Swing Pricing and Fragility in Open-end Mutual Funds*

Dunhong Jin, Marcin Kacperczyk, Bige Kahraman, Felix Suntheim

April 2019

Abstract:

In recent years, markets have observed an innovation that changed the way open-end funds are priced. Alternative pricing rules (known as *swing* or *dual pricing*) adjust funds' net asset values to pass on funds' trading costs to transacting shareholders. Using data on open-end corporate bond mutual funds, we show that alternative pricing rules eliminate the first-mover advantage arising from the traditional pricing rule and significantly reduce redemptions that are observed during stress periods. Using unique data available at the end-investor level, we confirm that alternative rules alter investors' behavior. Fund companies perceive their pricing schemes as a substitute to other means of liquidity risk management.

JEL classification: G2; G23; G010

Keywords: Liquidity Mismatch; Runs on Funds; Fragility; Pricing Rules

---

Dunhong Jin: Said Business School, University of Oxford, email: dunhong.jin@sbs.ox.ac.uk; Marcin Kacperczyk: 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 David Ng and Sophie Shive, and seminar participants at the Chicago Financial Institutions Conference, Hebrew University Summer Finance and Accounting Conference, London Empirical Asset Pricing Workshop, Texas A&M Young Scholars Finance Consortium, the Finance Day Workshop at Koç University, HEC Paris, Oxford Said Business School, European Central Bank, IMF, USC 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

The growth in corporate bond open-end mutual funds has been of interest to several market participants and supervisory authorities because the open-end structure and portfolio profiles of such funds can pose a significant risk to financial stability (IMF, 2015). As experienced during the financial crisis of 2008, when market conditions deteriorate, investors may run on funds, causing fire sales and significant market dislocations (Coval and Stafford, 2007). The effects of fire sales can be particularly severe when funds invest in relatively illiquid assets such as corporate bonds.

One of the key drivers behind the runs can be the pricing mechanism used by open-end funds (Chen, Jiang, and Goldstein, 2010; Goldstein, Jiang, and Ng, 2017). Under the traditional pricing rule, mutual fund investors have the right to transact their shares at the daily-close net asset values (NAV). However, 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 transaction requests. The costs of providing liquidity to transacting shareholders are therefore 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 creates incentives to run on funds. Run incentives are stronger when funds hold illiquid assets because shareholder transactions in such cases impose higher costs.

In recent years, markets have observed an innovation that changed the way open-end funds are priced. 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 the alternative pricing rules is to protect the interests of non-transacting shareholders. In this paper, we conduct an empirical analysis to systematically evaluate the impact of alternative pricing rules on the dynamics of fund flows. Specifically, we ask: To what extent are the new, alternative pricing rules effective? Do they help funds to retain investor capital during periods of high market stress? Are funds able to prevent dilution in fund performance and eliminate first-mover advantage? How do fund investors respond to fund companies' alternative pricing rules?

Regulations permitting alternative pricing rules have 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 alternative pricing rules, we obtain data on corporate bond open-end funds domiciled in various E.U. jurisdictions through the Financial Conduct Authority (FCA). The data have a number of unique features. For instance, the data provide detailed information on funds' pricing practices including the daily adjustment factor. Moreover, we observe the monthly holdings of funds' end-investors. The data cover a sample period from January 2006 to December 2016, spanning a number of high-stress episodes such as the 2008 global financial crisis, the European debt crisis, the downgrade of the U.S. government credit rating, and the Taper Tantrum.

Funds are permitted, but not required, to use alternative pricing mechanisms, and in practice, alternative pricing rules take three different forms. The first one is *full swing pricing*, whereby a fund NAV is adjusted up or down on every calculation 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 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 NAV applies to all transacting shareholders whether they are redeeming or subscribing. The third form, commonly referred to as *dual pricing* or *bid-ask pricing*, is similar to full swing pricing in that the fund NAV is adjusted on every calculation day without a requirement to cross the threshold. However, it differs in that a fund trades at two NAVs - 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).

We begin our empirical analysis by examining the determinants of the dilution adjustment factor - the factor by which a fund's NAV is adjusted on a given day. If the pricing rules are to matter for fund flows, we should expect fund companies to implement adjustments in times of low liquidity and/or market stress. This is precisely what we find. The adjustment factor is significantly higher when portfolio illiquidity is higher and during periods of stress. In fact, illiquidity of a fund's holdings appears as the most important determinant of a fund's dilution adjustment factor.

We next investigate whether alternative pricing rules affect the level of fund flows during stress periods. Our analysis is informed by an ongoing debate amongst market practitioners and regulatory bodies and the views are mixed. One view is that alternative pricing rules can mitigate runs on funds by removing the negative externalities arising from transacting investors' flows.[1] An alternative view, however, expresses concerns that alternative pricing rules can increase fragility. Anticipating an increase in near-term future liquidation costs, investors may exhibit heightened sensitivity to negative shocks.[2]

Consistent with the literature (e.g., Mitchell, Pedersen, and Pulvino, 2007; Ben-David, Franzoni, and Moussawi, 2011), we find that open-end funds with traditional pricing rules experience significant outflows during market stress. This effect, however, is almost *completely* reversed for funds that use alternative pricing rules, lending support to the view that such rules can reduce run risks. To allay possible concerns that the findings may reflect ex-ante heterogeneity among funds with different pricing structures, we match each fund in one structure to one in another structure along various fund characteristics associated with fund flows. We also use a wide array of fixed effects to account for differences in funds' investment objectives, regions of sale, investment areas, and fund family characteristics. Our findings are similar across all the tests both qualitatively and quantitatively.

A potential concern with the interpretation of the cross-sectional findings is that investors with different characteristics may self-select into different structures. If so, the effect we capture would result not from the differences in pricing structure but from the differences in investor types. To address this concern, we zoom in on the subsample of funds that switch their pricing methods from traditional to alternative during our sample period, and we examine individual (same) investors' behavior before and after the switch.

We match the sample of switchers to non-switchers along various characteristics and estimate the treatment effect at the end-investor level. Empirically, we employ a triple differences test in which we compare end-investor flows of switchers vs. non-switchers

[1] Blackrock Viewpoint Series titled *Fund structures as systemic risk mitigants* (2014).
[2] In a New York FED study, Cipriani et al. (2014) provide a theoretical model of pre-emptive runs when intermediaries impose gates or redemption fees.

before and after the switching when the aggregate market is turbulent. We additionally take advantage of end-investor fixed effects, which allows us to study the behavior of the same investor before and after the change. The results from this analysis corroborate our earlier findings. The same investor is significantly less likely to redeem his/her shares during a stress period at times when the fund uses an alternative pricing rule than at times when the fund uses the traditional rule. This analysis provides strong support for the hypothesis that alternative pricing structures moderate investors' behavior and mitigate runs on funds.

To gain insights into the underlying economic mechanism, we conduct a number of cross-sectional tests. The theoretical model of Chen et al. (2010) predicts that funds with illiquid assets and dispersed ownership are more vulnerable to run risks. We test this prediction by testing if the results are stronger for funds with higher ex-ante run risks. We find that our effects are indeed stronger for funds with illiquid assets and dispersed ownership.

Next, we analyze investors' flow-performance sensitivity, motivated by a recent finding that corporate bond funds' outflows are more sensitive to bad performance than their inflows are to good performance (Goldstein et al., 2017). Importantly, this study postulates that the concavity effect is driven by the run incentives arising from the traditional pricing rule. If swing/dual pricing is effective in mitigating run risks, then we should expect the concavity to be lessened. This is precisely what we find. While alternative pricing rules do not have a significant impact on the sensitivity of investor inflows to good performance, they significantly reduce the sensitivity of outflows to bad performance. The asymmetric nature of the response further supports the interpretation that alternative pricing rules mitigate the run incentives arising from fire-sale liquidations.

One negative consequence of the traditional pricing rule is the dilution effect of large outflows for non-transacting investors. If our findings are due to alternative pricing rules, we should expect these funds to be able to remove the first-mover advantage arising from fund outflows. Results are striking. Consistent with the literature, for our sample funds with the traditional pricing rule, outflows negatively impact subsequent fund performance. However, the negative impact of outflows on fund performance almost completely dissipates for funds with alternative pricing rules. Funds appear to be able to use the alternative pricing rules effectively enough to eliminate dilution in fund performance.

While our results indicate that alternative pricing rules are beneficial for funds in that they reduce redemptions during crisis periods, these funds seem to have somewhat smaller flows outside stress periods, indicating that there are also costs associated with alternative pricing. One reason could be that some investors fear that they might be penalized more than it is warranted by existing liquidation costs. Alternatively, costs might also arise due to an increase in funds' tracking errors. 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. These factors can then make it more difficult to attract new investors. In line with these ideas, we find that funds with alternative pricing mechanisms indeed have higher tracking errors and investors strongly consider funds' tracking errors in their investment decisions. Consequently, funds attract fewer new investors, on average.

In the final set of results, we show that funds with alternative pricing rules tend to treat this preventive tool as a substitute to other means of liquidity risk management, such as cash holdings or portfolio diversification. In particular, we find that such funds hold less cash and have slightly more concentrated portfolios compared to funds with traditional pricing.

Related Literature. Our paper contributes to the burgeoning literature on financial stability risks posed by open-end mutual funds. Several papers document significant declines in fund performance due to fund flows. Examples include Edelen (1999), Coval and Stafford (2007), Alexander, Cici, and Gibson (2007), and more recently, Feroli et al. (2014) and Christoffersen, Keim, Musto, and Rzeznik (2018). Based on this empirical finding, Chen et al. (2010) build a global game model whereby they show that the traditional pricing rule used by open-end funds can lead to runs on open-end funds because predictable declines in NAV following fund outflows generate first-mover advantages. Consistent with the predictions of the model, they document that flow-to-performance relationship is stronger for funds investing in less liquid stocks. Goldstein et al. (2017) echo the message by showing that corporate bond funds exhibit a concave flow-to-performance relationship. We contribute to this literature by showing that alternative pricing rules, which allow for dilution adjustment on fund NAV, reduce the first mover advantages arising from the traditional pricing rule and substantially reduce the outflows that are observed during crisis periods.

We also add to the recent literature on mutual fund liquidity risk management, which examines funds' cash management. Holding cash is costly due to associated opportunity costs; however, cash may also provide a buffer against redemption shocks. An earlier paper by Chordia (1996) shows, in a static model, that funds hold more cash when there is more uncertainty about redemptions. Specifically, he examines loads, which are persistent sales charges that do not vary with aggregate market conditions. Loads are economically differently than alternative pricing rules in a number of ways. Most important, loads do not eliminate the first-mover advantage because proceeds from loads are not retained in the fund; rather loads are used to compensate brokers for their services (Chen et al., 2010). Moreover, starting from mid 1990s, with the rise of new distribution channels in the mutual fund industry, the traditional broker channel has lost an important portion of its market share.

Recently, Simutin (2013) and Chernenko and Sunderam (2016) examine the determinants of cash management by equity and corporate bond mutual funds. Chernenko and Sunderam (2016) conclude that funds' cash holdings are not sufficiently large to eliminate fire sales. In his theoretical model, Zeng (2018) argues that cash management cannot prevent runs; instead, cash usage can actually exacerbate the runs on open-end funds. Our analysis adds to this strand of literature by showing that alternative pricing rules can be effective tools of liquidity risk management for open-end mutual funds and can be substitutes to other liquidity management tools.

In a recent paper, Capponi et al. (2018) show theoretically that swing pricing transfers liquidation costs from the fund to redeeming investors and, by removing the nonlinearity stemming from the first-mover advantage, it reduces these costs and prevents fund failure. Further, they show that risk management under larger fund outflows requires a larger swing factor. Our paper corroborates the theoretical results empirically and provides additional cross-sectional and time-series tests of the theory.

2. Institutional Background

Open-end mutual funds provide daily liquidity to their shareholders. Typically, mutual fund investors have the right to transact their shares at the daily-close NAV on any given day. Trading activity and other changes in portfolio holdings associated with shareholder transactions may occur over multiple business days following the transaction requests; therefore, the costs of providing liquidity to transacting shareholders are borne by non-transacting fund investors. Such costs deteriorate fund performance, thus diluting the interests of non-transacting shareholders (Edelen, 1999; Coval and Stafford, 2007; Feroli et al., 2014; Goldstein et al., 2017).

To address the potential dilution effect arising from transacting shareholders' flows, alternative pricing rules which allow open-end mutual funds to adjust funds' NAV have emerged. These pricing rules, commonly known as *swing* or *dual* pricing, are allowed in many European domiciles such as Finland, France, Ireland, Jersey, Norway, Switzerland, and the U.K. All registered open-end management investment companies domiciled in these jurisdictions are eligible to use the new pricing rules. In the U.S., the Securities and Exchange Commission (SEC) adopted rules permitting funds to use the new pricing rules in 2016 and they have become effective starting November 2018. [3]

In European jurisdictions, two main alternative pricing mechanisms are employed: swing pricing and dual pricing. When a fund uses swing pricing, NAV is moved up or down, depending on whether there is a net inflow or a net outflow: NAV swings up if a fund faces a net inflow, and swings down if a fund faces a net outflow. The size of the swing, while at the discretion of the asset manager, 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

[3] Other countries allowing swing/dual pricing are Australia, Cayman Islands, and Hong Kong.

depend on the direction of the daily fund flow or it can be set on a long-term basis based on expected flows.[4] In both types of swing pricing, there is a single NAV that applies to all transacting shareholders (whether they are redeeming or subscribing).

Different from swing funds, which trade at a single price, dual priced funds trade at two separate prices: bid and ask. They are purchased at the ask price and sold at the bid price. Depending on the net fund flows, fund managers can adjust the spread between the fund's bid and ask prices up to the bid-ask spread of the fund's underlying assets.[5] Proceeds from net inflows or net outflows are reinvested in the fund, which protects non-transacting shareholders from dilution.[6] Compared with swing funds, prices of dual priced funds are more transparent as both bid and ask prices are publicly available.

Funds are permitted, but not required, to use dilution adjustments. Although there is no regulation, several swing funds choose to cap their swing factors (often self-impose a cap of 2%). The pricing rule is typically (but not always) determined at the start of the fund, and the dilution adjustment is applied uniformly across all share classes (that is, prices swing by the same amount in each share class). If a fund uses swing or dual pricing, it must disclose this information in the fund's prospectus; however, funds are not required to report swing factors and swing threshold. Investors observe the final price.

Funds are required to ensure an equitable treatment of their investors. Most funds set up valuation and pricing committees, either as a standalone committee or as part of the funds' board, to oversee the use of dual/swing pricing. Moreover, depositary banks, which in the E.U. provide fiduciary and custodian services to investment funds authorized to trade 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

[4] For full swing funds, direction of daily swing factors lines up with the direction of daily flows 85% of the time.

[5] 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 additional charges.

[6] 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 1 April 2019, require fund managers to return box profits to the fund investors. https://www.fca.org.uk/publication/policy/ps18-08.pdf.

is, for instance, Goldman Sachs is not allowed to oversee the mutual funds offered by Goldman Sachs.

Other liquidity and dilution management tools are also available to fund managers; however, these alternative tools tend to be perceived as costly and 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).[7] 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 redemption 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 can be associated with important opportunity costs. A recent study by Zeng (2018) casts doubt on the effectiveness of cash and cash equivalents in mitigating runs on funds. Most importantly, the presence of alternative tools goes against finding significant effects due to swing/dual pricing.

3. **Data**

3.1. Sample Construction and Measures

We use data obtained through a data request sent by the FCA to major UK based asset management companies with corporate bond fund offering.[8] The FCA requested data on all corporate bond mutual funds that are domiciled in the UK or whose investment management decisions are taken from the UK. Through this data request, the FCA received data on corporate bond mutual funds (including dead funds) of 26 asset management companies.[9] For the purpose of the data request a fund is defined to be a corporate bond fund if at least 50% or more than £100m of its portfolio is invested in corporate bonds; however, the majority of

[7] For example, in the aftermath of the UK's EU referendum six daily dealing property funds were suspended (See FCA, 2017).
[8] This includes UK subsidiaries of non-UK asset management companies.
[9] 20 funds offered by four asset management companies with combined assets under management of about GBP 3.4bn (as of the end of 2016) failed to respond to the data request. This is a relatively small portion of the overall sample.

funds in our sample have bond holdings of more than 80%. The data include funds from leading U.S. and European multinational asset management companies, covering the period from January 2006 to December 2016.

The data we obtain through the FCA have unique features. First, the data include comprehensive information on funds' dilution adjustment practices. We observe fund prices, swing factors, and thresholds at a 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 (in monthly frequency). In addition, we 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 (expense ratios) and institutional class indicators.

Since pricing rules are applied uniformly across all share classes, we follow related studies in the literature (e.g., Kacperczyk, Sialm, and Zheng, 2005) and aggregate observations to the fund level. For qualitative attributes (e.g., year of origination and country of domicile), we use the observation of the oldest class. For fund size (the TNA 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).

The sample includes open-end corporate bond mutual funds that are open to new and existing investors. The sample excludes ETFs, money market funds, and index funds. In the final sample, we have 221 corporate bond mutual funds, 18% of which use the traditional pricing rule, and the rest use alternative rules. Within the latter group, 22%, and 65% use full and partial swing pricing, respectively. The remaining 13% use dual pricing. The funds in our sample are domiciled in various jurisdictions, the majority of which are in the United Kingdom, Luxembourg, and Ireland representing, respectively, 55%, 31%, and 12% of the sample.[10]

[10] 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.

We conduct our baseline analysis at the 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 fund's total net assets. Both the numerator and the denominator are measured as of time *t* to prevent a potential contamination arising from the dilution adjustment on fund price. Notably, our measure is based on direct observation of flows (as the data report funds' outstanding shares) rather than indirect measures imputed from fund size commonly used in the literature.[11]

Return is the fund's monthly raw return net of expenses. Following 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 regression model of monthly excess returns on excess aggregate bond market and aggregate stock market returns. Market indices are obtained from Barclays. *Size* is the natural logarithm of a fund's total net assets; *Age* is the natural logarithm of fund 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.[12] Biais and Declerck (2013) used these data to examine the illiquidity of the European corporate bond market. We winsorize all variables at the 1% level. We provide details on variable definitions in Appendix A.

To examine the behavior of fund flows under stress market conditions, we follow Rey (2015) and Cella et al. (2013), 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 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.

[11] 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*. We believe our measure is cleaner than the traditionally used flow measure in our empirical setting as funds adjust their prices.

[12] When available we use the Thomson Reuters Composite price which is an average price from multiple pricing sources. When missing we use instead the Thomson Reuters Pricing Service Evaluated price which is provided daily by the Fixed Income Pricing Service team at Thomson Reuters. This pricing service uses proprietary evaluation models and is used by many industry participants, e.g. for net asset value calculations. If this price is missing as well we use prices provided by iBOXX or ICMA.

3.2. Descriptive Statistics

Table 1 presents the descriptive statistics for the characteristics of funds in our sample. For brevity, we categorize funds into two groups: Funds that use the traditional pricing rule versus those with alternative pricing rules. Panel A shows the descriptive statistics for funds with alternative pricing rules; Panel B shows the descriptive statistics for funds with a traditional pricing rule.

Table 1 shows that funds which use the traditional pricing rule appear to be similar to those with alternative pricing rules in a number of ways. First, they have similar total net assets (*Size*). For instance, the average *Size* for funds with alternative pricing rules is 18.77 while average *Size* for funds that use the traditional pricing rule is 18.78. In addition, they also have similar expenses, with an average expense ratio of 0.88 for funds that use the traditional pricing rule and an average expense ratio of 0.75 for funds with alternative pricing rules. Funds with alternative pricing rules appear to be slightly older: 2.07 vs. 1.75. Overall, our sample funds appear quite similar in characteristics to the U.S. corporate bond mutual funds analyzed by Goldstein et al. (2017).

The last two columns in Table 1 report the descriptive statistics on asset illiquidity and investor type for the two groups of funds. Funds with alternative pricing rules hold more illiquid assets. On average, the value-weighted bid-ask spread of assets held by funds with alternative pricing rules is about 94 bps and it is 80 bps for funds that use the traditional pricing rule. This finding is consistent with the hypothesis that funds with more illiquid assets have higher run risks and thus are more likely to use an alternative pricing rule. Moreover, ownership by retail investors in funds with alternative pricing rules tends to be higher (77% vs 66%). Being more sentiment-driven, retail investors might be more susceptible to panic sales during market turbulence (Barrot, Kaniel, and Sraer, 2016), triggering runs on funds. Therefore, benefits of alternative pricing might be more pronounced for funds that are offered to retail clients. We further evaluate these ideas in Section 4.5.

4. Empirical Results

4.1 Dilution Adjustment Factor across Funds and Time

We start our empirical analysis by examining the time-series patterns in dilution adjustment factors and associated fund characteristics. We define *Adjustment Factor*, measured at a daily frequency, as the *absolute value* of swing factor for swing funds, equal to the half spread of the funds' bid and ask prices, *0.5*(ask-bid)/mid,* for dual funds.[13] During our sample period, *Adjustment Factor* used by full swing and dual pricing funds is approximately 33 bps. For partial swing funds, median *Adjustment Factor* is zero because swinging is invoked only when daily net flows cross a specific threshold. As reported in the Table A.1 of the Internet Appendix, the most commonly used thresholds (in absolute terms) are 1% and 3%. 90% of partial swing funds use thresholds that are less than 3%.[14] While median *Adjustment Factor* is zero for partial swing funds, when we focus on non-zero days, we see that the average dilution adjustment factor for partial funds is 57 bps during the sample period.

Figure 2 shows the time-series variation in average *Adjustment Factor* of swing and dual pricing funds during our sample period. The figure reveals a striking time-series pattern: The dilution adjustment factor substantially increases in adverse market conditions. Outside the crisis periods, average dilution adjustment factor appears relatively small, varying from 18 bps to 25 bps. However, the average adjustment 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 average dilution adjustment factor line up with the findings documented by related studies. Among others, Biais and Declerck (2013) document that, outside the crisis periods (from 2003 to 2005), effective spreads in European corporate bonds range between 12 bps and 22 bps. Moreover, Dick-Nielsen, Feldhutter, and Lando (2011) document dramatic increases in corporate bond illiquidity measures (such as price impact and bid-ask spreads) during 2008.[15]

[13] For dual funds, the adjustment factor, by construction, is the spread; therefore, it is a positive value. For swing funds, we define the adjustment factor in absolute terms for consistency.

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

[15] Funds that adopt swing or dual pricing rules are permitted to adjust their NAVs to eliminate the dilution effect from trading costs, such as price impact, bid-ask spreads, and explicit trading costs. To assess trading costs, funds typically use a measure known as "implementation shortfall", a measure first proposed by Perold (1988). Implementation shortfall is analogous to effective spread in that it takes into account costs due to price impact of trades and bid-ask spreads. Compared with implicit costs, explicit costs of trading tend to be low. Commission fees are often waived, and other explicit costs, such as stamp duty and taxes make up about 5 bps (e.g., Busse et al., 2017).

Next, we evaluate the fund characteristics that are associated with dilution adjustment factor. Since we do not observe the orders submitted and the transactions executed, estimating funds' trading costs is beyond the scope of this paper; however, we examine the role of fund characteristics that are associated with funds' adjustment factors. Since trading illiquid assets is more costly than trading liquid assets, we expect the degree of illiquidity of funds' assets to be an important determinant of a fund's dilution adjustment factor. Moreover, because trading costs tend to surge during stress market conditions, we would expect the adjustment factors to be particularly high during periods of turmoil. To test these predictions, we start by estimating 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 as of the end of the previous month. Furthermore, in 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.

We report the results in Table 2. In column (1), we present the 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' dilution 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 dilution 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. Overall, the results in Table 2 show that the illiquidity of funds' assets is the most important determinant of the adjustment factor.

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

Under the traditional pricing rule, fund investors have the right to redeem their shares at the fund's daily-close net asset value. Following substantial outflows, a fund will need to adjust its portfolio and conduct costly and unprofitable trades, which can damage subsequent fund returns. As mutual funds execute most of the resulting trades after the day of redemption, most of the costs are not reflected in the NAV paid out to redeeming investors, but rather borne by those who stay in the fund, creating a first-mover advantage, therefore run incentives. If the alternative pricing rules protect the interests of remaining investors by passing on the trading costs to redeeming investors, then first-mover advantage could be mitigated and the extent of redemptions could be reduced. An alternative view, however, expresses concerns that alternative pricing rules can exacerbate the vulnerabilities. Pre-empting an increase in near-term liquidation costs, investors may exhibit heightened sensitivity to negative shocks.

To systematically evaluate the impact of alternative pricing rules on fund flows, we estimate the following regression model:

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

where *Flow* is the monthly capital flow into fund *i* in month *t* divided by the fund's total net assets at time *t*; *Alternative* is an indicator variable which equals one if a fund is using one of the alternative pricing mechanisms; *Stress* is an indicator variable that equals one if *VIX* in month *t* is above the 75th percentile of the sample. 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, we report the results for the univariate regression specification (in column (1)) and the regression model with fund controls (in column (2)). We find that *Alternative x Stress* is significantly positive in the two specifications. The positive coefficient of *Alternative x Stress* nearly cancels out the negative coefficient of *Stress*. For instance, in column (1), the coefficient of *Alternative x Stress* is 1.04 and that of *Stress* is -0.99. These results indicate that alternative pricing rules are effective in reducing outflows in bad times. At the same time, we 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, we further decompose the effect of the alternative pricing into specific sub-components (full swing, partial swing, and dual pricing). All three individual components affect flows similar to what we observe for the aggregate. Overall, our results show that, while the alternative pricing rules are useful in helping funds retain investor capital during stress periods these rules also have some drawbacks.

Our sample in columns (1)-(2) may be unbalanced to the extent that funds with different pricing rules may have different characteristics. To sharpen the interpretation of our findings, we match each of our swing/dual funds to the sample of funds which rely on traditional pricing. In the spirit of Loughran and Ritter (1997), we find the 'nearest' corporate bond fund by 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 keep the unique observations.

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, while in column (7) style fixed effects. The findings reported across the specifications appear robust.[16] If anything, we

[16] In Table IA4 (columns 1-4), we provide additional robustness of the regression with respect to different fixed effects, such as location domicile, investment objective, investment area, or region of sale. Columns 6-8 of the table provide additional robustness of the main specification with respect to different definitions of market stress.

find that the results are both statistically and economically more significant when we use the matched sample.

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

One potential concern with the results presented in Section 4.2 is that cross-sectional differences in flows to funds with different characteristics may result from underlying differences across funds with different structures or may reflect self-selection of funds into different structures. While including various 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. Over the period 2006-2016, 34 funds from 6 asset management companies switched their pricing schemes from the traditional to alternative structures.[17] In Panel A of Table 4, we provide the list of the dates when the switch took place.

To assess that the switch in pricing rule is plausibly exogenous with respect to our empirical investigations, we first examine the reasons for these changes. Anecdotal evidence from the companies' interviews 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 the switch was purely family based. Finally, the staggered nature of the switches makes it less likely that the change in structure reflected a structural aggregate change in the market.

For our analysis, we specify a window of 48 months, with 24 months prior to and 24 months after the switch. We define an indicator variable *Post* that equals one for the period after the change and equals zero before the change. We further define an indicator variable *Treated* that equals one for all funds that have changed their structure. Similarly, for each treated fund, we find a control fund using the same matching algorithm as before. The funds in a control group are specified by the value of *Treated* being equal to zero.

In Figure 3, we present the time-series dynamics of average values for various fund characteristics around the event time, namely [-24, 24]. We do not observe significant

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

difference in pre-trends or differential effects of the post event for most of the characteristics. The exception is fund size for which funds in the control sample seem to exhibit some pre-trend.

In Panel B of Table 4, we provide statistical verification that the events themselves do not induce important changes in fund characteristics for treated funds relative to control funds. To this end, we estimate a difference-in-differences regression model using key fund characteristics as dependent variables. Specifically, we estimate:

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

Columns (1) to (7) of Panel B in Table 4 show results for *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, *Inst*, and *N of Inv*, respectively. Across all columns, we find that both coefficients β_2 and β_0 are statistically insignificant for all characteristics. The exception is the coefficient of β_0 for *Size.* These results suggest that the switch itself, on average, does not induce important differential effects in fund characteristics.

Next, we evaluate the impact of changes in a fund structure on fund flows conditional on the level of stress in the market, similar to our specification in (2). Specifically, we estimate the following regression model:

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

Our coefficient of interest is β_0. We present the results in Table 5. In column (1), we report the results for the specification that does not include any controls or fixed effects. We find a strong positive and statistically significant effect of treatment on flows during market stress. Moreover, as before, we find that β_3, which measures the difference in flows between treated and control group in the absence of stress, is negative. In column (2), we add the control variables as in Section 4.2. The main coefficient, β_0, remains positive and statistically significant. In column (3), we additionally 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 of the triple interaction term is positive and statistically significant.

Even though our empirical identification based on switchers helps to trace down the importance of pricing schemes for fund flows, one remaining concern is related to investor heterogeneity. In particular, our underlying assumption is that investor base remains similar following the treatment and any differences reflect the change due to pricing rule only. However, it is quite possible that the data before and after the treatment may aggregate different pools of investors with different preferences. To address this possibility, we exploit a unique feature of our data, which is that we can observe fund investor decisions at the individual level. Specifically, we can track the response of *a given* investor (during a stress period) both before and after the change in a fund's pricing rule.

Therefore, we re-estimate the regression model in (4) at the investor level. We now use the dependent variable, *Flow EndInv*, which is percentage monthly change in an investor's holding defined in number of shares. In this specification, we include investor fixed effects, which allows us to control for individual specific differences and measure the differential effects due to pricing change (specifically, from traditional to alternative). 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).[18]

The results indicate that the pool of investors in funds that switched their pricing rules react less to stressed market conditions in terms of their withdrawals. On the other hand, the control group does not seem to react significantly in the post period. If anything, the effect is slightly negative, though insignificant. In column (3), we combine the two groups together within one regression model using a triple-differences model. The results we obtain are qualitatively similar to those we obtained from our fund-level estimation. Investors in alternative structure take out less of their money than investors in traditional funds during

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

periods of high market stress. In contrast, they seem to put less money to alternative funds outside stress.

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' investment 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 an alternative pricing rule than if the fund uses a traditional rule. This is a useful finding both for identification purposes as well as understanding the broader market implications of the regulation which allows but does not require funds to use an alternative pricing rule. With such regulation, investors with different liquidation tendencies may self-select into different types of funds, therefore the regulation may primarily affect the distribution of redeeming investors into different types of funds while not necessarily reducing the total amount of redemptions in the entire market. Contrary to this, the analysis of this section shows that alternative pricing rules change investors' redemption behavior.

4.4. Investment Stability and Alternative Pricing

Our results so far suggest that open-end funds with alternative structures enjoy greater flow stability, especially during market stress. In this section, we provide additional evidence to further buttress this finding. First, we look at investors' flow-performance sensitivity. Second, we look at the volatility of individual investors' flows.

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 mutual funds and finds that contrary to convexity results found in equity funds, corporate bond funds exhibit a concave shape. Corporate bond funds' outflows appear to be more sensitive to bad performance than their inflows are sensitive 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 rule used by open-end funds leads to a first-mover advantage and thus strategic complementarities amongst shareholders. The expectation that some investors may redeem their shares boosts the incentives of other investors to redeem.

If alternative pricing rules effectively remove the first-mover advantage arising from the traditional pricing practice, we would expect the concavity to be lessened for swing/dual funds. In this section, we test this hypothesis. Although our main analysis focuses on examining the impact of alternative pricing rules on fund flows during market stress, the analysis on flow-performance sensitivity complements the time-series analysis by exploiting the variation in performance in the cross-section of funds.

To assess the impact of dual/swing pricing on the sensitivity of a fund's flows to its past performance, we first examine the shape of the flow-performance relationship at the fund level and estimate the following regression model using the full sample of funds:

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

where *Flow* is the net monthly capital flow into a fund *i* in month *t+1*; *Alpha* is the average monthly fund alpha in the past 12 months; *NegAlpha* equals *Alpha* if it is below zero and it is set to zero, otherwise; *Alternative* is an indicator variable equal to one if the fund is using one of the alternative pricing rules. Control variables include lagged *Size, Age, Expense, Illiquidity*, and *Inst,* all measured at time *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 the differences in average flow-performance sensitivity. In column (2), to evaluate any potential concavity, we add *NegAlpha* and the interaction term with *Alternative*. Consistent with Goldstein et al. (2017), we find that flows of corporate bond funds are significantly positively related to funds' past performance and that this relationship is more pronounced for funds with poor performance, signifying concavity. Most importantly, the results show that concavity is significantly reduced for funds using alternative pricing. In column (2), estimated coefficients for *NegAlpha* and *NegAlpha x Alternative* are 5.8227 versus -4.0730, and both are statistically significantly at 1%. While sensitivity to negative performance is significantly lower for funds with alternative pricing, we do not find any significant difference in sensitivity to positive performance for funds with different pricing methods. Column (3) repeats the analysis for the matched sample and confirms the robustness of these findings.

We also estimate the flow-performance sensitivity at the end-investor level using the sample of switching funds and their matching pairs. Specifically, we regress *Flow EndInv* on *NegAlpha x Treated x Post* and *Alpha x Treated x Post* along with all the lower 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 differences. 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*. Specifically, our results show that, in a switching fund, the same investor is significantly less likely to redeem his/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 - e.g., in column (3), the coefficient of *NegAlpha x Treated x Post* is -4.5641, significant at 5%.

These results suggest that dual/swing pricing affects only the sensitivity to poor performance. The asymmetry of the effects supports the interpretation that the new pricing methods mitigate the run incentives arising from the traditional pricing practice. 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; Pollet and Wilson, 2008). As we show in

Section 4.6, in the absence of dilution adjustment on fund NAV, funds with poor performance experience outflows and continue to perform poorly.

Fund Flow Volatility

Another way through which fund stability may manifest is volatility of individual investors' flows. To the extent that alternative pricing structure may reduce outflows in stress times and reduce inflows in other times, we should expect individual investors' flow volatility to be reduced. We implement the test using our experiment with switching funds.

Specifically, for each investor, in pre and post periods, we calculate *Vol of Flow EndInv* as the percentage monthly change in each investor's number of shares in the fund. Subsequently, we estimate the following regression model:

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

We present the results from the estimation in Table 8. The results indicate that, following the change in a fund's pricing, fund investors in the treatment group have less volatile holdings than investors in funds that do not undergo the pricing change.

4.5. When Do Alternative Pricing Rules Matter More?

In this section, we examine the cross-fund differences in our main results. We test whether the differences between funds using traditional and alternative pricing rules are more pronounced for funds that have higher ex-ante run risks. We expect the funds with highly illiquid assets to have a higher run risk under the traditional pricing rule because the dilution effect arising from outflows is more severe when funds hold illiquid assets. Moreover, run risk is likely to be higher for funds with many small investors (Chen et al., 2010).

To test these hypotheses, in Table 9, we add another interaction term. The interaction term in column (1) is *Illiquidity*. In Column (2), we examine the role of ownership concentration by using the Herfindahl–Hirschman Index. Specifically, *Dispersed Ownership* equals the negative of the Herfindahl–Hirschman Index of end-investors' ownership in a given fund. Therefore, a higher value of *Dispersed Ownership* indicates more dispersed ownership. Finally, in column (3), we use *Retail* (1- *Inst)*, defined as the fraction of a fund's total net assets held by retail investors. These various triple interactions allow us to evaluate the differential impact of alternative pricing rules for different types of funds. All fund characteristics are measured as of previous month-end and the tests use matched sample.

We observe important differences in results among various groups of funds. For instance, we see that the effects of alternative pricing rules are larger for funds with more illiquid assets (column 1). Similarly, the effects are stronger for funds with more dispersed ownership (column 2), and funds with more retail investors (column 3), who are arguably more susceptible to panic sales during periods of market stress. Overall, the results in this section strengthen the interpretation of our findings as being driven by run risks.

To gain further insights to the mechanism driving the results, we also examine end-investors' holding periods. Specifically, we examine whether the effect of alternative pricing rules is due to funds' having more long-term investors - funds with alternative pricing rules might be attracting more long-term investors as they provide protection to these investors during turmoil periods. To assess this hypothesis, we measure the holding periods of end-investors who made their first purchases after the first date the fund's end-investors holdings data are available. Table IA.3 presents the descriptive statistics showing the average and median end-investor holding periods across funds in our sample. In columns (1) and (2), we include new purchases until December 2014, and in columns (3) and (4), we include new purchases until 2012 (sample period ends in December 2016). The results show that funds with alternative pricing rules indeed attract more long-term investors; however, the differences do not seem particularly large. For instance, the average difference in column (1) is 26 vs. 33 months, and in column (3), it is 31 vs. 36 months.

4.6. Do Alternative Pricing Rules Affect Fund Performance?

One negative consequence of the traditional open-end pricing rule is 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; Greene and Hodges, 2002; Johnson, 2004; 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 adjustment factors reduce the dilution in fund performance due to large investor flows: outflows and inflows. If alternative pricing is effectively used by funds to reduce dilution, we should expect the negative impact of investor flows on subsequent fund performance to dissipate. Moreover, this result should be particularly strong for funds with highly illiquid portfolios. This effect should hold true only for outflows, as outflows trigger forced liquidations. At the same time, inflows need not to be immediately put to force if they are to create undesired consequences.

To assess this hypothesis, we relate future fund performance to its flows, conditional on fund's pricing method. Specifically, we estimate the following regression model:

$$\begin{aligned} &Abnormal\ Return_{i,t+1} \\ &= \propto + \beta_0 Net\ Outflow\ (or\ Inflow)_{i,t}\ x\ Alternative_{i,t} + \beta_1 Net\ Outflow\ (or\ Inflow)_{i,t} \\ &+ \beta_2 Alternative_{i,t} + \beta_5 Controls_{i,t} + Time\ FE + \varepsilon_{i,d} \quad (8) \end{aligned}$$

where *Abnormal return* in month *t+1* is calculated as the difference between fund's return and fund's exposure to global bond market and global stock market returns. In this analysis, we calculate fund returns using unadjusted fund prices, since our focus is on the performance of fund's fundamentals. Funds' exposures to benchmarks are calculated as $\beta 1_{t \to t-11}\ x\ Bond\ market\ return_{t+1}$ and $\beta 2_{t \to t-11}\ x\ Stock\ market\ return_{t+1}$. *Net Outflow* is the net monthly outflow at *t*, which equals *Flow* if *Flow<0*, and equals zero if *Flow>=0*. *Net Inflow* is the net monthly inflow at *t*, which equals *Flow* if *Flow>0*, and equals zero if *Flow<=0.* We cluster standard errors by fund and month.

We present the results in Table 10. In column (1), we consider the full sample and the effect of large outflows on future performance. Consistent with the literature, we observe that large outflows deteriorate subsequent fund performance for our sample funds with traditional pricing rules. However, the negative impact of large outflows on fund performance is almost fully eliminated for funds with alternative pricing rules, providing strong evidence that alternative pricing rules are used effectively in passing on trading costs to transacting shareholders. 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 large inflows. The results are statistically insignificant, which corroborates our view that large inflows may be less distortionary because fund companies have flexibility to deploy their new capital to mitigate the associated costs.

4.7. Ability to Attract New Investors Outside Market Stress

In our analysis, we observe that the coefficient of *Alternative* tends to be negative throughout the analysis even though its statistical significance varies across tests. This finding suggests that funds with alternative pricing rules have less inflows outside the periods of high market stress. In this section, we examine the potential drivers of this finding.

On the one hand, this finding might be due to a possible concern amongst investors that fund managers' discretion in setting dilution levels may be detrimental to performance of their portfolios. Alternatively, it might be a reflection 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. To the extent that tracking error is a metric that investors take into account in their investment decisions, an increase in tracking error can reduce inflows.

To examine these ideas, we measure *Tracking Error* as the R-squared obtained from the rolling 12-month factor model regressions where we regress fund returns on excess fund returns on excess global bond market and global stock market returns. We multiply it by *-1* so that a higher value indicates higher tracking error. In addition, 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.

The results presented in Table 11 are quite revealing. In column (1), we estimate a cross-sectional regression model with *Tracking Error* as a dependent variable, and an indicator variable *Alternative* and various other fund characteristics. We find a significant positive coefficient of *Alternative*. In columns (2) and (3), we observe that *Tracking Error* is in fact an important determinant of fund flows; importantly, after including *Tracking Error,* the coefficient of *Alternative* becomes nearly zero, suggesting an important part of the negative effect captured by *Alternative* is in fact explained by *Tracking Error.* In column (4), we focus on periods outside crisis periods and find that funds with alternative pricing have significantly fewer new investors.

4.8 Do Fund Companies Internalize their Investors' Decisions?

Given that a fund's pricing structure is one 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. Two immediate possibilities are increased cash holdings and reduced asset concentration. While both are legitimate hedging methods, the story of cash being able to reduce run risk is less clear (see, Zeng, 2018).

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. We assess the cross-sectional relationship between pricing structure and the alternative hedging instruments by estimating the following regression model:

$$Hedging\ Instrument_{i,t+1} = \propto + \beta_0 Alternative_{i,t} + \beta_1 Controls_{i,t} + Time\ FE + \varepsilon_{i,d} \quad (9)$$

where *Hedging Instrument* is a generic name for the *Cash* and *Asset Conc.* We present the results in Table 12. We find that funds with alternative pricing rules hold less cash, on average, consistent with the hypothesis that cash and alternative pricing rule are substitutes for each other. On the other hand, the coefficient for asset concentration, though negative, is statistically insignificant. In sum, we find some evidence that funds, which already have alternative pricing rules in place, may be less inclined to use other means to protect themselves against potential runs. This may suggest that such funds consider the alternative pricing rule to be sufficient protection against runs.

5. Conclusion

In this paper, we analyze the impact of alternative pricing rules that allow for dilution adjustment of funds' net asset values. Regulations permitting these pricing rules have become effective in the U.S. only recently, in November 2018; however, these pricing rules have been used in several European jurisdictions over the past few decades. This feature allows us to study the regulatory effects for those markets and also hypothesize about potential effects on the U.S. market. Through the FCA, we obtain detailed data on corporate bond mutual funds domiciled in E.U. jurisdictions. The data include detailed information on funds' pricing practices, various fund characteristics and investor level ownership.

Our findings indicate that alternative pricing rules change open-end funds' operations in a way that enables funds to more effectively manage their liquidity risk. Specifically, alternative pricing rules help funds to retain their investor capital during periods of high market stress. This result is robust across several empirical tests, including a wide range of fixed effects and the use of granular data on end-investors' investment decisions. Although not such a significant effect, our analysis also documents a cost associated with alternative pricing rules: funds with alternative pricing rules have difficulty attracting new investor capital outside the crisis periods.

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.

Barrot, J. N., Kaniel, R., and Sraer, D. (2016). Are retail traders compensated for providing liquidity? Journal of Financial Economics 120(1), 146-168.

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.

Blackrock (2014). Fund structures as systemic risk mitigants. Viewpoint Series. https://www.blackrock.com/corporate/literature/whitepaper/viewpoint-fund-structures-as-systemic-risk-mitigants-september-2014.pdf

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.

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.

Cella, C., Ellul, A., and Giannetti, M. (2013). Investors' horizons and the amplification of market shocks. Review of Financial Studies, 26(7), 1607-1648.

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.

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.

Chordia, T. (1996). The structure of mutual fund charges. Journal of Financial Economics 41(1), 3-39.

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.

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.

Financial Conduct Authority (2017). Illiquid assets and open-ended investment funds. Discussion Paper, DP17/1

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

Foucault, T., Pagano, M., and Röell, A. (2013). Market liquidity: theory, evidence, and policy. Oxford University Press.

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.

Greene, J. T. and Hodges, C. W. (2002). The dilution impact of daily fund flows on open-end mutual funds. Journal of Financial Economics 65(1), 131-158.

Huang, J., Sialm, C., and Zhang, H. (2011). Risk shifting and mutual fund performance. Review of Financial Studies 24(8), 2575-2616.

Johnson, W. T. (2004). Predictable investment horizons and wealth transfers among mutual fund shareholders. Journal of Finance 59(5), 1979-2012.

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.

Manconi, A., Massa, M., and Yasuda, A. (2012). The role of institutional investors in propagating the crisis of 2007–2008. Journal of Financial Economics 104(3), 491-518.

Rey, H. (2015). Dilemma not trilemma: the global financial cycle and monetary policy independence (No. w21162). National Bureau of Economic Research.

Perold, A. F. (1988). The implementation shortfall: Paper versus reality. Journal of Portfolio Management 14(3), 4-9.

Pollet, J. M. and Wilson, M. (2008). How does size affect mutual fund behavior? Journal of Finance 63(6), 2941-2969.

Simutin, M. (2013). Cash holdings and mutual fund performance. Review of Finance 18(4), 1425-1464.

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* 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	Percentage 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	Funds' 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, ICMA.	
Inst	Fraction of fund's total net assets held by institutional investors	%
Dispersed Ownership	*-1* times *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. Equals to *Flow* if *Flow*>0; equals to 0 if *Flow*<=0	
Net Outflow	Net monthly outflows. Equals to *Flow* if *Flow*<0; equals 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 holdings–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	
New Investor	Number of new investors divided by the fund's total number of investors in each month	*%*

Table 1: Descriptive Statistics

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. The sample includes 221 funds, 18% of which use the traditional pricing rule, and the rest alternative rules. 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)
Constant	0.0742	0.5055	-0.1937	0.2902***	0.6182	-0.3970
	(0.0708)	(0.3613)	(0.5285)	(0.0361)	(0.5372)	(0.4962)
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*. The results in columns (1) and (2) are based on the full sample; while those in columns (3) to (7) use the matched sample. We cluster standard errors by fund and month. *, **, *** indicate 10%, 5% and 1% level of significance, respectively.

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)
Constant	1.5715***	-2.1247	-2.3609	17.2053***	-3.1279	1.7809	-1.3685
	(0.5061)	(3.2023)	(3.2054)	(4.9711)	(3.1551)	(1.9569)	(2.8865)
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

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.

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) Illiquidity	(6) Inst	(7) N of Inv
Post	-0.1051	1.0993**	0.4063***	0.0421	-0.0008	-6.1094	1.0164***
	(0.0849)	(0.4527)	(0.0911)	(0.0897)	(0.0011)	(5.0780)	(0.3916)
Treated	-0.1060	1.0749	0.1414	-0.1445	0.0003	-13.1110	0.4978
	(0.1328)	(0.6759)	(0.2179)	(0.1774)	(0.0021)	(14.7518)	(0.9662)
Post x Treated	-0.0409	-1.2342**	-0.0733	-0.0432	0.0002	-3.0875	-0.5424
	(0.1325)	(0.5744)	(0.1088)	(0.0933)	(0.0016)	(5.9807)	(0.4291)
Constant	0.4031***	18.0190***	1.4431***	0.7691***	0.0092***	57.8703***	3.7191***
	(0.0842)	(0.6345)	(0.1756)	(0.1517)	(0.0018)	(12.5188)	(0.8254)
Observations	1,466	2,125	2,125	1,432	1,601	2,125	1,652
R-squared	0.028	0.032	0.076	0.033	0.003	0.041	0.024

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)
Constant	0.9210**	-10.4228**	1.0114***	-10.2423**
	(0.3889)	(4.6904)	(0.2505)	(4.6778)
Observations	1,374	1,042	1,374	1,042
R-squared	0.060	0.124	0.276	0.194
Controls	N	Y	N	Y
Fund FE			Y	
Time FE				Y

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

This table shows the effect of alternative pricing rules on end-investor flows during periods of market stress using the sample of switchers and their matched funds. Event period is [-24, 24] months. Matching algorithm is described in the text. Unit of observation is investor-month. Dependent variable is *Flow EndInv*, which is the percentage monthly change in each investor's holding (in number of shares). Columns (1) and (2) show the results for switchers and their matching pairs, respectively; column (3) presents the matched sample results. *Treated* is an indicator variable that equals one for switching funds; *Stress* is an indicator variable that equals one if monthly *VIX* is above the 75th percentile of the sample; *Post* is an indicator variable that equals one for the period after the switch. Control variables include lagged values (previous month-end) of *Alpha*, *Size*, *Age*, *Expense*, *Illiquidity*, and *Inst*. Variable definitions are available in Appendix A. We cluster standard errors by investor and month. *, **, *** indicate 10%, 5% and 1% level of significance, respectively.

VARIABLES	(1) Switchers	(2) Control group	(3) Matched sample
Stress x Treated x Post			0.6341***
			(0.2230)
Stress x Post	0.2596*	-0.3205	-0.3869**
	(0.1346)	(0.2163)	(0.1817)
Stress x Treated			-0.3941**
			(0.1929)
Treated x Post			-0.6698***
			(0.1597)
Post	-0.2127*	0.5194***	0.5219***
	(0.1106)	(0.1376)	(0.1303)
Treated			
Stress	-0.1581**	-0.1020	-0.2525
	(0.0736)	(0.2131)	(0.1789)
Alpha	0.2757***	0.4374**	0.3281***
	(0.1040)	(0.1704)	(0.0856)
Size	-0.5059**	-0.7041***	-0.6739***
	(0.1919)	(0.1294)	(0.1157)
Age	-1.4022*	-1.6378***	-1.7709***
	(0.7129)	(0.4361)	(0.3480)
Expense	-1.8653***	-1.1982	-1.6870***
	(0.6098)	(1.3946)	(0.5755)
Illiquidity	-3.6082	72.1860***	-3.2257
	(8.6290)	(25.3514)	(8.0409)
Inst	-0.0232	-0.0137	-0.0199**
	(0.0139)	(0.0121)	(0.0087)
Constant	15.8495***	19.4701***	20.0237***
	(4.7258)	(3.0159)	(2.3946)
Observations	251,718	132,675	384,393
R-squared	0.250	0.363	0.338
Investor FE	Y	Y	Y
Controls	Y	Y	Y

Table 7: Flow-Performance Sensitivity

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

Panel A. Using Fund Flows for the Full Sample

The dependent variable is *Flow*, which is the net monthly capital flows into a fund divided by fund's total net assets. *NegAlpha* equals lagged *Alpha* if it is below zero; it is set to zero otherwise. *Alternative* is an indicator variable that equals one if the fund is using one of the alternative pricing mechanisms. Column (3) presents results for the matched sample.

	(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)
Constant	3.9221	4.5855	-1.8135
	(2.9418)	(2.9543)	(2.5941)
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.

VARIABLES	(1) Flow EndInv	(2) Flow EndInv	(3) 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)
Constant	19.3629***	19.0259***	19.3685***
	(1.3923)	(1.4124)	(1.4023)
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: 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)
Constant	5.0276**
	(2.3176)
Observations	15,824
R-squared	0.778
Investor FE	Y
Controls	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 *Dispersed Ownership,* which is -1 times 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 Dispersed Ownership		6.0387*	
		(3.5858)	
Stress x Dispersed Ownership		-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 Dispersed Ownership		-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)		
Dispersed Ownership		6.8252***	
		(2.0888)	
Retail			0.0194*
			(0.0101)
Constant	2.0252*	1.9501	-2.2166
	(1.0705)	(1.6067)	(3.2272)
Observations	9,670	8,303	9,670
Controls	Y	Y	Y
R-squared	0.031	0.027	0.026

Table 10: Fund Flows and Future Fund Performance

Dependent variable is the abnormal fund return in month *t+1*, which is calculated as the difference between fund's return (calculated using unadjusted fund prices) and fund's exposure to global bond market and global stock market returns. Fund's exposure to global bond market and global stock market returns are calculated as $\beta 1_{t \to t-11}\ x\ Bond\ market\ return_{t+1}$ and $\beta 2_{t \to t-11}\ x\ Stock\ market\ return_{t+1}$. *Net Outflow* is the net monthly outflows in *t*, which equals *Flow* if *Flow<0*, and it equals zero if *Flow>=0*. *Net Inflow* is the net monthly inflows in *t*, which equals *Flow* if *Flow>0*, and it equals to zero if *Flow<=0. Alternative* is an indicator variable that equals one if the fund is using one of the alternative pricing mechanisms. Control variables include year-month fixed effects, as well as *Size, Age, Expense, Illiquidity*, and *Inst* measured as of time *t*. Appendix A lists detailed 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)
Constant	0.7422***	-2.0315***	0.7452***	-2.0135***
	(0.2045)	(0.2010)	(0.2098)	(0.1976)
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 11: 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 (3) uses periods outside stressed market conditions. Details of 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 (previous month-end) values 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	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)
Constant	0.0699	2.2470	-1.3413	3.1706**
	(0.0431)	(3.1707)	(2.9436)	(1.5471)
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 12: Pricing Rules and Fund Portfolio Adjustments

This table shows the effect of alternative pricing rules on fund's cash holdings (column 1) and asset concentration (column 2). *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. Details of 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.

VARIABLES	(1) Cash	(2) Asset Conc
Alternative	-3.1972**	-0.0051
	(1.2866)	(0.0120)
Alpha	-0.2011	-0.0177*
	(0.5504)	(0.0092)
Size	-0.0542	-0.0009
	(0.2751)	(0.0018)
Age	-0.7095	0.0049
	(0.4824)	(0.0062)
Expense	0.9841	0.0155*
	(1.2394)	(0.0093)
Illiquidity	13.4856	-1.1019**
	(63.3771)	(0.4332)
Inst	-0.0078	0.0000
	(0.0107)	(0.0001)
Constant	14.8765*	0.0186
	(8.7370)	(0.0386)
Observations	9,694	11,111
R-squared	0.279	0.038
Controls	Y	Y
Time FE	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: End-Investors' Holding Periods

This table presents the descriptive statistics on end-investors' holding periods. *Average* columns report the average investor's holding period in each fund, and *Median* columns show the median investor's holding period. The analysis uses end-investors who first purchased their shares after the first date the fund's end-investors holdings data are available. Descriptive statistics show the cross-sectional averages across all funds in the sample. Columns (1) and (2) (2014 cutoff) use the new purchases until December 2014; columns (3) and (4) (2012 cutoff) until December 2012.

		2014 cutoff		2012 cutoff	
		Average	Median	Average	Median
Traditional	P1	2.0000	2.0000	14.0394	7.0000
	P5	16.4559	13.5000	14.0394	7.0000
	P25	23.3939	18.0000	26.9719	20.0000
	P50	27.2816	26.0000	32.4286	26.5000
	Mean	26.5251	23.7723	31.7543	30.0610
	P75	30.0763	30.0000	36.9677	44.0000
	P95	35.6157	34.0000	44.8333	51.0000
	P99	37.0760	35.0000	47.4688	51.0000
Alternative	P1	5.1126	1.0000	5.7578	1.0000
	P5	16.6364	13.0000	15.5805	12.0000
	P25	25.2869	23.0000	27.4242	23.0000
	P50	31.8182	29.0000	37.1537	31.0000
	Mean	33.0450	29.8844	36.6145	34.0405
	P75	39.7753	37.0000	44.8695	49.0000
	P95	52.7470	56.0000	56.5299	59.0000
	P99	62.8428	65.0000	65.1300	65.0000

Table IA.4: 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) excludes funds which occasionally use levies. 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)	(7)	(8)	(9)
Alternative	-0.2480	-0.1044	-0.5181	-0.8621*	-1.0936*	-0.6912	-0.6779	-0.7053	-0.6494
	(0.5619)	(0.6332)	(0.5482)	(0.5157)	(0.5920)	(0.5189)	(0.5113)	(0.5770)	(0.5529)
Alternative x Stress	1.1808**	1.3295**	1.1951**	1.2982**	1.4705**	1.7446***	1.9577***	1.2229*	1.6387**
	(0.5446)	(0.5744)	(0.5319)	(0.5489)	(0.6410)	(0.6415)	(0.7220)	(0.6540)	(0.7516)
Stress	-1.2712***	-1.3592***	-1.2335***	-1.3075***	-1.4538***	-1.0096**	-1.0631*	-1.0970**	-1.1284*
	(0.3809)	(0.3795)	(0.3565)	(0.3884)	(0.5240)	(0.5134)	(0.5629)	(0.4866)	(0.5832)
Alpha	0.4070**	0.3655*	0.4253**	0.5901***	0.2777	0.3676*	0.3457*	0.3366	0.3390
	(0.2034)	(0.2078)	(0.2015)	(0.2094)	(0.2121)	(0.2139)	(0.2075)	(0.2052)	(0.2091)
Size	0.3036*	0.3159*	0.3005*	0.2648*	0.2479	0.3196*	0.3212*	0.3184*	0.3230*
	(0.1590)	(0.1636)	(0.1715)	(0.1515)	(0.1673)	(0.1683)	(0.1686)	(0.1695)	(0.1696)
Age	-1.3313***	-1.2086***	-1.1293***	-1.0009***	-1.1790***	-1.3070***	-1.3049***	-1.3092***	-1.3047***
	(0.2779)	(0.2994)	(0.2891)	(0.2630)	(0.2900)	(0.2884)	(0.2881)	(0.2872)	(0.2875)
Expense	0.0096	0.2916	0.2198	-0.3392	0.6856	0.5866	0.5805	0.5740	0.5670
	(0.4339)	(0.4399)	(0.4441)	(0.4365)	(0.4180)	(0.4270)	(0.4280)	(0.4361)	(0.4325)
Illiq	20.7656	22.2174	29.9386	32.1082	7.2770	5.1964	8.3828	8.8242	2.8547
	(25.8153)	(25.7392)	(25.7499)	(25.4202)	(26.2589)	(24.9627)	(25.1391)	(24.7731)	(25.1502)
Inst	-0.0178***	-0.0176***	-0.0138***	-0.0143***	-0.0131***	-0.0132***	-0.0132***	-0.0128***	-0.0129***
	(0.0043)	(0.0047)	(0.0041)	(0.0040)	(0.0045)	(0.0040)	(0.0040)	(0.0040)	(0.0040)
Constant	-1.8973	-2.7726	-2.4877	-1.3685	-0.9543	-2.4808	-2.5445	-2.3853	-2.5194
	(3.0238)	(3.1667)	(3.3131)	(2.8865)	(3.2123)	(3.2085)	(3.2167)	(3.2440)	(3.2438)
Observations	9,670	9,670	9,510	9,670	9,050	9,670	9,670	9,670	9,670
R-squared	0.035	0.030	0.028	0.040	0.022	0.026	0.026	0.025	0.026
Region of Sale FE	Y								
Domicile FE		Y							
Investment Area FE			Y						
Investment Objective FE				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 to include corporate bonds.

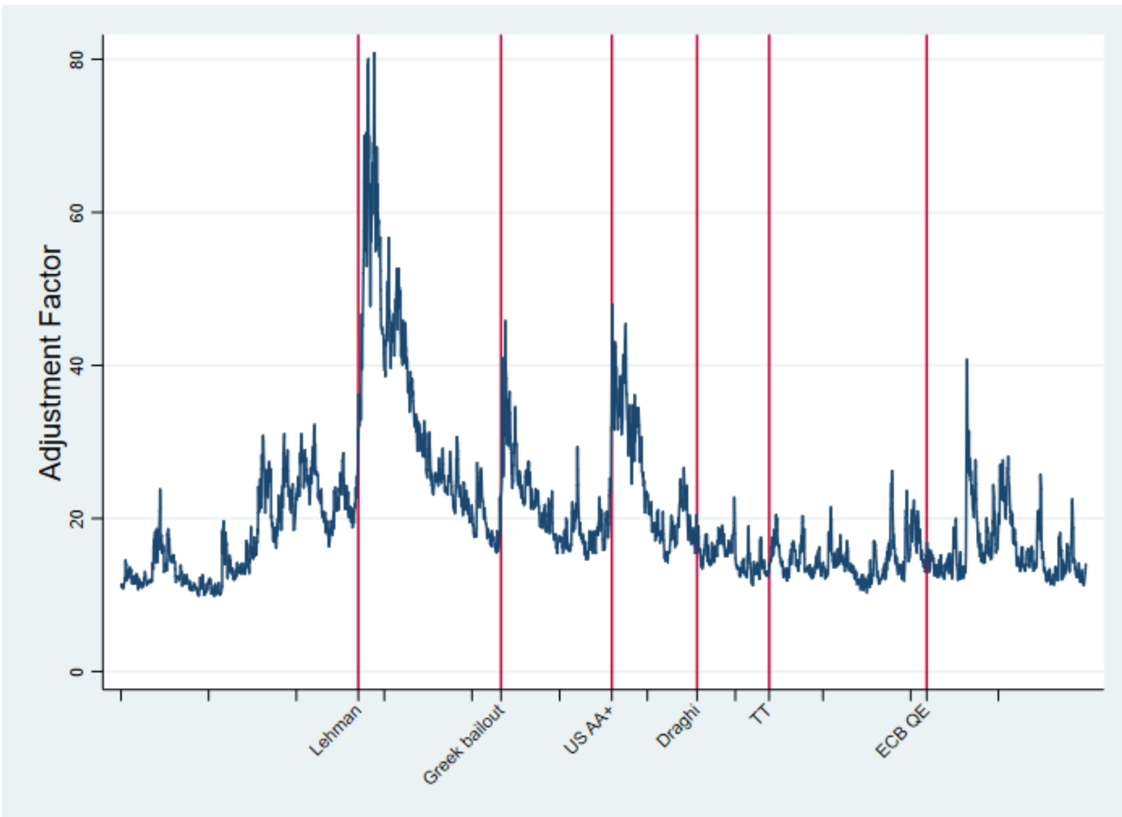


Figure 2: Dilution Adjustment Factor

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 important events described in Figure 1.

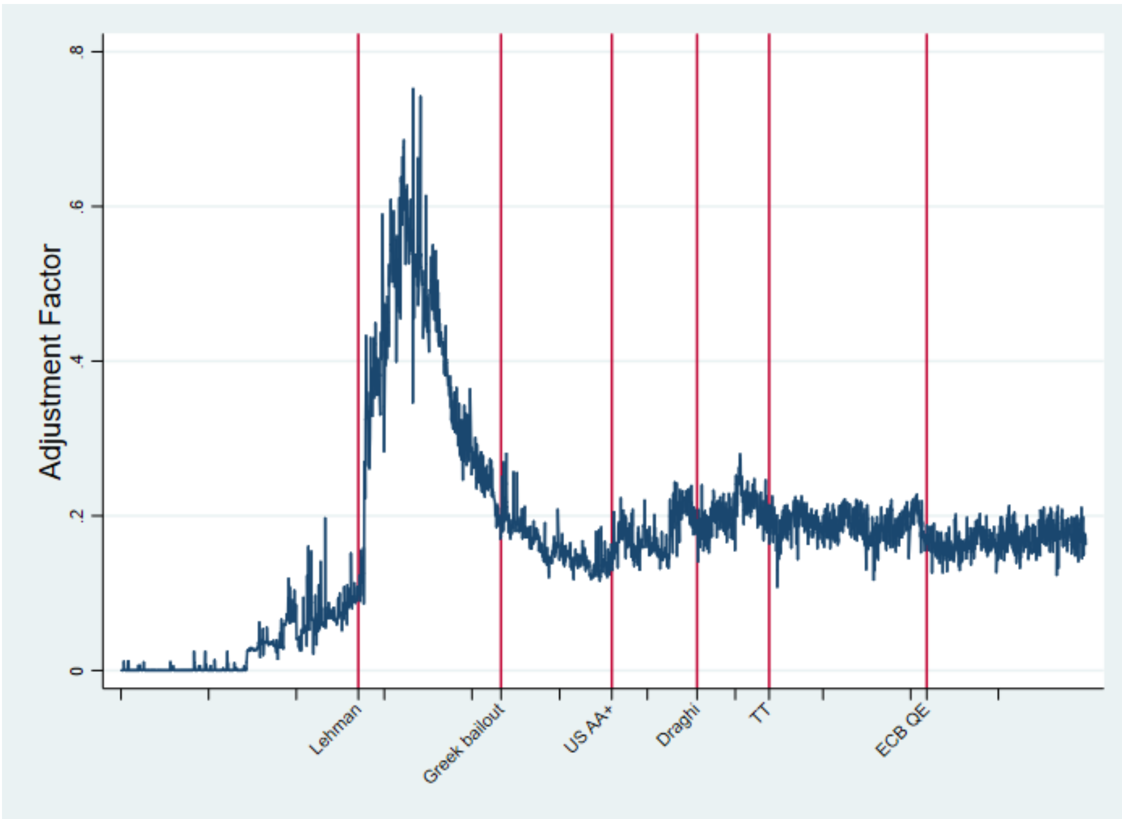


Figure 3: Fund Characteristics during the Event Period for Switchers and their Matched Funds
Figures below show the mean fund characteristics for switchers and their matched funds over the event period, which is [-24 months, 24 months]. Blue lines represent mean values for treated funds (switchers); 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.

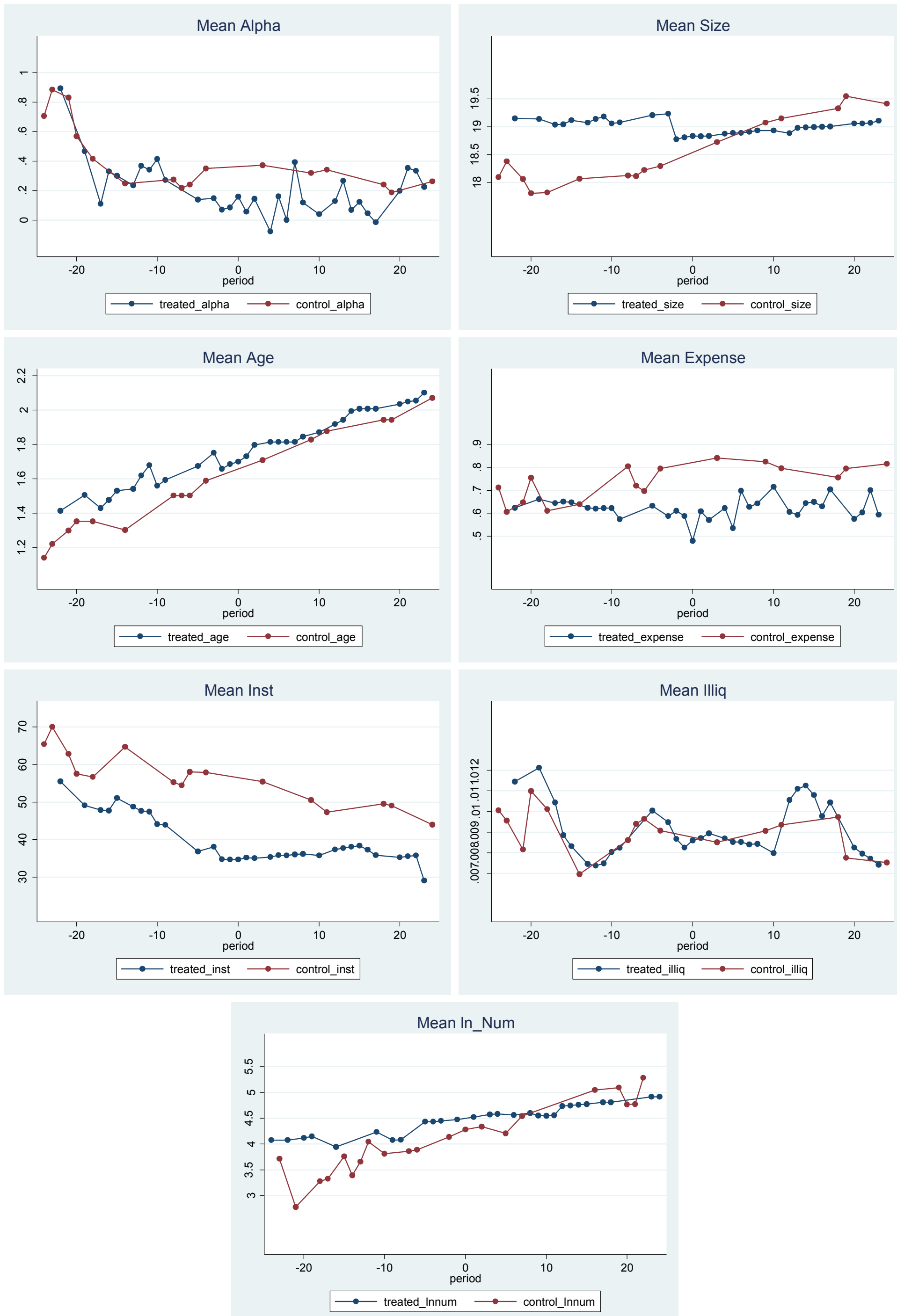
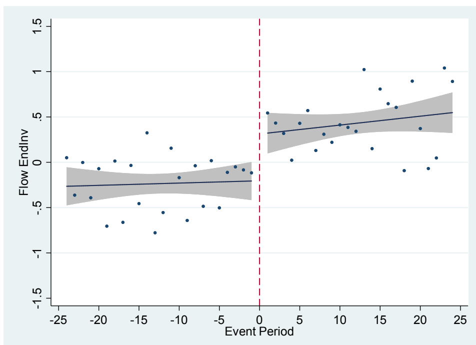


Figure 4: End Investor Flows Before and After the Switch

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 high-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