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Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

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Abstract

How to prevent runs on 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 periods. The stabilizing effect is internalized particularly by institutional investors and investors with longer investment horizons. The positive impact of alternative pricing rules on fund flows reverses in calm periods when costs associated with higher tracking error dominate the pricing effect.

JEL Classification: G2, G23, G10

Keywords: liquidity mismatch, fund runs, fragility, swing pricing, strategic complementarity

Dunhong Jin - dunhong.jin.dphil@said.oxford.edu
Oxford University

Marcin Kacperczyk - m.kacperczyk@imperial.ac.uk
Imperial College London Business School and CEPR

Bige Kahraman - bige.kahraman@sbs.ox.ac.uk
Saïd Business School, University of Oxford and CEPR

Felix Suntheim - felix.suntheim@gmail.com
IMF

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Swing Pricing and Fragility in Open-end Mutual Funds*

Dunhong Jin, Marcin Kacperczyk, Bige Kahraman, Felix Suntheim

August 2019

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Dunhong Jin: Said Business School, University of Oxford, email: dunhong.jin@sbs.ox.ac.uk; Marcin Kacperczyk (*corresponding author): Imperial College London and CEPR, email: m.kacperczyk@imperial.ac.uk; Bige Kahraman: Said Business School, University of Oxford and CEPR, email: bige.kahraman@sbs.ox.ac.uk; Felix Suntheim: International Monetary Fund, email: fsuntheim@imf.org. Work on this paper was carried out while Felix was an employee of the Financial Conduct Authority and the views expressed herein are those of the author and should not be attributed to the IMF, its Executive Board, or its management. We thank Valentin Haddad, Raj Iyer, Arvind Krishnamurthy, David Ng, Sophie Shive, Elu von Thadden, Russ Wermers, and seminar participants at the Chicago Financial Institutions Conference, the Finance Day Workshop at Koç University, Hebrew University Summer Finance and Accounting Conference, London Empirical Asset Pricing Workshop, Texas A&M Young Scholars Finance Consortium, University of Oregon Summer Finance Conference, European Central Bank, HEC Paris, IMF, Imperial College London, Oxford Said Business School, and University of Southern California for their useful suggestions. The views expressed in this paper are those of the authors and not the Financial Conduct Authority. All errors and omissions are our own.

1. Introduction

Runs on financial institutions pose 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, Babus, and Carletti, 2009; Gennaioli, Shleifer, and Vishny, 2013). As experienced during the financial crisis of 2008, when market conditions unexpectedly deteriorated, investors ran on open-end funds, causing fire sales and market dislocations.[1]

While understanding the origins of runs is certainly important, of equal importance is the question of how to mitigate the risk of runs. 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 runs (Zeng, 2018). In this paper, we evaluate empirically a hitherto unexplored mechanism to mitigate the risk of runs in open-end funds, swing pricing.

To better understand our empirical context, it is useful to outline the economic friction behind runs, 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 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 can produce a first-mover advantage and create incentives to run on funds, especially during

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

market-wide stress when market liquidity typically drops. The incentives to run on funds depend on the liquidity mismatch between assets invested in by funds and liabilities demanded by investors and the degree of strategic complementarities of fund investors.

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. Funds report that the goal of swing pricing is to protect the interests of non-transacting shareholders by offering them a better price and by reducing the ex-ante risk of runs. In this paper, we conduct a systematic empirical analysis to evaluate the impact of swing pricing on the dynamics of fund flows. Specifically, we ask: To what extent does swing pricing help funds to retain investor capital during periods of market stress? Are funds able to prevent dilution in fund performance and eliminate first-mover advantage? How do individual fund investors respond to fund companies' swing 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 redeem 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 rules 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 the 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 runs. The data have a number of unique features. Most relevant, we obtain detailed information on funds' pricing practices, including the daily adjustment factor. Moreover, we observe the holdings of the funds' end-investors, which allows us to look at individual-specific responses to pricing rules and address the identification concerns. Finally, 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 runs. In our study, we measure market stress using abnormal values of option-implied volatility index (VIX).

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 substantially higher (for instance, it nearly quadruples during 2008 crisis) in periods of higher portfolio illiquidity periods of market stress.

We next investigate whether swing pricing affects the level of fund flows during market stress. Our analysis is informed by the ongoing debate among market practitioners and supervisory authorities. One view is that swing pricing can mitigate runs on funds by removing the negative externalities arising from transacting investors' flows.[2] An alternative view postulates that swing pricing can increase fragility. Anticipating an increase in near-term future liquidation costs, investors could exhibit heightened sensitivity to negative shocks.[3] Thus, the impact of swing pricing on fund flows during stress periods is ultimately an empirical question.

[2] Blackrock Viewpoint Series titled *Fund structures as systemic risk mitigants* (2014).

[3] Cipriani et al. (2014) provide a theoretical model of pre-emptive runs when intermediaries impose gates or redemption fees.

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 swing pricing, lending support to the view that such rules reduce run risks. All results are robust to including a range of fixed effects (e.g., fund family, investment style, region of sale), front and back-end loads, and alternative definitions of market stress. The economic magnitude of the average effect is fairly sizable. During stress periods, an average traditional funds loses capital worth of £8.86 million every month (about 6.3% of total assets); the corresponding loss for funds with alternative pricing is only £0.2 million. However, evidence from quantile regressions shows that the magnitude of the effect substantially increases for a subset of funds with the highest flow sensitivity, supporting prior evidence on the heterogeneity of funds' run risks (Schmidt et al., 2016).

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 pin down 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 employ a triple-difference test in which we compare investor flows of switchers vs. non-switchers before and after the switching conditional on the level of stress in the aggregate market. We additionally take advantage of end-investor fixed effects, which

[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.

allows us to study the behavior of the same investor before and after the change. The staggered nature of switching dates is helpful in identifying the causal effects.

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 a fund uses swing pricing than when the fund uses traditional pricing. Moreover, funds that switch to alternative pricing structures attract less flows outside stress periods thereafter. For a limited sample of investors, we address a possible endogeneity concern due to time-varying investor-specific omitted variables by showing that the differential effect across two structures is similar when we compare the behavior of the *same* investor in two different funds, one of which switches the structure.

Next, we show results from a series of tests that provide additional insights into the economic mechanism behind the pricing rule. First, 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 supports the interpretation that swing pricing mitigates the run incentives arising from fire-sale liquidations. Second, funds with swing pricing have less volatile flows and are less likely to fully liquidate their portfolios during market stress, consistent with them being more resilient to stress events. Third, the mitigating role of a fund structure is particularly important for funds with illiquid assets and most dispersed ownership, that is, funds that are most vulnerable to run risks. Fourth, the swing pricing matters most for institutional investors, especially those who transact funds with broad retail ownership, and for investors with longer investment horizons. These results are consistent with the view that strategic complementarities, rather than mechanical rebalancing rules of unsophisticated investors, are more likely to drive our results.

To rationalize the co-existence of funds with different pricing structures, we evaluate the benefits and costs of swing pricing. One negative consequence of the traditional pricing rule is the dilution effect due to large outflows for non-transacting investors. If our findings are driven by swing pricing, we should expect these funds to be able to remove the first-mover advantage arising from fund outflows. We find that outflows indeed negatively impact *subsequent* fund performance. However, the negative impact of outflows on fund performance almost completely dissipates for funds with swing pricing. Funds appear to be able to use the swing pricing effectively enough to eliminate dilution in fund performance.

While swing pricing is beneficial for funds in that it reduces redemptions during market stress, these funds have smaller inflows in other periods. One reason is that dilution adjustment in fund prices can increase a fund's tracking error (as fund prices are adjusted to pass on the trading costs to transacting shareholders) and make the fund prices more volatile. Attracting new investors could then become more difficult. We find that funds with swing pricing indeed have higher tracking errors and investors strongly respond to funds' tracking errors in their investment decisions. Consequently, such funds attract fewer new investors, on average.

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 perspective, our paper contributes to a vast literature on stability of and runs on financial institutions. The main focus of this literature has been mostly banking sector. The proposed explanations of runs can broadly be divided into two classes: one based on coordination problems, where runs occur due to self-fulfilment of depositors' expectations concerning the behavior of other depositors, and another one based on asymmetric information, where bank runs are a result of asymmetric information among depositors regarding bank fundamentals.[5] We test the two channels empirically and find support for both.[6]

[5] Examples of models based on coordination problems among depositors include Bryant (1980); Diamond and Dybvig (1983); Postlewaite and Vives (1987); Goldstein and Pauzner (2005); Rochet and Vives (2005). Models based on asymmetric information include Chari and Jagannathan (1988); Jacklin and Bhattacharya (1988); Chen, (1999); Calomiris and Kahn (1991). A slightly different variant of the second type of model featuring uncertainty aversion is in Uhlig (2010).

[6] The example of runs based on asymmetric information in a non-banking context is Schmidt et al. (2016), who link run incidence to information production and adverse selection. They apply their framework to money market funds in which information insensitivity is particularly relevant.

Recent body of work acknowledges that non-banking institutions, such as asset management companies, can endure negative pricing effects due to flows. 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 have destabilizing effects (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 on explicitly studying runs in open-end bond funds and showing a tool to mitigate them using *disaggregated*, investor-level data.

To rationalize the existence of runs, 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 first-mover advantage. Consistent with the predictions of the model, they document that 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 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.

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.[7]

Two main alternative pricing mechanisms are employed in European jurisdictions: swing pricing and dual pricing. When a fund uses swing pricing, 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, should compensate non-transacting shareholders for the costs of trading due to capital activity by transacting shareholders. 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).

[7] Other countries allowing swing/dual pricing are Australia, Cayman Islands, and Hong Kong.
[8] For full swing funds, direction of daily swing factors lines up with the direction of daily flows 85% of the time.

Different from swing funds, which trade at a single price, dually 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 his 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, dually 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%). 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.

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 investment funds from the same financial group.

[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 some 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.

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 apply dilution levies to large transactions, and introduce redemption gates (deferring redemptions to the next valuation point), redemptions in kind (returning a slice of the portfolio instead of returning cash to redeeming shareholders), and fund suspensions (close the fund to all redemptions). Such measures are only used in exceptional circumstances, which are to be specified in the fund's prospectus. Except for the occasional use of dilution levies, funds in our sample do not seem to use these extreme liquidity management tools. 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 runs on funds. Whether alternative tools are substitute to alternative pricing is an empirical question that we examine in Section 4.8.

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.

[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.
[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.

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. 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.

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 corporate bond mutual funds in 22 families that are open to new and existing investors. The sample excludes ETFs, money funds, and index funds. 22% of the funds apply traditional pricing, and the rest use alternative pricing. Within the latter group, 22% and 57% use full and partial swing pricing, respectively. The remaining 21% use dual pricing. Even though all funds in our sample fall under the FCA scrutiny, they 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.[14]

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*

[14] Lewrick and Schanz (2018) analyze funds domiciled in Luxembourg. Their data span a short period, which does not include a major stress period. More importantly, they do not observe funds' pricing rules. This omission is crucial since Luxembourg-domiciled funds are permitted, but not required, to use the alternative pricing rules.

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.[15] *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. Bid-ask prices are obtained from Thomson Reuters Datastream.[16] 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.

3.2. Descriptive Statistics

Table 1 presents the descriptive statistics for the fund characteristics in our sample. For brevity, we categorize funds into two groups: funds that use the traditional pricing rule 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

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[15] 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*.

[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.

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 that of 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 face higher run risk 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 runs on funds differently.

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] 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.

[17] These thresholds approximately correspond to 5% and 10% tails of the daily net flow distribution.

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. Because trading illiquid assets is more costly than trading liquid assets, we expect the degree of illiquidity of a fund's assets to be an important determinant of its adjustment factor. Moreover, because trading costs tend to surge during stress market conditions, we expect the adjustment factors to be particularly high 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. Furthermore, in the latter specifications, we remove day fixed effects and include *Stress (VIX* is above the 75th percentile of the sample) to capture the time-series variation. We cluster standard errors by fund and day.

[18] To assess trading costs, funds typically use 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).

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 *Illiquidity* is significantly positive, indicating that asset illiquidity is an important determinant of funds' adjustment factors. Besides *Illiquidity*, 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, thus creating a first-mover advantage and risk of runs. Chen et al. (2010) show that this mechanism can produce a first-mover advantage and create incentives to run on funds, especially during market-wide stress when market liquidity dries up. To the extent that alternative pricing protects the interests of remaining investors by passing on the trading costs to redeeming investors, run risks can be mitigated.

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

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

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 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 cancels out 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 less inflows than traditional funds in good times. In Table IA.2 of the Internet Appendix, we decompose the effect of the alternative pricing into specific sub-components (full swing, partial swing, and dual pricing). For each individual component, we observe similar patterns.

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.3 of the Internet Appendix, we provide extended robustness tests using additional 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 effects may not seem large. We note, however, a significant variation in outflows in the cross-section of funds. To show this effect directly we resort to estimating quantile regression models. We center our regressions on 25^{th}, 50^{th}, 75^{th}, 90^{th}, 95^{th}, 99^{th}, and 99.5^{th} percentiles of the fund flow distribution. We present the results in Panel B of Table 3.

Results obtained from the OLS regression are similar for each cutoff between the 50^{th} and the 99.5^{th} percentile, 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 tail of the flow distribution. For example, the effect increases *five* times when we compare the response of a fund at the 75^{th} percentile to that of a fund in the 99.5^{th} percentile. Overall, results show that the economic significance of alternative pricing rules is particularly large for funds that suffer the biggest outflows during stress times.

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 results 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 its pricing method during our sample period for reasons plausibly exogenous to fund flows. 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 4 lists the dates when the switch took place.

To assess whether the switch in pricing rule is plausibly exogenous with respect to our empirical investigations, we first examine the reasons for these changes. Anecdotal evidence

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

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 of the 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 less likely that the change in structure reflected a structural aggregate 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.

The main concern for our empirical identification is that treatment funds are ex ante different from the control funds and the pre-trends 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 around the event time. We do not observe significant differences in pre-trends or differential effects after the event for most of the characteristics.

In Panel B of Table 4, we provide a formal statistical evaluation of any 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:

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

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 4 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 supports no significant differential pre-trends between the treatment and the control group during the event window. Further, 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:

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

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 on treated funds during market stress. The coefficient, β_0, is positive and statistically significant. Moreover, in the absence of stress, the difference in flows between treated and control group, measured by the coefficient β_3, is negative. In column (2), we add the same control variables as in Section 4.2. The coefficient β_0 remains positive and statistically significant. 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 both cases, the coefficient β_3 is positive and statistically significant.

4.3.2 Evidence from 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 assume 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 begin by presenting 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 individual ownership in the overall sample is 2.3%.

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 can be large. For instance, conditional on selling, the mean and median end-investors' outflows

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[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.

are 50% and 38% (of their total positions), respectively. About 40% of sales are full-position sales. Among purchases, we observe that 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 individual investor 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 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 we obtain are qualitatively similar to those we obtained from our 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 put less money to 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

[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.

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.

Designing an appropriate counterfactual to rule out such alternative explanations is generally challenging but we can take advantage of a unique feature in our data. We can observe 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 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. We estimate the same empirical model as in column (3) and report the results in column (4).

The coefficient of the triple interaction term is positive and statistically significant at the 10% level. During market stress, investors in switching funds withdraw less money than when they withdraw from traditional funds. The somewhat smaller statistical significance arguably results from a diminished power of our test. In particular, investors in our sample do not commonly hold shares in both treated and control funds at the same time. We identify about 2,800 observations (about 1% of the sample) that correspond to investors with cross-fund holdings in a given month. Still, finding results that are qualitatively similar is reassuring.

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 runs on funds. The same investor is significantly less likely to redeem her shares during a stress period if a 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

A well-established finding in the equity mutual fund literature is that fund flows are strongly associated with funds' 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 flow-performance sensitivity for corporate bond funds and finds that the relationship for corporate bond funds is concave. Corporate bond funds' outflows appear to be more sensitive to bad performance than their inflows are to good performance. Goldstein et al. (2017) interpret this finding within the theoretical model provided by Chen et al. (2010), which predicts that the traditional pricing used by open-end funds leads to strategic complementarities among investors. The expectation that some investors may redeem their shares boosts the incentives of other investors to redeem.

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, we first examine the shape of the flow-performance relationship at the fund level and estimate:

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

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*. We include year-month fixed effects to remove the time-series variation in average fund flows. 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.

Furthermore, 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. We report the results in Panel B of Table 7.

Our results are reassuring and 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 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 affects only the sensitivity 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* effect on the downside, there is unlikely to be a *run to enter* effect 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:

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

We present the results in Table IA.3 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 its pricing method.

4.4.3 Fund Exit

A direct consequence of significant fund outflows and high flow volatility is the possibility of fund exiting the market. In this section, we test this hypothesis by looking at the fund decisions to exit the market.

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. *Merged (Liquidated)* is an indicator variable 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. Main independent variable is *Alternative*. Control variables are measured in the last month before the exit occurs. Results are 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. The main reason for the difference in results could be that fund liquidations are fund-specific decisions to implement relative to mergers which require finding a proper suitor for the fund. Overall, our results indicate that alternative funds are less likely to liquidate their portfolios, possibly because they are less subject to market pressure due to fund outflows or 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 theoretical studies.

4.5.1 The Role of Fund Characteristics

Our first set of tests considers differences between funds in terms of their exposure to run risk. We explore three hypotheses. First, the sensitivity of funds to runs 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, run risk 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 capture 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 only 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 using the Herfindahl–Hirschman Index. 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's 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 to run risk. From the theory standpoint, runs can result from asymmetric information about fundamentals or lack of coordination among investors. In this section, we test the two channels using unique data on individual investor types. Specifically, we link asymmetric information to investor sophistication and coordination failure to investment horizons of investors. Empirically, institutional investors are more likely to be sophisticated (e.g., Kacperczyk and Schnabl, 2013, and Schmidt et al., 2016). On the other hand, investors with longer horizons suffer more from the dilution in fund performance due to trading costs. If alternative pricing mitigates runs, then we would expect it to be most effective among 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. We present the results in Table 10.

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

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. Column (1) shows the results for treated funds. Consistent with the strategic complementarity hypothesis, we find that institutional investors in switching funds alter their behavior more in that they are more likely to stay with the funds in times of stress. The behavior of institutional investors in traditional funds, in column (2), suggests no such stabilizing force. 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 our empirical test by asking whether the type of clientele investing in the same fund as a given institutional investor matters for the flow effect. In column (3), we consider investing in funds predominantly held by retail investors, while in column (4) the dominant investor are institutions. The results from this analysis show that institutional investors largely mitigate their outflows in alternative funds when other investors in the fund are of retail type. This result suggests that institutional investors are more likely to internalize strategic complementarities of trading coming from retail investors rather than institutional investors, perhaps because retail investors are less sophisticated and more dispersed and thus have lower ability to internalize their own trading effect on flows, consistent with the intuition and results in Chen et al. (2010). In this regard, the result reconciles our finding in Table 9 that retail-oriented funds respond more to switching shock. In fact, it is not the retail investors that react more but instead 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.[23] In column (5), we present the results for

[23] 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.

the sample of treated funds, and in column (6) for 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 the investor type seems a statistically and economically stronger factor.

4.6. Do Alternative Pricing Rules Affect Fund Performance?

A central tenet of runs on open-end funds is that traditional pricing induces the dilution effect of large flows for non-transacting investors. 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 alternative pricing reduces the dilution in *subsequent* fund performance.

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 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's return and 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.

4.7. The Costs of Alternative Pricing

Our analysis shows that funds with alternative pricing tend to mitigate redemption risk during stress periods. This result may suggest that funds with such pricing structure should be preferred over those with traditional pricing. Yet, we observe that the market features both types of funds, which warrants additional examination. A closer inspection of our results reveals that funds with alternative pricing tend to receive less inflows outside the periods of market stress, which could rationalize the existence of the two pricing structures. In this section, we provide more detailed explanation behind the results.

We propose two plausible channels. First, the finding might reflect a possible concern among investors that fund managers' full discretion in setting adjustment factors may be detrimental to performance of their portfolios. Alternatively, the finding might be a consequence of an increase in funds' tracking errors. Funds with alternative pricing rules may arguably have higher tracking errors as these funds move their prices in response to flows which may not necessarily correspond to changes in underlying asset valuations. In our tests, we focus on the tracking error channel. Notably, while the tracking error force operates at all times, its relative detriment to investors is higher in good market conditions when the run-mitigating benefits of alternative pricing are relatively smaller. Hence, the overall effect on fund flows that we observe in the data could plausibly vary over the market conditions.

We define *Tracking Error* as the R-squared obtained from the rolling 12-month factor model regressions of fund returns on global bond market and global stock market excess returns. We multiply this value by *-1* so that a higher value indicates higher tracking error. Subsequently, we estimate the regression model with *Tracking Error* as the dependent variable and *Alternative* as the main independent variable. We also include the same set of controls as before. We present the results in column (1) of Table 12.

Consistent with our hypothesis, we find a positive and statistically significant coefficient of *Alternative*, which means that funds with alternative pricing generate higher tracking errors. The relevant question is whether the higher error inhibits the level of flows these funds receive. In column (2), we provide a benchmark specification of fund flows conditional on the pricing structure. The coefficient of *Alternative* is negative but borderline insignificant. In column (3), we additionally include *Tracking Error* as an explanatory variable. The results indicate that tracking error is in fact an important determinant of fund flows; the coefficient of *Tracking Error* is negative and statistically highly significant. At the same time, once we include *Tracking Error* in the regression, the coefficient of *Alternative* becomes nearly zero, suggesting that an important part of its negative effect on flows is captured by differences in tracking error.

As a final test, we evaluate whether the negative effect of tracking error diminishes the growth of investor base in funds with alternative pricing in good market conditions, which is when the effect of tracking error is particularly costly. To this end, we define *New investor*, which is the number of new investors entering a fund in a given month divided by the fund's total number of investors as of previous month-end. We present the results from estimating the regression of *New investor* on *Alternative*. Column (4) shows that funds with alternative pricing are in fact able to attract significantly fewer new investors outside periods of high market stress.

4.8 Do Fund Companies Internalize their Investors' Decisions?

Given that a fund's pricing structure is a way to alleviate possible fund runs, and the alternative pricing rules carry potential costs, the question is whether fund companies use additional means to protect themselves against runs or whether they 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 13. 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 on are consistent with those of Chen et al (2010) who argue that loads cannot eliminate first-mover advantage and therefore cannot mitigate run risks 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 first-move advantage pose a significant threat of runs on such companies. Mitigating the possibility of such runs seems 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 address 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.

Although the results indicate that swing pricing may be a useful financial stability tool, our analysis also documents an important cost associated with such rules: funds with alternative pricing rules have difficulty attracting new investor capital outside the crisis periods, largely because their portfolios exhibit greater tracking errors. The clear dominance of alternative pricing structure is therefore difficult to establish. Future research can aim to 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. However, such concerns may be muted 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.

References

Alexander, G. J., Cici, G., and Gibson, S. (2006). Does motivation matter when assessing trade performance? An analysis of mutual funds. Review of Financial Studies 20(1), 125-150.

Allen, F., Babus, A., and Carletti, E. (2009). Financial crises: theory and evidence. Annual Review of Financial Economics 1, 97–116.

Ben-David, I., Franzoni, F., and Moussawi, R. (2011). Hedge fund stock trading in the financial crisis of 2007–2009. Review of Financial Studies 25(1), 1-54.

Biais, B. and Declerck, F. (2007). Liquidity, competition, and price discovery in the European corporate bond market (No. 475). Institut d'Économie Industrielle (IDEI), Toulouse.

Bryant, J. (1980). Model of reserves, bank runs, and deposit insurance. Journal of Banking and Finance 4, 335-344.

Busse J., Chordia T., Jiang L., and Tang, Y. (2017). Mutual fund trading costs and diseconomies of scale. Working Paper. Research Collection Lee Kong Chian School of Business.

Calomiris, C. and Kahn, C. (1991), The role of demandable debt in structuring optimal banking arrangements. American Economic Review 81, 497 -513.

Capponi A., Glasserman P., and Weber, M. (2018). Swing pricing for mutual funds: breaking the feedback loop between fire sales and fund runs. Working Paper, Columbia University.

Carhart, M. M. (1997). On persistence in mutual fund performance. Journal of Finance 52, 57-82.

Chari, V. V. and Jagannathan, R. (1988). Banking panics, information, and rational expectations equilibrium. Journal of Finance 43, 749-763.

Chen, Y. (1999). Banking panics: the role of the first-come, first-served rule and information externalities. Journal of Political Economy 107, 946-968.

Chen, Q., Goldstein, I., and Jiang, W. (2010). Payoff complementarities and financial fragility: evidence from mutual fund outflows. Journal of Financial Economics 97(2), 239-262.

Chen, J., Hong, H., Huang, M., and Kubik, J. D. (2004). Does fund size erode mutual fund performance? The role of liquidity and organization. American Economic Review 94(5), 1276-1302.

Chernenko, S. and Sunderam, A. (2016). Liquidity transformation in asset management: evidence from the cash holdings of mutual funds (No. w22391). National Bureau of Economic Research.

Chernenko, S. and Sunderam, A. (2018). Do fire sales create externalities? Journal of Financial Economics, forthcoming.

Chevalier, J. and Ellison, G. (1999). Career concerns of mutual fund managers. Quarterly Journal of Economics 114(2), 389-432.

Choi, J. and Shin, S. S. (2018). Liquidity sensitive trading and fire sales by corporate bond mutual funds. Working Paper, University of Illinois.

Christoffersen, S., Keim, D., Musto, D., and Rzeznik, A. (2018). Valuable information and costly liquidity: Evidence from individual mutual fund trades. Working Paper, University of Toronto.

Cipriani, M., Martin, A., McCabe P., and Parigi, B. (2014). Gates, fees, and preemptive runs. Federal Reserve Bank of New York, Staff Report No. 670.

Coval, J. and Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86(2), 479-512.

Diamond, D. W. and Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. Journal of Political Economy 91 (3), 401–419.

Dick-Nielsen, J., Feldhütter, P., and Lando, D. (2012). Corporate bond liquidity before and after the onset of the subprime crisis. Journal of Financial Economics 103(3), 471-492.

Edelen, R. M. (1999). Investor flows and the assessed performance of open-end mutual funds. Journal of Financial Economics 53(3), 439-466.

Feroli, M., Kashyap, A., Schoenholtz, K., and Shin, H. (2014). Market tantrums and monetary policy. Working Paper, University of Chicago.

Gennaioli, N., Shleifer A., and Vishny, R. W. (2013). A model of shadow banking. Journal of Finance 68 (4), 1331–1363.

Goldstein, I., Jiang, H., and Ng, D. T. (2017). Investor flows and fragility in corporate bond funds. Journal of Financial Economics 126(3), 592-613.

Goldstein, I. and Pauzner, A. (2005). Demand deposit contracts and the probability of bank runs. Journal of Finance 60, 1293-1328.

Iyer, R. and Puri, M. (2012). Understanding bank runs: the importance of depositor-bank relationships and networks. American Economic Review 102 (4), 1414–45.

Jacklin, C. and Bhattacharya, S. (1988). Distinguishing panics and information-based bank runs: welfare and policy implications. Journal of Political Economy 96, 568-592.

Kacperczyk, M. and Schnabl, P. (2013). How safe are money market funds? Quarterly Journal of Economics 128(3), 1073-1122.

Kacperczyk, M., Sialm, C., and Zheng, L. (2005). On the industry concentration of actively managed equity mutual funds. Journal of Finance 60, 1983-2012.

Lewrick, U. and Schanz, J. (2017). Is the price right? Swing pricing and investor redemptions. BIS Working Papers, No 664.

Loughran, T. and Ritter, J. R. (1997). The operating performance of firms conducting seasoned equity offerings. Journal of Finance 52(5), 1823-1850.

Morris, S. and Shin, H.S. (1998). Unique equilibrium in a model of self-fulfilling currency attacks. American Economic Review 88, 587–597.

Morris, S., Shim, I., and Shin, H.S. (2017). Redemption risk and cash hoarding by asset managers. Journal of Monetary Economics 89, 71-87.

Postlewaite, A. and Vives, X. (1987). Bank runs as an equilibrium phenomenon. Journal of Political Economy 95, 485-491.

Rochet, J-C. and Vives, X. (2004). Coordination failure and the lender of last resort. Journal of European Economic Association 2, 1116-1147.

Schmidt, L., Timmermann, A., and Wermers, R. (2016). Runs on money market mutual funds. American Economic Review 106, 2625-2657.

Uhlig, H. (2010). A model of a systemic bank run. Journal of Monetary Economics 57, 78-96.

Vives, X. (2014). Strategic complementarity, fragility, and regulation. Review of Financial Studies 27, 3547-3592.

Zeng, Y. (2018). A dynamic theory of mutual fund runs and liquidity management. Working Paper, University of Washington.

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 using quantiles ranging from the 25^{th} to the 99.5^{th}. 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) q25	(2) q50	(3) q75	(4) q90	(5) q95	(6) q99	(7) q99.5
Alternative x Stress	-0.2902**	0.1766**	2.0331***	5.0801***	7.8583***	7.6198***	11.6437***
	(0.1220)	(0.0761)	(0.2843)	(0.7331)	(1.3784)	(2.8641)	(4.3022)
Stress	0.0460	-0.2071***	-1.9531***	-4.6803***	-6.7904***	-7.4700***	-10.3889***
	(0.0872)	(0.0660)	(0.2516)	(0.6683)	(1.0768)	(2.0653)	(2.6709)
Alternative	0.0293	-0.1058**	-1.3017***	-3.2272***	-4.9201***	-5.4366***	-6.2156**
	(0.0657)	(0.0517)	(0.2334)	(0.5644)	(0.9338)	(1.8101)	(2.5474)
Alpha	0.1805***	0.1650***	0.5467***	0.8600***	0.3221	1.8043	4.7913***
	(0.0446)	(0.0374)	(0.1017)	(0.2251)	(0.4953)	(1.3493)	(1.8070)
Size	0.1536***	0.0847***	0.0191	-0.8382***	-1.9402***	-4.9824***	-4.9958***
	(0.0258)	(0.0158)	(0.0450)	(0.1099)	(0.1766)	(0.2724)	(0.3708)
Age	-0.5550***	-0.2548***	-0.6920***	-1.4509***	-2.2994***	-3.6133***	-3.5406***
	(0.0336)	(0.0331)	(0.0862)	(0.2290)	(0.4492)	(0.6806)	(1.0434)
Expense	0.0869	0.0716	0.9409***	2.5723***	2.5669***	0.5738	-2.8741
	(0.0566)	(0.0543)	(0.1677)	(0.3922)	(0.7234)	(1.5059)	(2.1769)
Illiquidity	7.9140**	5.2756**	7.4657	-21.4796	-44.6820	29.1972	-2.0181
	(3.6732)	(2.2371)	(8.0395)	(16.4298)	(39.5059)	(81.9912)	(95.5381)
Inst	-0.0021***	-0.0026***	-0.0097***	-0.0174***	-0.0306***	-0.0748***	-0.0897***
	(0.0006)	(0.0004)	(0.0014)	(0.0038)	(0.0075)	(0.0192)	(0.0267)
Observations	9,670	9,670	9,670	9,670	9,670	9,670	9,670

Table 4: 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 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. Column (4) is the same as column (3) except that we choose the control funds from the same fund family. *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	(4) Matched sample
Stress x Treated x Post			0.6341***	0.2491*
			(0.2230)	(0.1353)
Stress x Post	0.2596*	-0.3205	-0.3869**	0.0138
	(0.1346)	(0.2163)	(0.1817)	(0.6802)
Stress x Treated			-0.3941**	-0.7095**
			(0.1929)	(0.3333)
Treated x Post			-0.6698***	-0.4729**
			(0.1597)	(0.2275)
Post	-0.2127*	0.5194***	0.5219***	0.2697
	(0.1106)	(0.1376)	(0.1303)	(0.2190)
Treated				-0.0361
				(0.2425)
Stress	-0.1581**	-0.1020	-0.2525	0.5766*
	(0.0736)	(0.2131)	(0.1789)	(0.3205)
Alpha	0.2757***	0.4374**	0.3281***	-0.0712
	(0.1040)	(0.1704)	(0.0856)	(0.1051)
Size	-0.5059**	-0.7041***	-0.6739***	0.2742***
	(0.1919)	(0.1294)	(0.1157)	(0.0632)
Age	-1.4022*	-1.6378***	-1.7709***	-0.8070***
	(0.7129)	(0.4361)	(0.3480)	(0.1218)
Expense	-1.8653***	-1.1982	-1.6870***	-0.9307***
	(0.6098)	(1.3946)	(0.5755)	(0.2614)
Illiquidity	-3.6082	72.1860***	-3.2257	0.0007
	(8.6290)	(25.3514)	(8.0409)	(0.0028)
Inst	-0.0232	-0.0137	-0.0199**	7.5632
	(0.0139)	(0.0121)	(0.0087)	(10.2481)
Observations	251,718	132,675	384,393	272,770
R-squared	0.250	0.363	0.338	0.108
Investor FE	Y	Y	Y	Y
Controls	Y	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.

	(1)	(2)	(3)
			Matched Sample
VARIABLES	Fund Flow	Fund Flow	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 $\beta1_{t\rightarrow t-11}\ x\ Bond\ market\ return_{t+1}$ and $\beta2_{t\rightarrow t-11}\ x\ Stock\ market\ return_{t+1}$. *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: Tracking Error and New Investors

In column (1) and (2), the dependent variable is *Tracking Error* defined as *-1* times the R-squared obtained from the rolling 12-month one-factor regression; in column (3), the dependent variable is *Flow* defined as the net monthly capital flows into a fund divided by the fund's total net assets.; in column (4), the dependent variable is *New Investors* defined as the number of a fund's new investors divided by the fund's total number of investors in each month. Columns (1) to (3) use the full sample; column (4) uses periods outside stress. Control variables include lagged (previous month-end) values of *Alpha*, *Size*, *Age*, *Expense*, *Inst*, and *Illiquidity*. Definitions of variables are in Appendix A. We cluster standard errors by fund and month. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	Tracking Error	Fund Flow	Fund Flow	New Investors
Alternative	0.0989***	-0.3721	-0.0318	-0.8640**
	(0.0306)	(0.5098)	(0.5122)	(0.4247)
Tracking Error			-3.2157**	
			(1.4418)	
Alpha	0.0153	0.6748**	0.7278**	0.4183**
	(0.0109)	(0.3133)	(0.3213)	(0.2084)
Size	-0.0038*	0.3214**	0.3085*	0.1150
	(0.0020)	(0.1638)	(0.1624)	(0.0829)
Age	-0.0037	-1.2900***	-1.3029***	-1.5679***
	(0.0085)	(0.2791)	(0.2777)	(0.2288)
Expense	-0.0448*	0.5208	0.4037	0.5554
	(0.0231)	(0.4461)	(0.4607)	(0.3911)
Inst	-0.0007***	-0.0135***	-0.0155***	-0.0036
	(0.0002)	(0.0041)	(0.0043)	(0.0045)
Illiquidity	4.0906***	-12.0907	0.9509	40.1989
	(1.0807)	(27.9568)	(28.6336)	(37.2428)
Observations	10,604	10,125	10,125	7,259
R-squared	0.257	0.045	0.047	0.087
Controls	Y	Y	Y	Y
Month-Year FE	Y	Y	Y	Y

Table 13: 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: 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 75th percentile of the sample. Columns (1) to (3) compare traditionally priced funds to full swing, partial swing, and dual priced funds, respectively. Column (4) uses the full sample; column (5) reports the matched sample results. *Full* is an indicator variable that equals one if the fund is a full swing fund; *Partial* 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 is the 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)	(5)
VARIABLES	Full Swing	Partial Swing	Dual	Full Sample	Matched Sample
Full x Stress	1.0782**			1.0782**	1.3324*
	(0.5301)			(0.5285)	(0.7819)
Partial x Stress		0.8211*		0.8211*	1.3070**
		(0.4969)		(0.4967)	(0.5507)
Dual x Stress			1.9450**	1.9450**	2.1814
			(0.9662)	(0.9633)	(1.6003)
Full	-1.1169**			-1.1169**	-0.8210
	(0.5308)			(0.5293)	(0.5649)
Partial		-0.4036		-0.4036	-0.7123
		(0.5419)		(0.5416)	(0.5724)
Dual			-1.9327**	-1.9327**	-2.4882**
			(0.8517)	(0.8489)	(1.0934)
Stress	-0.9890***	-0.9890***	-0.9890***	-0.9890***	-1.2943***
	(0.2776)	(0.2769)	(0.2778)	(0.2767)	(0.3905)
Constant	1.5715***	1.5715***	1.5715***	1.5715***	1.3470**
	(0.5075)	(0.5064)	(0.5078)	(0.5061)	(0.5443)
Observations	6,552	11,729	5,468	16,693	10,069
R-squared	0.008	0.002	0.009	0.006	0.008

Table IA.3: 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.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6) TED	(7) Libor	(8) MOVE	(9) 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.4: 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.

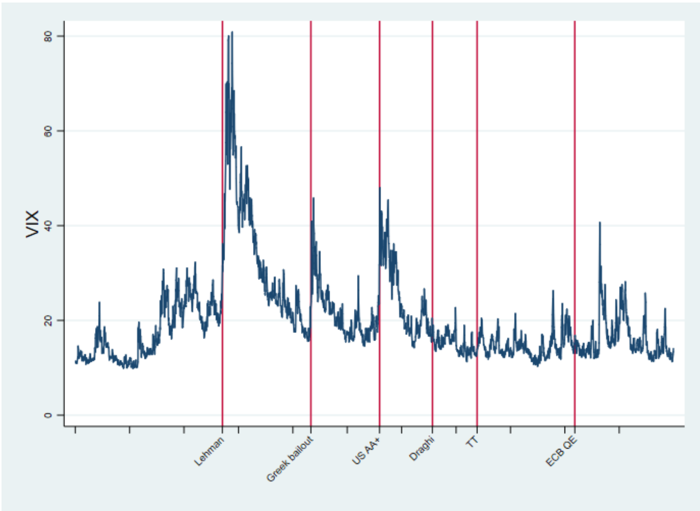


Figure 2: Dilution Adjustment Factor
A fund's dilution adjustment factor, *Adjustment Factor,* is the factor by which the fund NAV is adjusted on a given day. It equals the *absolute value* of swing factor for swing funds; for dual funds, it equals the half spread of the difference in dual funds' bid 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.

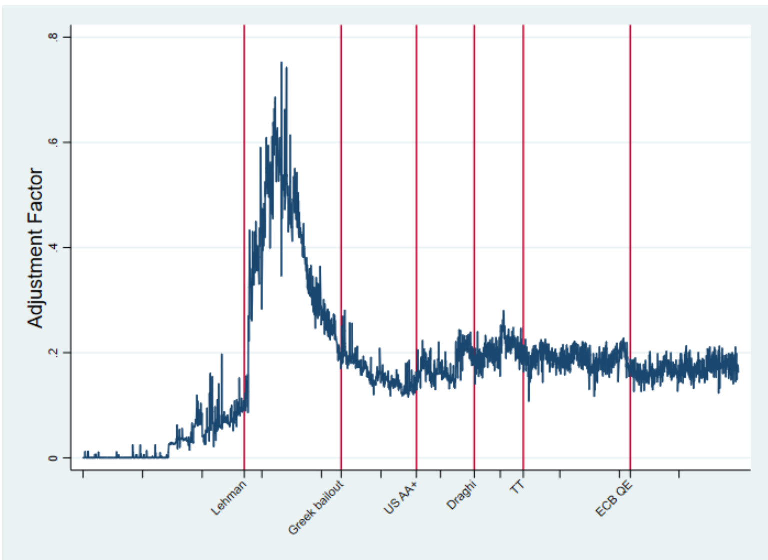


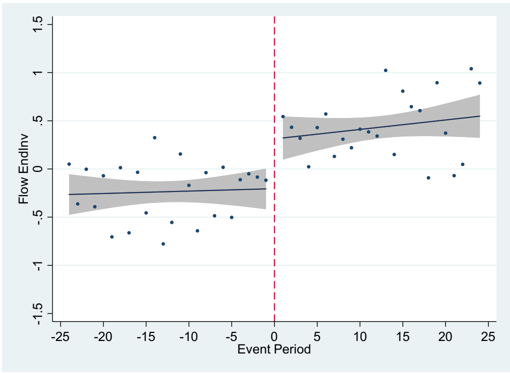
Figure 3: Fund Characteristics Before and After the Switching Event

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