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Swing Pricing Calibration

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Abstract

Calibrating a key component of swing pricing, the swing factor, is difficult, particularly for mutual funds (MFs) that invest substantially in thinly traded debt. We propose a novel way to estimate swing factors by exploiting the structural similarities and differences between MFs and exchange-traded funds (ETFs) with similar underlying portfolios. Our MF liquidity cost is derived as the difference between an ETF's share price and the value of its underlying assets, conditioned on MF net flows and other factors. We find statistical evidence of substantial ETF discounts associated with MF net outflows during periods of stress; the magnitude of corresponding discounts increases with larger MF net outflows. Thus, our proxy for liquidity costs, ETF discounts, is strongly correlated with MF net outflows during stress, and therefore can be used to approximate MF swing factors. Although we focus on swing pricing, our methodology can also be useful in calibrating other economically equivalent mechanisms, such as redemption fees.

Keywords: swing pricing, mutual funds, liquidity and redemption risks, runs

JEL Classification: G10, G23, G28

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1. Introduction

Over the past couple of years, policymakers and researchers have highlighted "liquidity transformation" as a prominent risk to financial stability posed by open-ended, mutual funds (MFs, see, for, e.g., International Monetary Fund (2015), Anadu and Cai (2019), Financial Stability Report (2020), and Financial Stability Board (2021)). MFs permit investors to redeem their shares daily, regardless of the liquidity and credit profile of the funds' underlying holdings. This structure may incentivize investors to redeem *en masse* from a MF (or other similarly structured vehicles), as the costs of such actions are largely absorbed by the fund's remaining investors, resulting in an unfair first-mover advantage. Thus, large redemptions from MFs, particularly those that invest in less liquid assets, such as corporate debt, could result in "fire sales" which impair broader financial markets.[3]

Swing pricing is the process of adjusting a MF's net asset value per share (NAV), by a swing factor, down (up) in response to net investor redemptions (purchases). If properly designed, swing pricing could dampen investors' incentives to redeem from a MF. However, calibrating swing factors is difficult, particularly for funds that invest primarily in thinly traded debt instruments, such as high-yield debt, which may be illiquid even during normal times. This becomes even more challenging during periods of stress, which is usually associated with vanishing liquidity and arduous price discoveries.

Following Anadu et al. (2022), we use pricing dynamics for exchange-traded funds (ETFs) to empirically calibrate swing factors for MFs that invest in similar assets as the ETFs. More specifically, we extend Anadu et al. (2022) in three ways. First, we use a systemic matching algorithm (and an expanded data sample) to match MFs and ETFs. Second, our swing-factor proxy is a function of the level of MF net flows, which is an improvement from the net-flow-agnostic indicative ranges, by fund type, as proposed in Anadu et al (2022). Finally, our analysis focuses on intermediate- to long-term investment grade corporate (IG) and high-yield

[3] MF-fire-sale dynamics were at play in Spring 2020, amid the onset of the Covid-19 pandemic. During this time, several types of non-government MFs, including corporate bond MFs, experienced unusually large redemptions in March 2020. These large redemptions, resulted in some funds liquidating their underlying bonds at large price discounts, which contributed to increased volatility in those assets (see, for e.g., Jiang et al. (2022), Financial Stability Report (2020)).

corporate (HY) bond funds, given the degree of liquidity transformation performed by these funds. In comparison, Anadu et al. (2022) focus on short-term bond funds.[4]

We find statistical evidence that ETF discounts, our proxy for liquidity are correlated with MF net outflows, during periods of stress; the magnitude of the corresponding ETF discounts increases with larger MF net outflows. More specifically, on average, a one percent increase in a MF's net outflows is associated with an additional 65 basis points (bps) and 104 bps discount or "swing factor" for HY and IG funds, respectively. Moreover, the relationship between MF net outflows and the "swing factor" is nonlinear, as we find the "swing factor" increases towards the lower tails (lower percentiles) which correlate with larger net outflows. In particular, at the 5th percentile, the magnitude of additional swing factor for a one percent MF net outflow increases to 339 and 419 bps for HY and IG funds, respectively.

Our findings suggest that ETF discounts are strongly correlated with net outflows in MFs that hold similar portfolios to the ETF, during periods of stress, and therefore, can be used to approximate a MF's swing factor. The larger estimates of "swing factor" for IG can be attributed to the idiosyncratic nature of the Covid-19 stress episode and is consistent with recent empirical literature studying this period. For example, in a study of the corporate bond market dysfunction in March 2020, Liang (2020) found that IG bonds experienced larger spreads than HY bonds, driven, in part, by large redemptions from IG MFs. This finding is in line with the reverse pecking order established in Haddad et al. (2021) as well as Ma et al. (2020): U.S. Treasury and IG bonds are sold off first to meet MFs' redemption-induced liquidity drought. Furthermore, HY funds in our sample had more cash than their IG counterparts prior to the pandemic-induced stress, on average.[5] This higher cash position could have acted as a buffer to better absorb liquidity shock.

The rest of the paper is structured as follows. Section 1 provides background information on swing pricing, including a literature review of its efficacy. Sections 2 and 3, respectively, describe our data and methodology. Results are in Section 4, and caveats are discussed in Section 5. A conclusion follows.

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[4] Future work will apply this methodology to MFs that Morningstar, Inc. classifies as Intermediate Core and Municipal Bonds.
[5] As of 12/31/2019, HY had 5.56% in cash and cash equivalent holding, while IG only had 2.39%.

1.1 Background

Swing pricing 101. Swing pricing is the process of adjusting a MF's NAV by an amount, the swing factor, in response to the fund's net purchase and redemption activity. A well-designed swing pricing process, or an economically equivalent mechanism, can disincentivize large redemptions from MFs, as it forces the redeeming investors to internalize some of the costs of their redemption activity.

There are two broad approaches to a swing pricing. The first is full swing pricing, under which a MF's NAV is adjusted (by a swing factor) anytime it experiences net redemptions or purchases (or net flows). The second is partial swing pricing in which a MF's NAV is adjusted only if its net flows exceed a pre-determined level, the swing threshold. Under both arrangements, the swing factor can be fixed, or tailored to the level of net investor activity. Our calibration exercise assumes a full swing pricing setup.

In 2016, the U.S. Securities and Exchange Commission (SEC) amended its rules to permit MFs to use swing pricing; however, no U.S. MF has voluntarily adopted swing pricing, which the industry largely attributes to operational impediments.[6] In contrast, swing pricing is more prevalent in Europe, although it is not mandatory. Both academics and financial regulators have taken advantage of the contrast to investigate the efficacy of swing pricing, which we will describe later.

Calibrating swing factors. Swing factors should broadly reflect the total liquidity costs (including transaction, bid-ask spread, and market impact) generated by the level of a MF's net flows, all else equal. However, as described in Anadu et al. (2022), swing factors are not easy to calibrate for three related reasons. First, MFs' liquidity costs are not directly observable from their net investment activity. Since MFs' "share price" is its NAV struck at end of the day, there

[6] Several participants in the asset management industry have raised operational impediments to implementing swing pricing in the U.S. (see, for example, BlackRock (2016)). The primary issue cited is that U.S. MFs are required to accept buy and sell orders until 4:00 p.m. EST, the same time that U.S. equity markets close. However, data on MF net flows are typically not available until the next day. Thus, MFs do not have sufficient time to determine whether net flows exceed the swing threshold, compute NAVs, and then impose the swing factor, if warranted.

On November 2, 2022, the SEC proposed changes to its swing pricing rule, including the requirement that all MFs, excluding money market mutual funds and ETFs, use swing pricing under certain conditions. (As previously noted, the use of swing pricing is currently optional for U.S. MFs.) To address the operational impediments, the SEC also proposed a "hard close" requirement of 4:00 p.m. for all MF transactions (see, SEC Open-End Fund Liquidity Risk Management Programs and Swing Pricing; Form N-PORT Reporting).

is no price discovery mechanism at a higher frequency that allows for observations related to liquidity costs.

Second, MFs that engage in the most extreme forms of liquidity transformation hold assets that are not frequently traded. Indeed, liquidity costs associated with these assets are difficult to estimate even in benign market conditions, and thus, price opacity is further exacerbated in stress markets, when swing pricing is needed the most. Finally, the dynamic nature of swing pricing requires some mechanism by which swing factors are adjusted quickly, in response to unexpected deteriorating market conditions.

To resolve some of these issues, we use the pricing dynamics for ETFs to infer swing-factor-proxies for MFs that invest in similar assets. More specifically, like MFs, ETFs have a NAV that is struck at end of day. Unlike MFs, ETFs, like other exchange-traded products, also have a bid price and an ask price, which reflect prices at which the ETF shares can be traded on exchanges. ETFs also have an intraday NAV that is struck at a higher frequency throughout the day as an intraday indicative value of the ETFs' underlying assets. During periods of stress, an ETF's NAV may take longer to adjust than its exchange-traded share price, resulting in premiums and discounts to its NAV.[7]

[Figure 1 here]

As previously noted, estimates in Anadu et al. (2022) are agnostic to the level of net outflows and use coarse fund categories to classify funds. We build on this by empirically estimating ETF premiums and discounts, our swing factor proxy, as a function of MF net flows and other variables. Thus, instead of just providing a range for swing factors by fund category, these new estimates suggest swing factors conditioned on the level of net outflows, as described further below. Figure 1 reports the distribution of ETF discounts/premiums to NAV (top panel) and the distribution of MF net flows (bottom panel), between December 2019 to December 2020, respectively. These charts show that ETF discounts appear to be positively correlated with MF net outflows, during periods of stress. Our empirical work seeks to exploit this relationship.

[7] The spread between an ETF's share price and the value of its underlying assets, the premium or discount, could serve as a useful, albeit imprecise, proxy for liquidity costs. During normal periods, this difference is usually subdued. However, during periods of stress, the premium or discount can widen considerably, as observed for certain bond ETFs in March 2020. A large discount, for example, would represent the amount by which a MF's NAV might need to be adjusted downwards when it experiences net redemptions. The converse is true for premiums.

1.2 Literature Review

Is swing pricing effective in reducing the first-mover advantage in MFs? The existing literature is generally supportive of the efficacy of swing pricing. For example, in an empirical study comparing Luxembourg- and U.S.-domiciled funds, Lewrick and Schanz (2017a) find that swing pricing dampens outflows in response to poorer fund performance and supports fund returns, but only has a limited effect in a stress scenario. The muted effect in stress might have resulted from a combination of using Luxembourg-domiciled funds and focusing on the 2013 taper tantrum.

In another study with more detailed investor-level transaction information on UK corporate bond funds, Jin et al. (2021) find evidence that swing pricing not only eliminates the first-mover advantage, but also reduces outflows during periods of market stress. Furthermore, a study by the Bank of England (2021) also finds suggestive evidence that swing pricing may have reduced fund net outflows. Although swing pricing could be useful in reducing run incentives, the paper notes that fund managers' discretionary application of swing pricing, including the swing factor, likely dampened its efficacy.

To formalize the mechanism through which swing pricing reduces first-mover advantage, theoretical models usually build on a feedback loop between MF net outflows and asset illiquidity, such as in Zeng (2017) and Capponi et al. (2020). Swing pricing constitutes a commitment device that transfers liquidation costs arising from large redemptions to redeeming investors and therefore removes first mover advantage. Lewrick and Schanz (2017b) further derive analytical bounds for swing factors, which depend on trading costs. With anecdotal data from a few funds, Malik and Lindner (2017) suggest that state-contingent swing factors, which are dynamically adjusted upward in times of significant market stress, could be made a mandatory requirement by authorities. Such enhancement would more effectively deter redemptions and act as systemic risk mitigant. These insights generally align with our calibration outcomes.

2. Methodology

In order to calibrate the swing factor, we propose a two-step approach. First, we systemically match MFs with ETFs based on net return correlation. As previously noted, Anadu et al. (2022) match MFs and ETFs by broad fund characteristics (e.g., fraction of funds that hold over 50 percent in corporate bonds), which is infeasible in a large cross section. With expanded data samples, the systemic matching approach leads to more consistent and reliable outcomes. Then, based on the matched pairs, we estimate the swing factor by running difference-in-difference regressions of ETF discounts/premiums on MF net flows. We describe these two steps and their results in detail below.

Step 1: Return Correlation Matching

Across funds classified as HY and IG corporate, we match each MF to an ETF with the highest net return correlation, over the training period September 2019 through January 2020. Since there are fewer ETFs than MFs in each of our fund categories, an ETF can be matched to multiple MFs. To be sure, return correlation matching does not guarantee that each ETF and MF pair will hold the exact same underlying assets. However, our general premise is that ETFs and MFs that have similar underlying assets should have similar fund performance, on balance.

Step 2: Difference-in-Difference Regressions

For each pair i of ETF and MF, we consider the following specification:

$$ETF\ NAVDiscount/\Pr e mium_{i,t} = \beta_0 + \beta_1 * MF\ Flow_{i,t} + \beta_2 * Dummy + \beta_3 * \left(MF\ Flow_{i,t}\ * Dummy\right) + \alpha_i + \epsilon_{i,t} \quad (1)$$

where the left-hand side variable $ETF\ NAVDiscount/Premium_{i,t}$ denotes the NAV discount/premium for the matched ETF on day t. It is constructed as follows

$$ETF\ NAV\ discount\ premium_{i,t} = \frac{ETF\ Bid\ price_{i,t} - ETF\ NAV_{i,t}}{ETF\ NAV_{i,t}}.$$

$MF\ Flow_{i,t}$ on the right-hand side denotes the fund flow for MF i on day t. It is calculated by normalizing fund net flow with fund asset on day t-1. β_0 is the intercept, α_i is the pair fixed effect, and $\epsilon_{i,t}$ is the residual term.

We consider two approaches to define the dummy variable, $Dummy$. In the first approach, we define $Dummy$ as $MF\ Outflow_{i,t}$, which equals one if MF i has an outflow on day

t and zero otherwise. The coefficient β_3 implies how much additional ETF NAV discount/premium is associated with a one percent MF net outflow; or the incremental NAV discount during net outflow periods, which serves as a proxy for the incremental swing factor during outflow periods. This specification with fund specific net outflow dummy focuses on the asymmetry of the relationship between fund net flow and ETF NAV discount/premium.

In the second approach, $Dummy$ is defined as $Stress_t$, which is a financial market stress indicator that equals one during stress periods on day t and zero otherwise. This specification focuses on analyzing the relationship between fund net flows and the ETF NAV discount/premium, during periods of stress, as specified by a macroeconomic indicator, in particular the incremental swing factor implied by the coefficient β_3 during market stress. More specifically, we consider three options for the financial market stress indicator, $Stress_t$. First, following Jin et al. (2022), we define $Stress_t$ using abnormal values of option-implied volatility index (VIX), as equal to one if the VIX on that day is above its 75th percentile during the regression sample period February 2020 through May 2020.

Second, $Stress_t$ equals to one if the financial stress indicator (FSI) on that day is above its 75th percentile during the regression sample period. Third, $Stress_t$ depends on the aggregate flow of MFs in our regression sample, and it equals to one if the aggregate MF flow on day t is negative (i.e., an outflow).

For each group, we run regressions based on Eq. (1) using both specifications (i.e., the two definitions of $Dummy$). For each specification, we implement both mean regression, which studies the average relationship, and quantile regression, which helps to analyze whether the relationship is linear or nonlinear when the matched ETF's NAV discount/premium changes (approximately when the magnitude of MF net outflow changes).

3. Data Sources

Our data are from Morningstar, Inc., Bloomberg, and funds' filings with the Securities and Exchange Commission (SEC).

We first identified two groups of MFs and ETFs that Morningstar, Inc. classifies as "US Fund High-Yield Bond" and "US Fund Corporate Bond." As defined by Morningstar, Inc., the former, High-Yield Bond funds invest at least 65 percent of their net assets in bonds that are unrated or rated below investment grade. In contrast, the latter group, Corporate Bond funds, invest at least 65 percent of their net assets in investment-grade corporate bonds.[8] (Future work will include other Morningstar, Inc. categories, including Core Bond and Municipal Bond.)

From Morningstar, Inc., we also obtained daily net assets, daily estimated net flows, daily returns, and some portfolio-level information such as duration, credit rating, and maturity, for both MFs and ETFs. We downloaded end-of-day ETF premium and discount to NAV data from Bloomberg, which is the main variable of interest in our empirical analysis. We limit our sample to those funds with inception dates before September 2019, and consistent net flow data.

Table 1 presents summary statistics of the main variables, including ETF NAV discount/premium and MF net flows based on the sample period February 2020 through May 2020.

[Table 1 here]

4. Empirical Results

For the HY and IG group, we first do return correlation matching to find the matched ETF for a given MF. Then, based on the matched pairs, we run mean and quantile regressions following Eq. (1) using both the MF specific dummy and the macro market stress dummy variables. Based on the regression results, we further study the economic significance of the estimated results.

4.1 High-Yield Corporate Bond Funds

In this section, we present the empirical results for the group of high-yield corporate bond funds.

[8] Per Morningstar: Corporate bond portfolios concentrate on investment-grade bonds issued by corporations in U.S. dollars, which tend to have more credit risk than government or agency-backed bonds. These portfolios hold more than 65% of their assets in corporate debt, less than 40% of their assets in non-U.S. debt, less than 35% in below-investment-grade debt, and durations that typically range between 75% and 150% of the three-year average of the effective duration of the Morningstar Core Bond Index.

High-yield bond portfolios concentrate on lower-quality bonds, which are riskier than those of higher-quality companies. These portfolios generally offer higher yields than other types of portfolios, but they are also more vulnerable to economic and credit risk. These portfolios primarily invest in U.S. high-income debt securities where at least 65% or more of bond assets are not rated or are rated by a major agency such as Standard & Poor's or Moody's at the level of BB (considered speculative for taxable bonds) and below.

In the first step of return correlation matching, we find a total of 141 matched pairs for the HY Bond Funds group, which covers about 60 percent in total net assets and 80 percent in terms of number of funds. Overall, the return correlation for the matched pairs is high (about 0.82 on average).

The first two columns of Table 2 report fund characteristics comparison between MFs and the matched ETFs in terms of size (in USD billions), daily return, and other fund characteristics including duration, credit rating and maturity. As we can see, on average, fund characteristics such as duration, credit rating and maturity are close between the MF and ETF in the matched pairs. Though the average size of MFs seems quite different from that of the match ETFs, we contend that we should not compare them in absolute size measure since the two groups are quite different in fund structure and have been experiencing different growth pattern during recent years (ETFs' exponential growth versus MFs' steady and slow growth). Therefore, we instead compare size relative to their respective sectors and find it is close on the relative size basis.

[Table 2 here]

The regression results based on the second step in the proposed methodology of estimating the swing factor are provided in the following sections.

4.1.1 Regression Results using Fund Specific Outflow Dummy

Based on Eq. (1) using fund specific outflow dummy, we run both mean regression and quantile regression, where both the dependent variable (ETF NAV Premium/Discount) and the main independent variable (MF Flow) are in percentage points. The mean regression results are reported in Table 3 Panel (a). As we can see, the coefficient β_1 on MF Flow is negative but statistically insignificant, indicating NAV changes are not significantly associated with MF net *inflows*, on average. The coefficient β_2 on the outflow dummy is negative and statistically significant, meaning, on average, MF outflow periods are associated with more NAV discount (approximately the liquidity cost).

Turning to the interaction term, its coefficient β_3 is statistically significant, implying that, on average, MF Flow is associated with NAV changes if it is an outflow; moreover, β_3 is positive telling us that larger MF outflow is associated with more NAV discounts (more liquidity cost). Specifically, on average, a one percent MF outflow corresponds with an additional 65 bps ETF NAV discount, or the incremental swing factor is 65 bps for one percent outflow. The result is also economically significant: a one standard deviation increase in MF outflow corresponds to an increase of 21 bps in NAV discount which is about 16% of its own standard deviation.[9]

[Table 3 here]

Next, we run quantile regression to investigate whether the relationship between outflows and ETF premiums/discounts is linear or nonlinear. The quantile regression results on the key coefficient β_3 on the interaction term are presented in Figure 2 Panel (a).[10] The estimate increases from the left to the right, in other words, from the median to lower 5th percentile (i.e., the lower tail, associated with larger NAV discounts or approximately larger outflows). Such pattern implies the relationship between the NAV change and MF outflow is nonlinear, and the estimated incremental swing factor increases with larger outflows. In particular, at the lower 5th tail, given one percentage outflow, the magnitude of the incremental swing factor increases to 339 bps. The result is economically significant as one standard deviation increase in MF outflow, corresponds to an increase of 96 bps in NAV discount which represents 72% of its standard deviation.

[Figure 2 here]

4.1.2 Regression Results using Market Stress Dummy

Differently from the previous section, which focuses on the symmetry results using Eq. (1) with fund specific outflow dummy, in this section, we investigate the relationship between NAV changes and MF flow during market stress, with Eq. (1) using market stress dummy.

From the mean regression results in Table 3 Panel (b), we find that the coefficient β_1 on MF flow itself is negative but statistically insignificant, meaning, on average, during non-stress periods, NAV changes are not significantly associated with MF flows. The coefficient β_2 on the

[9]The estimated coefficients for the terms involving MF outflow (β_1 and β_3) are -0.0203 and 0.645 respectively, and one standard deviation of the MF outflow is 0.33 from Table 1, so that (-0.0203*0.33+0.645*0.33) is about 0.21 which represents 16% of NAV discount's standard deviation (1.34, from Table 1).
[10]The results for the other two coefficients β_1 and β_2 are close to the mean regression results.

market stress dummy is negative and statistically significant, meaning, on average, market stress is associated with a larger NAV discount (or approximately more liquidity cost).

Turning to the interaction term, its coefficient β_3 is positive and statistically significant, implying that, on average, during periods of market stress, MF outflows are associated with more NAV changes (or approximately more liquidity cost). Specifically, one percent MF outflow corresponds with an additional 32 bps ETF NAV discount, or the incremental swing factor is 32 bps for one percent outflow during market stress. The result is economically significant, too: a one standard deviation increase in MF outflow, corresponds to an increase of 12 bps in NAV discount which is about 10% of its standard deviation.

Furthermore, we run quantile regression to check for linearity. Figure 2 Panel (b) provides the quantile regression results of the key coefficient β_3 on the interaction term.[11] Similar to our results when using a fund-specific outflow dummy, the estimate increases from the left to the right, in other words, from the median to lower percentiles of the NAV discount. Such pattern implies the relationship between NAV changes and MF outflows is nonlinear, and the estimated incremental swing factor increases with larger outflows. In particular, at the lower 5th tail, given one percentage MF outflow, the magnitude of the incremental swing factor increases to 85 bps for one percent outflow during market stress. The result is economically significant, as one standard deviation increase in MF outflow, corresponds to an increase of 26 bps in NAV discount which is about 20% of its standard deviation.

4.1.3 "Swung Factor"

Based on the regression results in the previous sections, we now study the "Swung Factor," which is defined as the estimated swing factor (in the following Eq. (2)), computed as the sum of these estimated three right-hand side terms in Eq. (1) related to MF flow. In other words, it is defined as the NAV discount associated with MF outflow.

$$Swung\ Facor\ (Estimated\ Swing\ Factor) = \beta_1 * MF\ Flow_{i,t} + \beta_2 * Dummy + \beta_3 * \left(MF\ Flow_{i,t} * Dummy\right) \qquad (2)$$

[11]The results for the other two coefficients β_1 and β_2 are close to the mean regression results.

As you can see from Figure 3 based on the choice of MF outflow dummy, the estimated swing factor became larger and more volatile during the onset of the Covid-19 shocks (March 2020), as large as one and half percentage point NAV discount per one percent outflow.[12]

[Figure 3 here]

4.2 Investment Grade Corporate Bond Funds

In this section, we discuss the empirical results for the group of IG corporate bond funds.

We again begin by matching MFs with ETFs that have the highest return correlation, during the pre-Covid period (September 2019 through January 2020). This produces 37 matched pairs for the IG Bond Funds group, which covers about 40 percent in total net assets and 76 percent in terms of number of funds. Overall, the return correlation for the matched pairs is high (about 0.90 on average).

As reported in Table 2, on average, the MF and ETF in the matched pairs are close in terms of some fund characteristics such as duration, credit rating and maturity. Similar to the analysis for the HY bond funds, instead of looking at the absolute size which seems quite different between MFs and the match ETFs, we compare their size on a relative size basis and find it is close.

The regression results of quantifying the swing factor based on the second step in the proposed methodology are discussed in following sections.

4.2.1 Regression Results using Fund Specific Outflow Dummy

The mean regression results based on Eq. (1) using fund specific outflow dummy are reported in Table 4 Panel (a). The results are qualitatively similar to those for HY bond funds. Specifically, the coefficient β_1 on MF flow as shown in Table 4 Panel (a), is negative but statistically insignificant, indicating, on average, NAV changes are not significantly associated with MF Flows if it is an inflow. The coefficient β_2 on the outflow dummy is negative and

[12]The results based on the Stress Dummy show a similar pattern.

statistically significant, meaning on average MF outflow periods are associated with larger NAV discount (approximately the liquidity cost).

Turning to the interaction term, its coefficient β_3 is statistically significant, indicating that, on average, MF flows are associated with NAV changes if it is an outflow; moreover, β_3 is positive implying that larger MF outflow is associated with larger NAV discount (more liquidity cost). Specifically, on average, a one percent MF outflow corresponds with an additional 104 bps ETF NAV discount, or the incremental swing factor is 104 bps for one percent outflow. The result is economically significant, as one standard deviation increase in MF outflow (0.39% for IG bond funds), corresponds to an increase of 50 bps in NAV discount which is about 40% of its standard deviation.

[Table 4 here]

Then, we again check to see if the relationship between ETF premium/discounts and MF flow is nonlinear. The quantile regression results on the key coefficient β_3 on the interaction term are presented in Figure 4 Panel (a).[13] The estimate increases from the left to the right, in other words, from the median to lower percentiles (approximately larger outflows). Such pattern implies the relationship between NAV changes and MF outflows is nonlinear, and the estimated incremental swing factor increases with larger outflows. In particular, at the lower 5th tail, given one percentage outflow, the magnitude of the incremental swing factor increases to 419 bps for one percent outflow during market stress. The result is economically significant, as one standard deviation increase in MF outflow, corresponds to an increase of 170 bps in NAV discount which represents about 130% of its standard deviation.

[Figure 4 here]

[13]The results for the other two coefficients β_1 and β_2 are close to the mean regression results.

4.2.2 Regression Results using Market Stress Dummy

In this section, we investigate the relationship between NAV changes and MF flows during market stress following Eq. (1) using market stress dummy. The results are qualitatively similar to these for HY bond funds.

From the mean regression results as shown in Table 4 Panel (b), we find that the coefficient β_1 on MF flow itself is statistically insignificant, meaning, on average, NAV changes are not significantly associated with MF flows if it is not during market stress specified by the market stress dummy. The coefficient β_2 on the market stress dummy is negative and statistically significant, meaning, on average, market stress is associated with more NAV discount (or approximately more liquidity cost).

Turning to the interaction term, its coefficient β_3 is positive and statistically significant, implying that on average, MF outflows are associated with larger NAV changes (or approximately larger liquidity cost) if it is during market stress. Specifically, one percent MF outflow corresponds with an additional 77 bps ETF NAV discount, or the incremental swing factor is 77 bps for one percent outflow during market stress. The result is economically significant, as one standard deviation increase in MF outflow, corresponds to an increase of 37 bps in NAV discount which is about 30% of its standard deviation.

We then run quantile regression to analyze whether the relationship is linear or nonlinear. Figure 4 Panel (b) plots the quantile regression results of the key coefficient β_3 on the interaction term. The estimate increases from the left to the right, in other words, from the median to lower percentiles of the NAV discount. Such pattern implies the relationship between NAV changes and MF outflows is nonlinear, and the estimated incremental swing factor increases with larger outflows. In particular, at the lower 5th tail, given one percentage outflow, the magnitude of the incremental swing factor increases to 116 bps for one percent outflow during market stress. The result is economically significant, as one standard deviation increase in MF outflow, corresponds to an increase of 41 bps in NAV discount which is about 31% of its standard deviation.

4.2.3 "Swung Factor"

Based on the regression results in the previous sections, we now study the "Swung Factor" which is defined as the estimated swing factor (as in Eq. (2)), or the NAV discount associated with MF outflow.

As you can see from Figure 5, which is based on the MF outflow dummy, similar to the finding as for HY bond funds, the estimated swing factor for IG bond funds also became larger and more volatile during the onset of Covid-19 (March 2020), as large as one and half percentage point NAV discount per one percent outflow. The results based on Stress Dummy show a similar pattern.

[Figure 5 here]

5. Discussions

In this section, we will discuss four implicit and explicit assumptions made in our estimation. First, our analysis assumes that ETF NAV discounts/premiums only reflect bid-ask, transaction and market impact costs and do not include the potential impact from other factors, such as non-price-related incentives of ETF Authorized Participants (AP).[14] This implies that the ETF share price might understate the liquidity costs of its underlying portfolio. Our estimation, for this reason, should be interpreted more rigorously as a lower bound for actual swing factors.

Second, our analysis is agnostic on clientele effects that may be contributing to the observed pricing dynamics. MFs and ETFs might inherently have different clientele due to their structural differences, which may muddy the degree to which premiums and discounts reflect just liquidity cost. With data limitation and a lack of clear mechanism, the direction of this clientele effect is ambiguous.

Third, MFs and ETFs in a matched pair might not be holding identical underlying assets. We matched MF and ETF systematically based on return similarities, in absence of holding information. However, funds with similar returns do not necessarily have the same underlying

[14] Due to the ETF creation and redemption mechanism, APs might act in ways to absorb some of the undesirable market shocks.

portfolio. In addition, daily flow data is only available for a limited number of MFs in Morningstar, which severely reduced the number of potential MF-ETF matches. This could also have an impact on how close underlying assets in matched funds resemble each other.

Lastly, our quantile regressions assumed a positive monotonic relationship between ETF discounts/premiums and MF net flows. While this assumption is generally true in our sample, there are a few pairs of exceptions.

6. Conclusion

MFs, and other similarly structured vehicles, particularly those that invest in relatively illiquid securities, are prone to large redemptions in times of market stress. If properly calibrated, swing pricing can reduce MF investors' incentives to redeem, as it forces them to bear some of the costs of their redemption activity. However, the effectiveness of swing pricing in reducing the first-mover advantage hinges on robust calibration.

In this paper, we propose using ETF pricing dynamics to calibrate swing factors for MFs with similar underlying assets. Our results show that, for HY and IG funds, the correlation between ETF NAV discounts/premiums and MF outflows are both statistically and economically significant, during periods of stress. In addition, we find that the magnitude of swing factors increases with the size of net outflows faced by MFs. These results support the use of our liquidity cost proxy, ETF discounts, to approximate MF swing factors (or other economically equivalent mechanisms, such as redemption fees), as it is strongly correlated with MF net outflows during stress.

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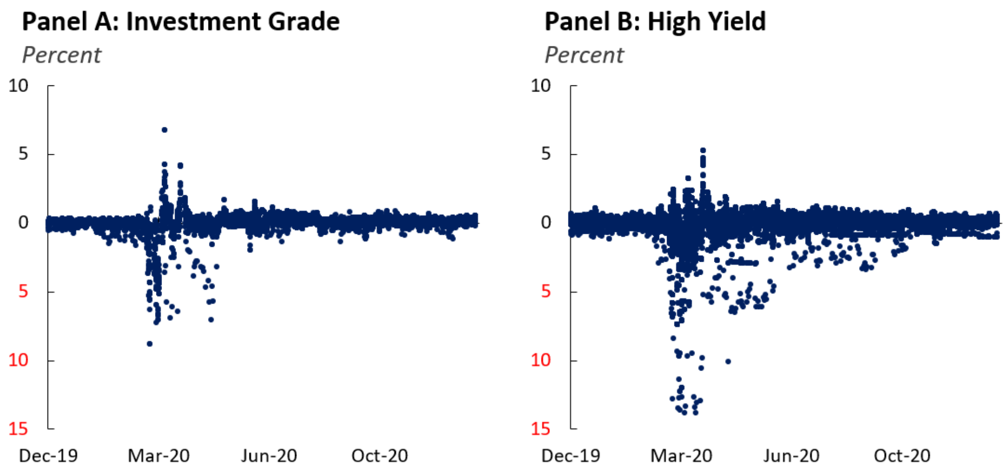
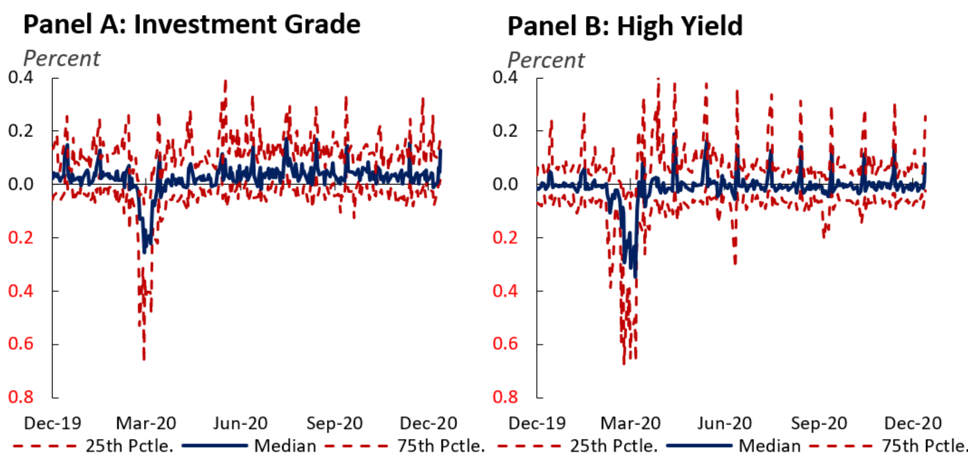
Exhibits

Figure 1. Distribution of ETF NAV Premiums/Discounts vs MF Net Flows

Part 1: Distribution of ETF NAV Premiums/Discounts Over Time



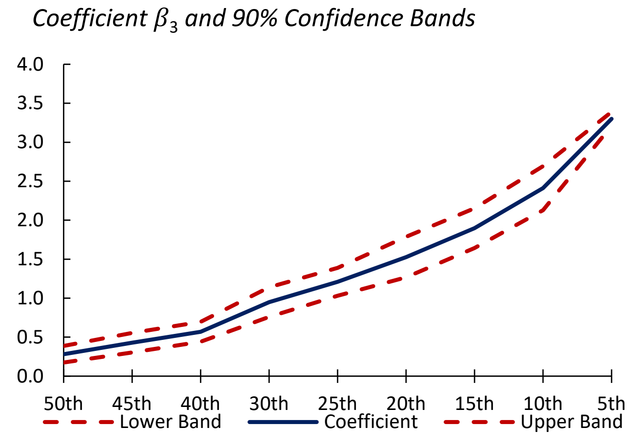
Part 2: Distribution of Mutual Fund Net Flows Over Time



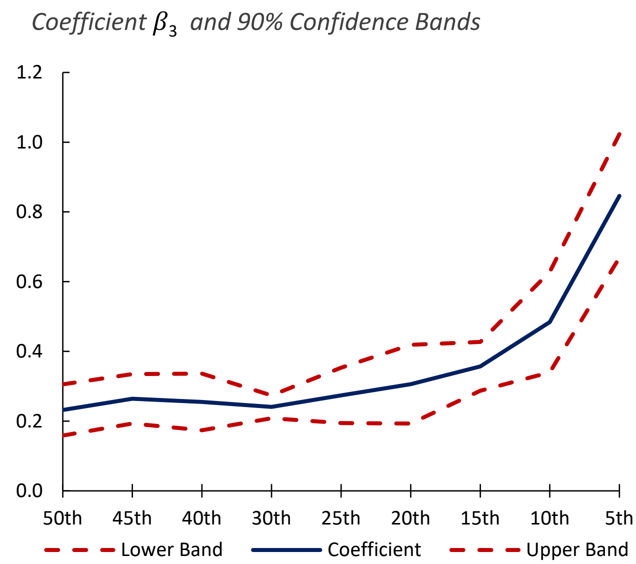
Notes: Figure 1 plots the distribution of ETF NAV premiums/discounts and MF net flows during December 2019 through December 2020, based on two groups (IG bond funds and HY bond funds) respectively.

Figure 2: Quantile Regression Results for HY Bond Funds

Panel (a) Regression Specification using MF Outflow Dummy

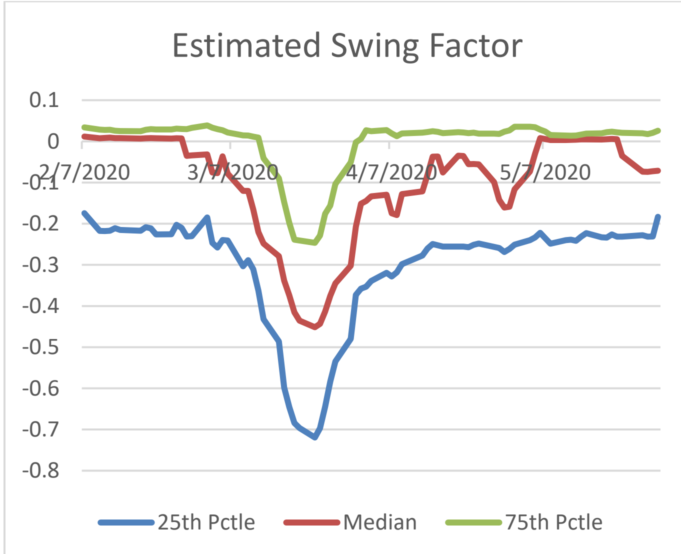


Panel (b) Regression Specification using Stress Dummy



Notes: Figure 2 plots the quantile regression estimates (based on HY bond funds) of the *Coefficient* β_3 in front of the interaction term, using Eq. (1) in Section 2.2, based on the regression sample period February through May 2020 that we mainly focus on.

Figure 3. Distribution of Estimated Swing Factor for HY Bond Funds

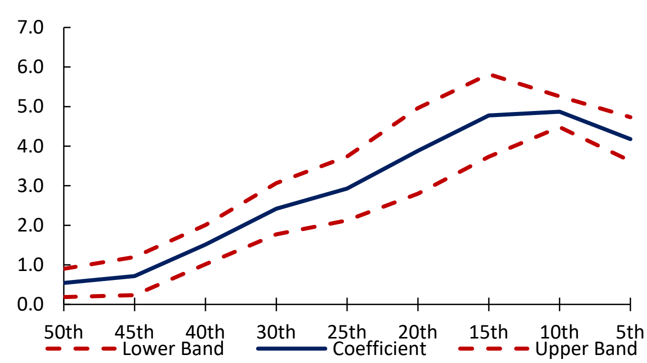


Notes: Figure 3 plots the distribution of the estimated "swung factor" based on the HY bond funds (reporting the median, 25th percentile and 75th percentile), as defined in Section 4.1.3.

Figure 4: Quantile Regression Results for IG Bond Funds

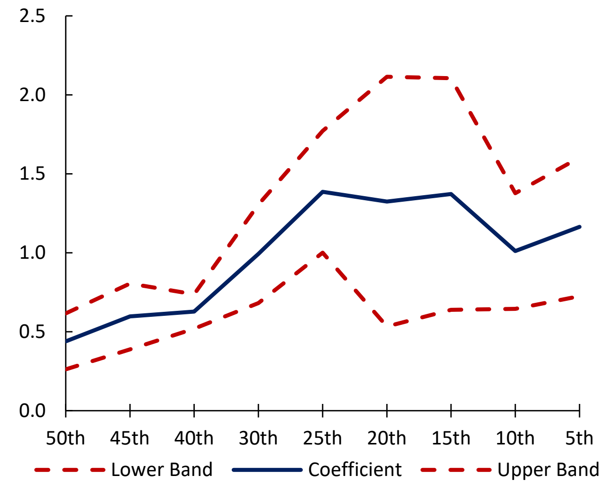
Panel (a) Regression Specification using MF Outflow Dummy

Coefficient β_3 and 90% Confidence Bands



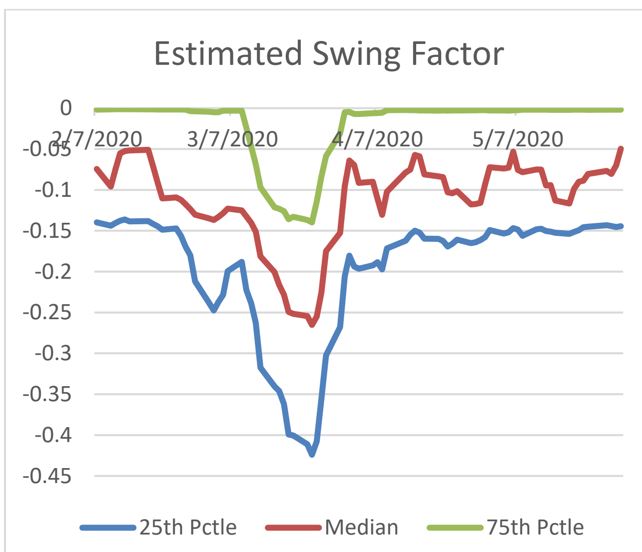
Panel (b) Regression Specification using Stress Dummy

Coefficient β_3 and 90% Confidence Bands



Notes: Figure 4 plots the quantile regression estimates (based on IG bond funds) of the *Coefficient* β_3 in front of the interaction term, using Eq. (1) in Section 2.2, based on the regression sample period February through May 2020 that we mainly focus on.

Figure 5. Distribution of Estimated Swing Factor for IG Bond Funds



Notes: Figure 5 plots the distribution of the estimated "swung factor" based on the IG bond funds (reporting the median, 25th percentile and 75th percentile), as defined in Section 4.2.3.

Table 1: Mutual Fund and ETF Price/Flow Summary Statistics

	Observations	Mean	25th Pctle.	Median	75th Pctle.	Stan. Dev.
HY Corporate						
ETF NAV Premium/Discount	3,109	-0.23	-0.29	0.00	0.28	1.34
MF Percent Flows	3,109	0.01	-0.07	0.00	0.09	0.33
IG Corporate						
ETF NAV Premium/Discount	11,757	-0.32	-0.59	-0.07	0.25	1.31
MF Percent Flows	11,757	-0.02	-0.11	-0.02	0.06	0.39

Notes: Data sourced from Morningstar. Sample period is our matching and regression sample combined (February 2020 through May 2020).

Notes: Table 1 provides summary statistics for both ETF NAV premium/discount variable and MF flow variable based on the regression sample period February through May 2020.

Table 2: Mutual Fund and Matched ETF Characteristics

	High Yield		Investment Grade	
	MF	ETF	MF	ETF
Number of Funds	141	23	37	11
Size - USD Billions	0.9	2.2	1.3	7.3
	(2.0)	*(5.1)*	*(4.0)*	*(15.8)*
Duration	3.5	3.8	7.6	8.4
	(1.0)	*(1.1)*	*(1.8)*	*(2.1)*
Credit Rating	B	B	BBB	BBB
	-	-	-	-
Maturity	5.5	5.1	11.1	11.0
	(2.3)	*(2.6)*	*(3.9)*	*(2.2)*
Return	5.5	5.1	3.1	3.6
	(1.7)	*(2.1)*	*(0.9)*	*(0.5)*

Notes: Table 2 reports the summary characteristics of mutual fund and the matched ETF, including number of funds, size (in USD billions), duration, credit rating, maturity and return. Both the average and the standard deviation (in italics) are provided. Data source is from Morningstar, based on the last observation in 2019.

Table 3: Mean Regression Results for HY Bond Funds

Panel (a) Regression Specification using MF Outflow Dummy

VARIABLES	ETF NAV Premium/Discount
MF Flows	-0.0203
	(0.0798)
Outflow Dummy	-0.105**
	(0.0478)
MF Flows x Outflow Dummy	0.645**
	(0.282)
Constant	-0.185***
	(0.0657)
Observations	11,757
R-squared	0.231

Panel (b) Regression Specification using Stress Dummy

VARIABLES	ETF NAV Premium/Discount
MF Flows	0.0311
	(0.0704)
Stress Dummy	-1.002***
	(0.2445)
MF Flows x Stress Dummy	0.3200*
	(0.1800)
Constant	-0.0367
	-0.769
Observations	11,757
R-squared	0.375

Notes: Table 3 provides mean regression results based on Eq. (1) in Section 2.2, based on the regression sample period February through May 2020 that we mainly focus on.

Table 4: Mean Regression Results for IG Bond Funds

Panel (a) Regression Specification using MF Outflow Dummy

VARIABLES	ETF NAV Premium/Discount
MF Flows	0.229
	(0.178)
Outflow Dummy	-0.188**
	(0.0861)
MF Flows x Outflow Dummy	1.039**
	(0.479)
Constant	-0.0593
	(0.0690)
Observations	3,109
R-squared	0.111

Panel (b) Regression Specification using Stress Dummy

VARIABLES	ETF NAV Premium/Discount
MF Flows	0.1877
	(0.1155)
Stress Dummy	-0.8022**
	(0.3044)
MF Flows x Stress Dummy	0.7658**
	(0.3415)
Constant	0.0491
	(0.0559)
Observations	3,109
R-squared	0.1811

Notes: Table 4 provides mean regression results based on Eq. (1) in Section 2.2, based on the regression sample period February through May 2020 that we mainly focus on.