	Y	Y			
Controls		Y	Y		Y	Y
Fund FE			Y		Y	Y

Table 3: Fund Flows during Market Stress

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. Control variables include 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. 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). * **, *** indicate 10%, 5%, and 1% level of significance, respectively.

Panel A. Least Squared Regressions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Alternative	-0.7866	-0.7260	-0.6895	-0.0993	-0.6579	-0.3028	-0.8621*
	(0.5297)	(0.5219)	(0.5393)	(0.6608)	(0.5413)	(0.7042)	(0.5157)
Alternative x Stress	1.0410**	0.9934*	1.3711**	1.6676***	1.6369***	1.1131**	1.2982**
	(0.4391)	(0.5589)	(0.5765)	(0.6368)	(0.5876)	(0.5191)	(0.5489)
Stress	-0.9890***	-1.0140***	-1.3467***	-1.7250***		-1.1241***	-1.3075***
	(0.2767)	(0.3688)	(0.3904)	(0.5021)		(0.3832)	(0.3884)
Alpha		0.3526*	0.3212	0.7116***	0.6712**	0.4920**	0.5901***
		(0.1993)	(0.2060)	(0.2190)	(0.3234)	(0.2040)	(0.2094)
Size		0.3001*	0.3164*	-0.6081**	0.3498**	0.0944	0.2648*
		(0.1660)	(0.1679)	(0.2432)	(0.1665)	(0.0902)	(0.1515)
Age		-1.2669***	-1.3062***	-1.0089*	-1.3192***	-1.4305***	-1.0009***
		(0.2811)	(0.2884)	(0.5299)	(0.2820)	(0.2162)	(0.2630)
Expense		0.5694	0.5711	-2.8110***	0.5419	0.3574	-0.3392
		(0.4194)	(0.4294)	(0.9704)	(0.4584)	(0.4003)	(0.4365)
Illiquidity		12.3444	11.3720	52.2817**	-16.1868	22.9051	32.1082
		(24.6152)	(25.9732)	(25.3218)	(28.6746)	(26.2625)	(25.4202)
Inst		-0.0126***	-0.0128***	-0.0278**	-0.0133***	-0.0085*	-0.0143***
		(0.0041)	(0.0040)	(0.0118)	(0.0041)	(0.0046)	(0.0040)
Observations	16,693	10,125	9,670	9,669	9,665	9,670	9,670
R-squared	0.002	0.026	0.026	0.164	0.048	0.057	0.040
Controls	N	Y	Y	Y	Y	Y	Y
Fund FE				Y			
Time FE					Y		
Family FE						Y	
Style FE							Y

Panel B. Quantile Regressions

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

Table 4: Full Swing versus Partial Swing versus Dual Priced

Dependent variable is *Flow*, which is the net monthly capital flows into a fund divided by fund's total net assets; *Stress* is an indicator variable that equals one if monthly *VIX* is above the 75^{th} 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; *Dual* is an indicator variable that equals one if the fund is a dual fund. Baseline category in each regression include the matching funds which use the traditional pricing rule. We cluster standard errors by fund and time. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	Partial Swing	Full Swing	Dual	All
Partial swing x Stress	1.3341**			1.3341**
	(0.5487)			(0.5483)
Full swing x Stress		1.3662*		1.3662*
		(0.8062)		(0.8032)
Dual x Stress			2.2829	2.2829
			(1.7599)	(1.7505)
Partial swing	-0.7073			-0.7073
	(0.5804)			(0.5799)
Full swing		-0.8312		-0.8312
		(0.5747)		(0.5726)
Dual			-2.6175**	-2.6175**
			(1.2289)	(1.2223)
Stress	-1.3154***	-1.3154***	-1.3154***	-1.3154***
	(0.3934)	(0.3946)	(0.3952)	(0.3931)
Observations	6,828	3,508	2,682	9,670
R-squared	0.003	0.006	0.014	0.008

Table 5: Fund Flows during Market Stress for Switchers and their Matched Funds

Unit of observation is fund-month. Dependent variable is *Flow*, which is the net monthly capital flows into a fund divided by fund's total net assets. Event period is [-24, 24] months relative to the switching date. *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; *Post* is an indicator variable that equals one for the period after the switch. Matching algorithm minimizes the sum of the absolute percentage differences in lagged values of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. Matching is performed with replacement. Control variables include lagged values (previous month-end) of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. Variable definitions are in Appendix A. We cluster standard errors by fund and month. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

VARIABLES	(1)	(2)	(3)	(4)
Stress x Treated x Post	2.4757**	2.6541*	3.5240*	2.6970*
	(1.0303)	(1.4025)	(1.7650)	(1.5681)
Stress x Post	-1.2530	-1.4835	-2.3806	-1.5535
	(0.9583)	(1.2186)	(1.6241)	(1.1058)
Stress x Treated	0.4778	-0.0509	0.2844	0.1874
	(0.6170)	(0.6646)	(0.7919)	(0.6212)
Treated x Post	-2.4801**	-1.5066**	-1.6612*	-1.5362*
	(1.0216)	(0.7094)	(0.8544)	(0.7972)
Post	2.0499**	1.5639**	1.1906	0.8393
	(0.9555)	(0.7033)	(0.7795)	(0.7084)
Treated	-0.3813	-0.5795		-0.6717
	(0.5039)	(0.5636)		(0.6080)
Stress	-0.7108	-0.3546	-0.7276	
	(0.5042)	(0.6225)	(0.7263)	
Alpha		0.3742		0.9244
		(0.3318)		(0.6159)
Size		0.6698***		0.6777**
		(0.2541)		(0.2531)
Age		-1.1006**		-1.1896**
		(0.4946)		(0.5790)
Expense		1.3328*		1.5484*
		(0.7993)		(0.8086)
Illiquidity		28.7498		14.0949
		(32.1364)		(47.5349)
Inst		-0.0153**		-0.0166**
		(0.0064)		(0.0079)
Observations	1,374	1,042	1,374	1,042
R-squared	0.060	0.124	0.276	0.194
Controls	N	Y	N	Y
Fund FE			Y	
Time FE				Y

Table 6: End-Investor Flows during Market Stress for Switchers and their Matched Funds

This table shows the effect of alternative pricing rules on end-investor flows during periods of market stress using the sample of switchers and their matched funds. Event period is [-24, 24] months. Matching algorithm is described in the text. Unit of observation is investor-month. Dependent variable is *Flow EndInv*, which is the percentage monthly change in each investor's holding (in number of shares). Columns (1) and (2) show the results for switchers and their matching pairs, respectively; column (3) presents the matched sample results. *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; *Post* is an indicator variable that equals one for the period after the switch. Control variables include lagged values (previous month-end) of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. Variable definitions are available in Appendix A. We cluster standard errors by investor and month. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

VARIABLES	(1) Switchers	(2) Control group	(3) Matched sample
Stress x Treated x Post			0.6341***
			(0.2230)
Stress x Post	0.2596*	-0.3205	-0.3869**
	(0.1346)	(0.2163)	(0.1817)
Stress x Treated			-0.3941**
			(0.1929)
Treated x Post			-0.6698***
			(0.1597)
Post	-0.2127*	0.5194***	0.5219***
	(0.1106)	(0.1376)	(0.1303)
Treated			
Stress	-0.1581**	-0.1020	-0.2525
	(0.0736)	(0.2131)	(0.1789)
Alpha	0.2757***	0.4374**	0.3281***
	(0.1040)	(0.1704)	(0.0856)
Size	-0.5059**	-0.7041***	-0.6739***
	(0.1919)	(0.1294)	(0.1157)
Age	-1.4022*	-1.6378***	-1.7709***
	(0.7129)	(0.4361)	(0.3480)
Expense	-1.8653***	-1.1982	-1.6870***
	(0.6098)	(1.3946)	(0.5755)
Illiquidity	-3.6082	72.1860***	-3.2257
	(8.6290)	(25.3514)	(8.0409)
Inst	-0.0232	-0.0137	-0.0199**
	(0.0139)	(0.0121)	(0.0087)
Observations	251,718	132,675	384,393
R-squared	0.250	0.363	0.338
Investor FE	Y	Y	Y
Controls	Y	Y	Y

Table 7: Flow-Performance Sensitivity

This table shows the effect of alternative pricing rules on flow-performance sensitivity. Panel A shows the results for the full sample (and their matching pairs) using fund flows. Panel B shows the results for the switching funds (and their matching pairs) using end-investor flows. Matching algorithm is described in the text. Control variables include lagged *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst.* Variable definitions are available in Appendix A. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

Panel A. Using Fund Flows for the Full Sample

The dependent variable is *Flow*, which is the net monthly capital flows into a fund divided by 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 results for the matched sample.

VARIABLES	(1) Fund Flow	(2) Fund Flow	(3) Matched Sample Fund Flow
NegAlpha		5.8227***	7.0479***
		(1.4523)	(1.8523)
NegAlpha x Alternative		-4.0730***	-5.0280***
		(1.4817)	(1.8578)
Alpha	1.5287***	0.2767	0.1114
	(0.5412)	(0.5690)	(0.6177)
Alpha x Alternative	-0.5253	0.2639	0.4354
	(0.4838)	(0.5415)	(0.5797)
Alternative	-0.3690	-0.8427	-0.9280*
	(0.5165)	(0.5441)	(0.5530)
Size	0.2743*	0.2766*	0.3005**
	(0.1459)	(0.1465)	(0.1494)
Age	-1.0158***	-1.0127***	-1.0070***
	(0.2576)	(0.2552)	(0.2630)
Expense	-0.3771	-0.2997	-0.3126
	(0.4647)	(0.4572)	(0.4695)
Illiquidity	12.3976	22.8068	20.3520
	(27.0505)	(27.5163)	(28.2355)
Inst	-0.0149***	-0.0138***	-0.0142***
	(0.0040)	(0.0039)	(0.0039)
Observations	10,125	10,125	9,670
R-squared	0.060	0.063	0.064
Time FE	Yes	Yes	Yes

Panel B. Using End-Investor Flows for Switchers and their Matched Funds

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. 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, otherwise. Regressions include the interaction terms of *Alpha (*and *NegAlpha)* with *Treated* and *Post.* We cluster standard errors by investor and month.

	(1)	(2)	(3)
VARIABLES	Flow EndInv	Flow EndInv	Flow EndInv
NegAlpha x Treated x Post		-1.5247*	-4.5641**
		(0.8013)	(1.8491)
NegAlpha x Post		1.3472*	4.4680**
		(0.7123)	(1.8426)
NegAlpha x Treated		-0.3741	0.6165
		(1.6914)	(1.8189)
NegAlpha		0.4240	0.5432*
		(0.6908)	(0.3189)
Alpha x Treated x Post	0.0180	0.2071	0.1053
	(0.1364)	(0.1588)	(0.1477)
Alpha x Post	0.0178	-0.1013	-0.0392
	(0.1268)	(0.1297)	(0.1220)
Alpha x Treated	-0.1445	-0.1122	-0.1750
	(0.1138)	(0.1208)	(0.1185)
Alpha	0.4578***	0.3965***	0.4675***
	(0.1059)	(0.0989)	(0.0977)
Treated x Post	-0.4371***	-0.5233***	-0.4847***
	(0.1010)	(0.1146)	(0.1075)
Post	0.4163***	0.4475***	0.4411***
	(0.1000)	(0.1000)	(0.0980)
Size	-0.6631***	-0.6537***	-0.6675***
	(0.0683)	(0.0697)	(0.0696)
Age	-1.7081***	-1.6450***	-1.6804***
	(0.2161)	(0.2202)	(0.2205)
Expense	-1.4161***	-1.4042***	-1.3883***
	(0.1848)	(0.1868)	(0.1852)
Inst	-0.0187***	-0.0181***	-0.0186***
	(0.0057)	(0.0057)	(0.0057)
Illiquidity	-1.7149	-0.9046	-1.7574
	(1.6117)	(1.8760)	(1.8032)
Observations	384,393	384,393	384,393
R-squared	0.338	0.338	0.338
Investor FE	Y	Y	Y
Controls	Y	Y	Y

Table 8: Fund Exit

Dependent variables are *Exit* defined as an indicator variable that is equal to one if the fund exits the market during our sample period, and equal to zero if the fund remains alive. *Merged* is 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. *Liquidated* 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*. Appendix A lists the detailed definitions and calculations of all variables in the regression. The unit of observation is fund-month. We cluster standard errors by fund and month. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

VARIABLES	(1) Exit	(2) Merged	(3) Liquidated	(4) Exit	(5) Merged	(6) Liquidated	(7) Liquidated Matched sample
Alternative	-0.0474	0.0611*	-0.1081*	-0.1229	0.0134	-0.1723**	-0.0885*
	(0.0599)	(0.0312)	(0.0560)	(0.0884)	(0.0472)	(0.0836)	(0.0479)
Alpha				0.0527	0.0425	0.0354	0.0423
				(0.0567)	(0.0508)	(0.0441)	(0.0453)
Size				-0.0422***	-0.0283***	-0.0256**	-0.0214**
				(0.0119)	(0.0105)	(0.0104)	(0.0095)
Age				0.0057	0.0395*	-0.0345	-0.0269
				(0.0256)	(0.0211)	(0.0211)	(0.0198)
Expense				0.1853***	0.0788	0.1703***	0.1492**
				(0.0649)	(0.0543)	(0.0590)	(0.0592)
Illiquidity				25.7466***	27.3780***	4.5239	4.2281
				(5.1310)	(4.3891)	(7.6024)	(7.7906)
Inst				0.0017***	0.0010*	0.0015***	0.0017***
				(0.0006)	(0.0006)	(0.0006)	(0.0006)
Constant	0.1739***	0.0256	0.1556***	1.0122***	0.5262**	0.8208***	0.6486***
	(0.0561)	(0.0254)	(0.0542)	(0.2819)	(0.2425)	(0.2753)	(0.2243)
Observations	299	281	277	174	167	163	159
R-squared	0.003	0.006	0.026	0.569	0.535	0.414	0.416
Controls	N	N	N	Y	Y	Y	Y
Family FE	N	N	N	Y	Y	Y	Y

Table 9: Cross-Fund Differences

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*, which is 1- *Inst*. Appendix A lists the detailed definitions and calculations of all variables in the regression. The unit of observation is fund-month. We cluster standard errors by fund and month. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

VARIABLES	(1)	(2)	(3)
Alternative x Stress x Illiquidity	26.7550*		
	(14.5103)		
Stress x Illiquidity	-28.7799*		
	(17.2803)		
Alternative x Stress x Ownership Concentration		-6.0387*	
		(3.5858)	
Stress x Ownership Concentration		3.9060	
		(3.0725)	
Alternative x Stress x Retail			0.0243**
			(0.0114)
Stress x Retail			-0.0121
			(0.0098)
Alternative x Stress	1.9128**	2.4103***	2.2904**
	(0.9164)	(0.6379)	(0.9016)
Stress	-1.8045***	-1.8842***	-1.9369**
	(0.6519)	(0.6172)	(0.7769)
Alternative x Illiquidity	-88.0525		
	(61.1618)		
Alternative x Ownership Concentration		6.1098***	
		(2.2760)	
Alternative x Retail			-0.0101
			(0.0118)
Alternative	-0.8307*	-1.8383***	-1.1000
	(0.4745)	(0.3880)	(0.9592)
Illiquidity	78.7570		
	(59.6897)		
Ownership Concentration		-6.8252***	
		(2.0888)	
Retail			0.0194*
			(0.0101)
Observations	9,670	8,303	9,670
Controls	Y	Y	Y
R-squared	0.031	0.027	0.026

Table 10: End-Investor Flows during Market Stress: Role of Investor Characteristics

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. We cluster standard errors by investor and month. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Treated	Control	Treated Retail-oriented	Treated Inst-oriented	Treated	Control	Treated
Stress x Post x Inst Investor	0.4409**	0.1051	0.5693***	0.0074*			0.4604**
	(0.1970)	(1.1571)	(0.1841)	(0.0039)			(0.1992)
Stress x Post	0.1275	0.3316	0.3425	0.0009	0.1711	-0.2283	0.0564
	(0.1336)	(0.9681)	(0.2570)	(0.0689)	(0.1185)	(0.2295)	(0.1170)
Post x Inst Investor	-	-	-	-			-
Stress x Inst Investor	-0.2614*	-1.9006*	-0.3700***	-0.1270			-0.2604*
	(0.1351)	(1.0350)	(0.1236)	(0.2008)			(0.1360)
Stress x Post x Patient Investor					0.1249**	-0.1198	0.0881*
					(0.0581)	(0.2970)	(0.0446)
Post x Patient Investor					-	-	
Stress x Patient Investor					-0.0899	0.1691	0.0091
					(0.0563)	(0.2887)	(0.0363)
Post	-0.2025*	0.2645	-0.4499**	0.0074	-0.2160*	0.5246***	-0.2017*
	(0.1101)	(0.3958)	(0.2079)	(0.0584)	(0.1112)	(0.1382)	(0.1091)
Stress	-0.0541	-0.5807	-0.2204	-0.0178	-0.0975*	-0.0172	-0.0599
	(0.0620)	(0.7479)	(0.1986)	(0.0132)	(0.0543)	(0.2004)	(0.0468)
Inst Investor	-	-	-	-	-	-	-
Patient Investor	-	-	-	-	-	-	-
Observations	231,305	64,513	145,604	85,701	251,718	132,675	231,305
R-squared	0.250	0.404	0.284	0.187	0.251	0.363	0.250
Investor FE	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y
	p-value=0.071		p-value=0.066		p-value=0.064		

Table 11: Fund Flows and Future Fund Performance

Dependent variable is the abnormal fund return in month *t+1*, calculated as the difference between fund's return (calculated using unadjusted fund prices) and fund's exposure to global bond market and global stock market returns. Fund's exposure to global bond market and global stock market returns are calculated as $\beta 1_{t \to t-11}\ x\ Bond\ market\ return_{t+1}$ and $\beta 2_{t \to t-11}\ x\ Stock\ market\ return_{t+1}$. *Net Outflow* is the net monthly outflows in *t*, which equals *Flow* if *Flow<0*, and it equals zero if *Flow>=0*. *Net Inflow* is the net monthly inflows in *t*, which equals *Flow* if *Flow>0*, and it equals to zero if *Flow<=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 time *t*. Appendix A lists definitions of all variables in the regression. 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 fund-month. We cluster standard errors by fund and month. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

VARIABLES	(1) Full Sample	(2) High Illiquidity	(3) Full Sample	(4) High Illiquidity
Net Outflow	-0.0352**	-0.0546*		
	(0.0170)	(0.0300)		
Net Outflow x Alternative	0.0372**	0.0662**		
	(0.0184)	(0.0317)		
Net Inflow			0.0028	0.0079
			(0.0081)	(0.0111)
Net Inflow x Alternative			-0.0019	-0.0101
			(0.0117)	(0.0160)
Alternative	-0.0313	-0.0161	-0.0019	0.0461
	(0.0557)	(0.0589)	(0.0580)	(0.0679)
Size	-0.0157	0.0087	-0.0161	0.0082
	(0.0098)	(0.0128)	(0.0100)	(0.0128)
Age	0.0400	0.0099	0.0382	0.0109
	(0.0442)	(0.0467)	(0.0437)	(0.0454)
Expense	-0.2079***	-0.2039***	-0.2104***	-0.2122***
	(0.0792)	(0.0784)	(0.0783)	(0.0766)
Illiquidity	1.7642	-0.1276	1.7650	-0.2475
	(6.2322)	(7.3500)	(6.2592)	(7.3619)
Inst	0.0006	0.0006	0.0006	0.0006
	(0.0007)	(0.0008)	(0.0007)	(0.0008)
Observations	7,827	4,146	7,827	4,146
R-squared	0.415	0.480	0.415	0.479
Month-Year FE	Y	Y	Y	Y

Table 12: Pricing Rules and Fund Portfolio Adjustments

This table shows the effect of alternative pricing rules on fund's cash holdings (column 1), asset concentration (column 2) and load charges (column 3 and 4). *Cash* is fund's total cash holdings (including cash equivalents) divided by fund's total assets; *Asset Conc is H*erfindahl–Hirschman Index of 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) rear load charges across share classes of a given fund. Variable definitions are in Appendix A. *Alternative* is an indicator variable that equals one if the fund is using one of the alternative pricing mechanisms. Control variables include lagged values (previous month-end) of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. We cluster standard errors by fund and month. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	Cash	Asset Conc	Front Load	Back Load
Alternative	-3.2586**	-0.0051	-0.0679	-0.0972
	(1.2938)	(0.0123)	(0.3429)	(0.0837)
Alpha	-0.1688	-0.0181*	-0.1563	0.0092
	(0.5638)	(0.0094)	(0.1595)	(0.0100)
Size	-0.0470	-0.0010	-0.0335	-0.0070
	(0.2794)	(0.0019)	(0.0772)	(0.0060)
Age	-0.7100	0.0059	-0.0279	0.0135
	(0.5017)	(0.0068)	(0.1641)	(0.0189)
Expense	0.9906	0.0159	2.4685***	0.0159
	(1.3146)	(0.0100)	(0.3059)	(0.0375)
Inst	-0.0090	0.0000	0.0125***	-0.0005
	(0.0115)	(0.0001)	(0.0039)	(0.0005)
Illiquidity	13.5219	-1.1383**	20.1502	-1.5599
	(64.2152)	(0.4474)	(19.3040)	(1.1896)
Observations	9,158	10,563	10,254	10,254
R-squared	0.278	0.039	0.204	0.050
Controls	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Internet Appendix (not for publication)

Table IA.1: Swing Thresholds of Partial Swing Funds
This table shows the frequency distribution table for swing thresholds used by partial swing funds in our sample. *Threshold* is the swing threshold (in absolute terms) used by partial swing funds. *Frequency* is defined in %. For funds with multiple thresholds (around 1% of partial swing funds), we report the minimum.

Threshold	Frequency
0.01%	4.59
0.50%	3.1
1%	40.36
1.50%	1.17
2%	4.05
2.50%	2.29
3%	34.39
4%	1.2
5%	6.92
6%	0.22

Table IA.2: Extended Robustness Tests

Dependent variable is *Flow*, defined as the net monthly capital flows into a fund divided by the fund's total net assets. *Alternative* equals one if the fund is using one of the alternative pricing mechanisms. In columns (1) to (5), *Stress* equals one if monthly *VIX* is above the 75th percentile of the sample. Column (1)-(4) introduces fixed effects of *Region of Sale*, *Domicile*, *Investment Objective*, *Investment Area*. Column (5) includes front-end and rear-end load charges. Columns (6) to (8), we use alternative definitions of market stress. *Stress is* defined according to the 75th percentile of TED spread, LIBOR, and Merrill Lynch's MOVE index, respectively. In column (9), we use the 90th percentile cut-off. Regressions use the matched sample including the control variables of lagged *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. Appendix A lists the detailed definitions and calculations of all variables in the regression. The unit of observation is fund-month. We cluster standard errors by fund and month. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES						TED	Libor	MOVE	P90 VIX
Alternative	-0.2480	-0.1044	-0.5181	-0.8621*	-0.5013	-0.6912	-0.6779	-0.7053	-0.6494
	(0.5619)	(0.6332)	(0.5482)	(0.5157)	(0.5298)	(0.5189)	(0.5113)	(0.5770)	(0.5529)
Alternative x Stress	1.1808**	1.3295**	1.1951**	1.2982**	1.4562***	1.7446***	1.9577***	1.2229*	1.6387**
	(0.5446)	(0.5744)	(0.5319)	(0.5489)	(0.5652)	(0.6415)	(0.7220)	(0.6540)	(0.7516)
Stress	-1.2712***	-1.3592***	-1.2335***	-1.3075***	-1.4066***	-1.0096**	-1.0631*	-1.0970**	-1.1284*
	(0.3809)	(0.3795)	(0.3565)	(0.3884)	(0.3786)	(0.5134)	(0.5629)	(0.4866)	(0.5832)
Front load					0.1267				
					(0.0910)				
Rear load					0.9808				
					(0.6451)				
Observations	9,670	9,670	9,510	9,670	9,329	9,670	9,670	9,670	9,670
R-squared	0.035	0.030	0.028	0.040	0.029	0.026	0.026	0.025	0.026
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region of Sale FE	Y								
Domicile FE		Y							
Loads					Y				
Global Category FE				Y					
Investment Area FE			Y						

Table IA.3: Summary Information on Switching Funds

Panel A shows the frequency table of switch dates funds which switch from being a traditionally priced fund to a fund with an alternative pricing rule. Panel B reports the differences in fund characteristics between switchers and their matched pairs during the event period from -24 months before to 24 months after the switch. Matching is performed on the last (monthly) observation before the switch occurs. We describe the matching algorithm in the text. *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. Columns (1) to (7) show results for *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, *Inst*, and *N of Inv*, respectively. Variable definitions are in Appendix A.). * **, *** indicate 10%, 5%, and 1% level of significance, respectively.

Panel A. Dates of Switch

Switch Date	Freq.	Percent
2006-11	8	23.53
2007-10	3	8.82
2007-12	5	14.71
2010-11	2	5.88
2011-01	1	2.94
2011-03	2	5.88
2012-04	3	8.82
2012-05	6	17.65
2015-02	3	8.82
2016-01	1	2.94
Total	34	100.00

Panel B. Fund Characteristics during the Event Period

VARIABLES	(1) Alpha	(2) Size	(3) Age	(4) Expense	(5) Inst	(6) Illiquidity	(7) # Inv
Post	-0.0530	0.7280*	0.3698***	0.1061	-8.4894	0.0011	1.0645***
	(0.0759)	(0.4121)	(0.1133)	(0.0896)	(5.4755)	(0.0010)	(0.3967)
Treated	-0.0120	1.0215	0.2032	-0.1291	-14.3628	0.0022	0.6520
	(0.1508)	(0.6647)	(0.2412)	(0.1835)	(15.6695)	(0.0022)	(0.9748)
Post x Treated	-0.0638	-0.6143	-0.0418	-0.0856	6.2260	-0.0025	-0.6686
	(0.1463)	(0.4420)	(0.1258)	(0.0923)	(6.1336)	(0.0018)	(0.4258)
Constant	0.3595***	18.3541***	1.4856***	0.7350***	57.5929***	0.0083***	3.7339***
	(0.0760)	(0.6199)	(0.1953)	(0.1509)	(13.3108)	(0.0014)	(0.8401)
Observations	1,201	1,628	1,628	1,321	1,628	1,345	1,606
R-squared	0.009	0.059	0.085	0.041	0.023	0.010	0.026

Table IA.4: End-Investor Flows during Market Stress for Switchers and their Matched Funds: Robustness Tests

This table shows the results of the robustness tests for the analysis reported in Table 6. Event period is [-24, 24] months. Matching algorithm is described in the text. Unit of observation is investor-month. The analysis uses switchers and their matched funds. In column (1), the dependent variable is *Flow EndInv*, which is the percentage monthly change in each investor's holding (in number of shares). Column (1) is the same as column (3) of Table 6 except that we choose the control funds from the same fund family and include investor x time fixed effects. Column (2) is the same as column (3) of Table 6 except that we use *GBP Flow EndInv*, which is the GBP monthly change in each investor's holding (in thousands). *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; *Post* is an indicator variable that equals one for the period after the switch. Control variables include lagged values (previous month-end) of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. Variable definitions are available in Appendix A. We cluster standard errors by investor and month. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

VARIABLES	(1)	(2)
Stress x Treated x Post	0.3700**	20.2661**
	(0.1620)	(10.0143)
Stress x Post	-0.1614	-23.2665*
	(0.1627)	(13.5035)
Stress x Treated	-0.5964***	-11.3364
	(0.0870)	(11.0687)
Treated x Post	-0.3674***	-13.4425*
	(0.0978)	(7.2638)
Post	0.1628*	11.0915**
	(0.0952)	(4.9542)
Treated	-0.1211	-
	(0.1307)	
Stress	-	-5.3572
		(5.3542)
Alpha	-0.0758***	8.2812
	(0.0201)	(9.8101)
Size	0.2505***	-16.8371**
	(0.0391)	(7.4094)
Age	-0.7534***	-233.7087***
	(0.0803)	(57.6130)
Expense	-0.8612***	-94.3481
	(0.1518)	(60.6431)
Inst	0.0011	0.3571
	(0.0017)	(1.3463)
Illiquidity	8.1028***	535.5695
	(0.9325)	(578.2495)
Observations	272,601	402,843
R-squared	0.130	0.164

Table IA.5: Volatility of End-Investor Flows

The sample includes investors in funds that changed their pricing rules (switchers) along with investors in the control group of no-switchers. Dependent variable is the volatility of *Flow EndInv*, defined as the percentage monthly change in each investor's holding, in number of shares. *Treated* is an indicator variable that equals one for switching funds and zero for the matched sample; *Post* is an indicator variable that equals one for the period after the switch. The event period is [-24, 24] months around the pricing change. Matching algorithm is described in the text. Control variables include lagged values (previous month-end) of *Alpha*, *Size, Age, Expense*, *Illiquidity*, and *Inst*. Variable definitions are available in Appendix A. We also include investor fixed effects. We cluster standard errors by investor and month. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

VARIABLES	(1)
Treated x Post	-0.2121*
	(0.1119)
Post	0.2598**
	(0.1136)
Alpha	0.1491**
	(0.0658)
Size	-0.1124
	(0.1057)
Age	-0.8237*
	(0.4709)
Expense	-0.0645
	(0.3121)
Illiquidity	-0.1686
	(3.6408)
Inst	0.0098
	(0.0111)
Observations	15,824
R-squared	0.778
Investor FE	Y
Controls	Y

Figure 1: Daily VIX during the Sample Period
The figure shows the daily (end-of-day day) values of Chicago Board Options Exchange Volatility Index (VIX) during our sample period, which is from January 2006 to December 2016. Vertical dashed lines indicate a number of important events. *Lehman* marks the bankruptcy of Lehman Brothers on September 15 2008; *Greek bailout* marks the launch of the bailout loan to Greece on 2 May 2010; *U.S. AA+* marks the downgrade of U.S. sovereign debt by S&P on 5 August 2011; *Draghi* marks the 26 July 2012 when Mario Draghi announced that the ECB is ready to do 'whatever it takes' to preserve the Euro; *TT* marks the beginning of the bond market crisis called 'Taper Tantrum' on 22 May 2013, and *ECB QE* marks the 10 March 2016 when the ECB increased its monthly bond purchases to €80bn and started including corporate bonds.

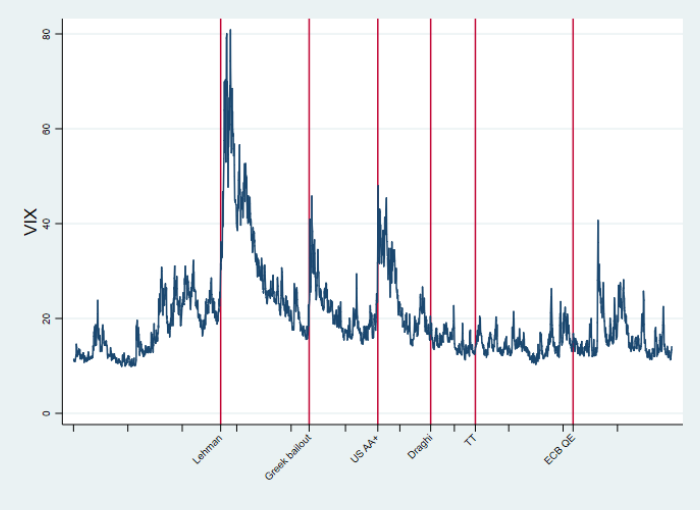


Figure 2: Dilution Adjustment Factor
A fund's dilution adjustment factor, *Adjustment Factor*, is the factor by which the fund NAV is adjusted on a given day. It equals the *absolute value* of swing factor for swing funds; for dual funds, it equals the half spread of the difference in dual funds' bid and ask prices, *0.5*(ask-bid)/mid*. Daily fund *Illiquidity* is the daily value-weighted average of bid-ask spreads of fund's assets. Vertical dashed lines indicate salient macroeconomic events described in Figure 1.

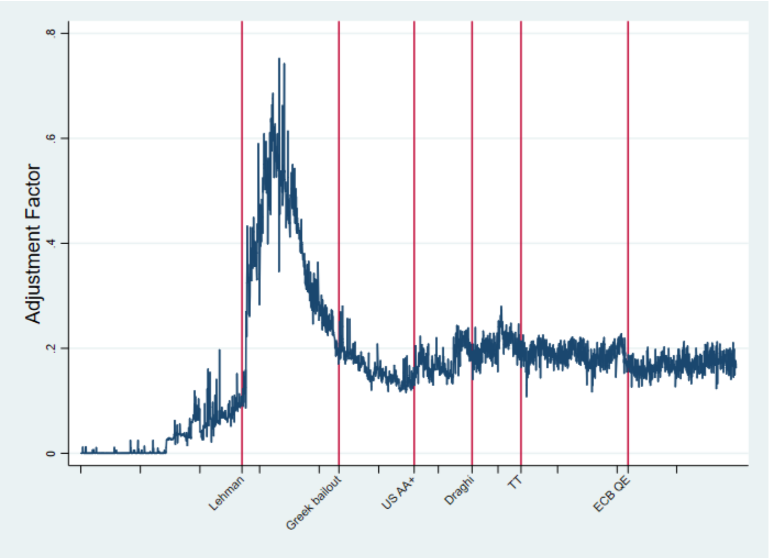


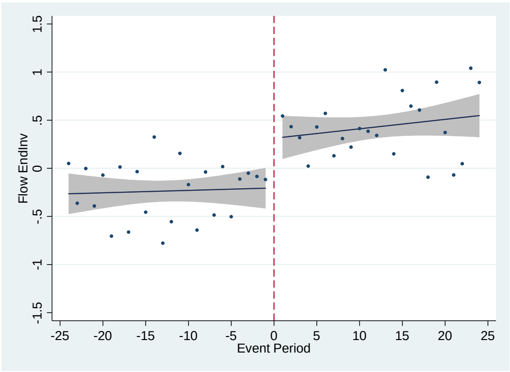
Figure 3: Fund Characteristics Before and After the Switching Event

Figures below show the mean fund characteristics for switchers and their matched funds over the event period [-24 months, 24 months]. Blue lines represent mean values for treated funds (switchers); red lines represent mean values for control funds. Figures show *Alpha*, *Size*, *Age*, *Expense*, *Illiq*, *Inst*, and *N of Inv*. Variable definitions are available in Appendix A.

Figure 4: End Investor Fund Flows Before and After the Switching Event

The graphs show the average difference in end investor flows, *Flow EndInv*, between switchers (treated) and their matched funds (control) after controlling for end-investor fixed effects. Differences are shown by event period 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. Figures include linear plots with 90% confidence intervals.

Panel A. During Stress



Panel B. Outside Stress