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Is the price right? Swing pricing and investor redemptions☆

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Abstract

How effective are available policy tools in managing liquidity risks in the mutual fund industry? We assess one such tool – swing pricing – which allows funds to adjust their settlement price in response to large net flows. Our empirical analysis exploits the fact that swing pricing is available to Luxembourg funds, but not yet to U.S. funds. We show that swing pricing dampens outflows in reaction to weak fund performance, but has a limited effect during stress episodes. Furthermore, swing pricing supports fund returns, while raising accounting volatility, and may lead to lower cash buffers.

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1. Introduction

The asset management industry has been growing at an exceptional pace over the past few years, reflecting a persistent shift from bank-based towards more market-based intermediation. Open-end mutual funds have been contributing to this trend, with their total financial assets increasing by more than 5.6 trillion U.S. dollars (USD) over the past 10 years in the United States alone. As a result, fund managers' trading activities have attracted increasing attention from other market participants as well as from supervisory authorities. Based on the experiences gained from the financial crisis of 2008/09 as well as other, shorter-lived episodes of market stress, a number of structural vulnerabilities associated with fund management activities have come to the fore (Financial Stability Board (2017)).

For open-end mutual funds, financial stability concerns focus on the risks related to the liquidity mismatch that is inherent in the funds' business model: they invest in assets that may prove difficult to liquidate under stressed market conditions, while granting fund investors the right to redeem their shares on a daily basis based on the end-of-day net asset value (NAV) per share of the fund. These risks are particularly pronounced for funds investing in relatively illiquid assets, such as corporate bonds. Fund managers are equipped with a variety of tools to manage the risk of large-scale redemptions (IOSCO (2015)). Relatively little is known, however, about the effectiveness of these tools in containing risks. This paper intends to shed some light on this issue by studying the effect of *swing pricing* on fund flows and other performance measures under both normal and stressed market conditions. Swing pricing is an innovative liquidity management tool that will be introduced as one of the U.S. Securities and Exchange Commission's measures to strengthen the resilience of U.S. open-end funds.[3]

Swing pricing allows the fund manager to adjust ("swing") the fund's NAV per share to reflect the estimated costs associated with investor redemptions and subscriptions. These costs arise whenever the fund manager needs to sell or buy assets in order to meet redemption requests or invest cash inflows. During tranquil market conditions, the cost of liquidating assets tends to be low, at least for transactions of limited size (Borkovec et al. (2016)). Yet during episodes of market stress, liquidation costs can suddenly spike (Dick-Nielsen et al. (2012), Friewald et al. (2012)). It is often during these times that fund investors redeem their shares to meet their liquidity needs. Absent swing pricing or other redemption charges that are redistributed to the fund, the cost of liquidating assets to satisfy redemptions will only be borne by those investors that stay with the fund. Anticipating this dilution of the NAV, investors may have a first-mover advantage in withdrawing from the fund – creating the breeding ground for a run on the fund.

Swing pricing can mitigate the first-mover advantage by levying the dilution costs on withdrawing investors. At the same time, it may induce fund managers to take on more liquidity

[3] In November 2016, the U.S. Securities and Exchange Commission adopted amendments to rule 22c-1 under the Investment Company Act to permit registered open-end funds, with the exception of money market funds and exchange-traded funds, to use swing pricing.

risk and could capture investors in low-performing funds. To identify these effects, we exploit the fact that swing pricing is available to funds registered in Luxembourg, whereas U.S. funds will not be permitted to swing prices until November 2018. These countries host two of the largest mutual fund industries worldwide.

Our comparative analysis, based on a large sample of open-end bond mutual funds, yields findings that are consistent with several predictions derived from our conceptual framework. Comparing Luxembourg and U.S. funds, we show that Luxembourg fund flows are less sensitive to negative returns during normal times. This is consistent with the predicted impact of swing pricing on investor incentives. That said, we find no evidence of a dampening effect on outflows during the 2013 U.S. "taper tantrum". We argue that current swing pricing rules, which tend to be based on applying a constant swing factor once outflows exceed a certain threshold, are unlikely to offset investor first-mover advantages in stressed market environments.

We also provide evidence that Luxembourg funds benefited from higher returns during the taper tantrum. This tallies with the prediction that swing pricing helps to contain the dilution of the fund value. Furthermore, we show that Luxembourg funds experienced a higher volatility of daily price changes. We relate this finding to our prediction that swing pricing increases the accounting volatility of funds. Finally, we assess whether swing pricing reduces fund managers' incentives to insure against liquidity risks. Controlling for a comprehensive set of fund characteristics, we find that Luxembourg funds hold less cash. While this is generally justified by the dampening effect of swing pricing on fund outflows during normal market conditions, reduced cash holdings could aggravate investor incentives to withdraw during stress episodes. This suggests that minimum liquidity requirements for funds could strengthen the effectiveness of swing pricing as a risk management tool.

Our paper is related to a young but growing strand of the literature that studies the financial stability concerns arising from mutual fund flow dynamics. Similar to one of our research questions, Malik and Lindner (2017) discuss the effect of swing pricing on fund outflows during times of stress. Based on analysing samples of three and six individual funds, they find evidence that investor first-mover advantages pertain to swinging funds during such periods. This result tallies with one of our hypotheses, and we find supporting empirical evidence based on assessment of a large sample of funds during the taper tantrum.

Our work also builds on Chen et al. (2010), who develop a model showing how costly redemptions dilute a fund's NAV per share, creating an incentive for investors to run on the fund. In line with their model, they provide evidence that equity funds investing in less liquid assets experience greater outflows in response to poor performance. Goldstein et al. (forthcoming) show that this effect is even more pronounced for corporate bond funds, given the higher cost of liquidating the underlying assets. Furthermore, their results imply a concave shape of the flow-to-performance relation for corporate bond funds, which means that – in contrast to the case of equity funds – bond fund outflows are more sensitive to bad performance than inflows are to good performance. This points to the risk of self-reinforcing redemptions during periods of weak fund performance. Our findings confirm the concave flow-to-performance relation for U.S. bond funds, while suggesting that flows for Luxembourg funds are less susceptible to bad performance.

Another part of this literature focuses on how funds manage their cash holdings, which provide a first line of defence against large redemption requests. The work of Chernenko and Sunderam (2016) illustrates how U.S. equity and long-term corporate bond funds use their cash buffers to accommodate fund flows rather than transacting in the assets they are invested in. They argue that cash, including cash substitutes (e.g., short-term debt securities), is the primary liquidity management tool of these funds. Other tools, such as redemption fees or lines of credit, are found to be of minor importance. In line with this, the authors show that funds investing in less liquid assets hold more cash. This is consistent with the results of Wang (2015), who shows that large cash buffers reduce investor incentives to run on corporate bond funds. Zeng (2017), by comparison, points to the dilemma that fund managers may face in using their cash. Accommodating redemptions by running down the fund's cash position today might force the fund to sell assets in future periods in order to replenish the cash buffer. Rational investors anticipate these future sales and the associated dilution of the fund's NAV and hence choose to run today. Our paper adds to this work by analysing how the design of swing pricing can complement cash buffers in reducing the redemption risks.

Morris et al. (2017) broaden the perspective on this issue by developing a model in which the fund manager can choose between liquidating assets in expectation of future redemptions and selling them at a fire-sale discount in response to actual redemption requests. This implies that fund managers may decide to sells assets in advance of fund outflows (i.e., "hoard" cash) if the associated costs are sufficiently low relative to the fire-sale discount. Based on a sample of global bond funds, Morris et al. (2017) and Shek et al. (2015) find support for advance selling by fund managers, pointing to a potential amplifying effect on market downturns.

Understanding how fund managers respond to market shocks is key to assessing their potential contribution to systemic risks. The study by Banegas et al. (2016) emphasises the impact of monetary policy shocks on fund flows. The authors show that an unexpected tightening of monetary policy induces persistent outflows from bond funds. Given the associated dilution effect on funds' NAV, this aggravates the first-mover advantage that funds investing in illiquid assets are exposed to. Feroli et al. (2014) illustrate how a growing fund industry may intensify the risk of concerted selling by fund managers in response to a perceived tightening of monetary policy, such as during the taper tantrum. These concerns echo the findings in studies on the herding behaviour of institutional investors (e.g., Cai et al. (2016)), and the references therein), which may propagate illiquidity across financial markets as documented in, for example, Manconi et al. (2012) or Jotikasthira et al. (2012). While our paper is not concerned with interactions among fund managers, our conceptual framework takes into account the adverse effect of fund sales on market liquidity. Indeed, a number of bond market trends suggest that such effects may have further increased in recent years (Committee on the Global Financial

System (2014, 2016)). One issue is reduced availability of liquidity services from dealer-banks, which implies that fund managers may need to accept higher discounts if they are forced to sell during episodes of market stress (Bao et al. (2016), Fender and Lewrick (2015)).

Finally, our paper connects with the literature on the design and effect of mutual fund fees or charges. Chordia (1996) develops a model to explain the diversity of open-end fund charges. His model predicts that fund managers can dissuade investor redemptions by charging front- or back-end load fees. As a result, funds charging such fees attract more long-term investors allowing the fund manager to hold less liquid assets in order to raise fund returns. Nanda et al. (2000), by comparison, focus on the interaction between load fees and management fees as well as fund manager skills. Similar to the result in Chordia (1996), their model suggests that the more skilled fund managers, who can generate higher returns, seek to attract long-term investors by charging low management fees, while charging a load fee to disincentivise subscriptions by short-term investors with high liquidity needs. In Lewrick and Schanz (2017), we develop a model showing that trading frictions and investors' liquidity needs determine the fund manager's ability to swing the settlement price in the presence of no-arbitrage conditions. Based on this, we derive welfare-optimal swing pricing policies.

Several empirical studies consider the dilution of fund value that arises from mutual fund flows. For one, Edelen (1999), using monthly flow data finds that liquidity-motivated trading has a significant adverse effect on open-end U.S. equity fund performance. Greene and Hodges (2002) confirm this result for international funds based on daily flow data, but find no significant effect for other fund categories. Greene et al. (2007) study the effect of redemption fees on fund flows. Their results point to a sizeable reduction in flows for funds that introduce redemption fees, with daily flows for U.S. bond funds declining by as much as 77%. This suggests that swing pricing could exert a powerful influence on investor behaviour since, as discussed in the next section, swing pricing and redemption fees affect investor payoffs in a similar manner.

The rest of the paper is organised in three sections. Section 2 presents the rationale for swing pricing, including the challenges associated with its implementation in practice. This provides the conceptual background to derive a number of testable predictions. We apply these predictions to the data in Section 3, where we assess the impact of swing pricing on several fund performance measures, highlighting the differences between the impact under normal market conditions and during the 2013 taper tantrum. Section 4 concludes.

2. The basics of swing pricing

This section presents a conceptual framework to organise our assessment of swing pricing. We start by illustrating the rationale for swing pricing and how funds implement it in practice. Based on this, we derive five testable hypotheses of the effect of swing pricing. We motivate these hypotheses by focusing on economic intuition, while also presenting a formal motivation based on a global games model in the appendix of this paper.

2.1. *How swing pricing reduces fund dilution*

Our analysis builds on the observation that net fund flows dilute the value of the fund whenever they prompt the fund manager to trade securities. To see why this matters for investor behaviour, we consider a stylised example of how the NAV per share of an open-end mutual fund is determined. At the end of each period t (typically a trading day), the fund manager calculates the NAV of the fund per outstanding share at t and collects all customer orders in terms of the number of shares to redeem or issue. Whenever redemptions exceed subscriptions to the fund (i.e., net fund inflows are negative), the fund manager sells securities in the next period ($t+1$) to raise enough cash to pay out investors. Likewise, the manager buys securities in $t+1$ in response to having received net inflows. In both cases, the fund manager incurs transaction costs (e.g., commissions, fees). When selling securities, the fund also faces liquidation costs. These are equal to the difference between the prices of the securities that are used in the calculation of the NAV at t (typically the mid-price at the end of period t) and the prices at which the securities are effectively sold at $t+1$. Liquidation costs arise if the price of the securities falls from t to $t+1$. But even in the absence of changes in the market price, the fund manager will usually not be able to sell at the mid-price, but only at the price offered by her market-maker (e.g., a dealer-bank), which will charge a spread for the liquidity service. This spread will often increase with the size of the trade, suggesting that the price moves against the fund manager if she wishes to sell a larger amount of securities.

Since trading is costly, net fund flows in t dilute the NAV of the fund. Yet the dilution does not show up before the calculation of the NAV per share in $t+1$. This is because the NAV at t does not reflect the future transaction and liquidation costs associated with net cash flows in t. The dilution is particularly pronounced if the fund sells relatively illiquid assets. Hence, funds that invest in thinly traded assets (e.g., high-yield corporate bonds) are more exposed to dilution than those investing in liquid assets (e.g,. government bonds of major economies). In addition, the cost of trading can spike during periods of elevated market uncertainty, when market-makers curtail their liquidity provision to mitigate their risks. These episodes are typically characterised by large net fund outflows, as investors seek to redeem their shares to meet their own liquidity needs or become more pessimistic about the future value of the fund.

Informed investors will anticipate that fund managers facing large net outflows in period t will be forced to sell securities – possibly at a large discount – in the next period, which will drive down the NAV per share in $t+1$. Particularly under strained market conditions, investors may also suspect that the prices of relatively illiquid assets that are used to calculate the NAV at t do not yet factor in the latest information (i.e., they are "stale") and could prove to be significantly higher than the prices at which the fund manager can actually sell the assets. Since the cost of liquidating assets is exclusively borne by the investors that remain with the fund, each individual investor may thus be tempted to withdraw from the fund, hoping to benefit from a first-mover advantage.

Swing pricing offers one policy option to reduce the dilution effect and the implied first-mover advantage. It allows the fund manager to reduce or raise the NAV per share (p_t) by the *swing factor* (s_t) in response to large net fund outflows and inflows, respectively. If the NAV per share is swung, all transactions are settled at price $\tilde{p}_t$, the "swung" NAV per share:

$$\tilde{p}_t = (1 - s_t)p_t. \tag{1}$$

The sign of the swing factor depends on the sign of total net fund flows in that period. If the fund manager applies a *full* swing pricing policy, she sets a positive (negative) swing factor whenever the fund experiences net outflows (inflows), while the swing factor is only equal to zero if fund flows net out. Given the operational cost of determining whether or not to activate the swing factor, a *partial* swing pricing policy is common in practice (ALFI (2015b)). In this case, the swing factor is positive (negative) only if total net outflows (inflows) exceed a specified threshold.[4] To keep investors from gaming the swing pricing policy, most funds do not disclose the threshold, whereas the swing factor is typically made available upon investor request.

Swing pricing partly, or fully, offsets the dilution that arises from net fund flows. There are several effects at work. First, for given net flows, a positive (negative) swing factor reduces (raises) the amount of cash the fund manager pays out to (receives from) trading investors. This effect raises the value of the fund, compared with the case of not swinging, regardless of the direction of net fund flows. Second, a positive (negative) swing factor reduces (raises) the amount of assets the fund manager sells (buys) in the next period to accommodate net flows today. For the case of net outflows, the reduction in the amount of assets that need to be sold reduces the dilution effect that arises from liquidation costs. For the case of net inflows, by contrast, the increase in the amount of assets purchased by the fund results in additional transaction costs, partly offsetting the anti-dilution effect.[5]

In practice, as confirmed by anecdotal evidence from industry experts, funds set the swing factor equal to the approximate cost of selling securities under normal market conditions. While some funds apply different swing factors depending on the amount of net outflows, most funds tend to set a uniform swing factor which is periodically reviewed by the fund company. Furthermore, many funds commit to not raising the swing factor above a maximum value, often around 2% of the NAV per share for bond funds (ALFI (2015a,b)). These design choices reflect the trade-off between approximating dilution effects, which may be difficult to attribute to individual investor transactions, and the need for operationally efficient and transparent rules of application.[6]

[4] In principle, the threshold and swing factor can differ depending on whether the fund faces net inflows or net outflows.

[5] Assuming that a fund with net inflows equivalent to n_t needs to purchase $n_t(1 + \lambda_t)$ worth of assets, with $\lambda_t > 0$, the revenue from swinging, $s_t n_t$, is weakly larger than the additional trading costs, $s_t n_t \lambda_t$, as long as $\lambda_t \leq 1$. This condition holds as long as the fund incurs not more than \$1 in trading costs to buy \$1 worth of assets.

[6] The future costs of selling (or buying) assets are arguably unknown to the fund manager at the time she has

2.2. How swing pricing affects investor behaviour and fund manager incentives

We derive five testable predictions that follow from the application of swing pricing. The first one stems from the effect of swing pricing on investor incentives to withdraw from the fund. As noted above, swing pricing affects these incentives in two ways. First, a positive swing factor reduces the payout to redeeming investors, which discourages investors from withdrawing from the fund. Second, for any given amount of net outflows, a positive swing factor reduces the dilution of the fund value, which, in turn, raises the expected return from remaining invested in the fund. We expect these effects to be strongest when past fund performance is weak. This is because, for bond funds, weak performance has been found to predict future fund outflows, whereas strong performance has only a moderate effect on inflows (e.g., Goldstein et al. (forthcoming)). Investors in a fund that performs badly are thus likely to expect other fund investors to withdraw, which would prompt the fund to swing the NAV downwards in order to contain dilution. As a result, investors in a fund that applies swing pricing would have fewer incentives to withdraw than those invested in a fund that does not swing. We summarise these consideration in Hypothesis 1:

Hypothesis 1. *Swing pricing reduces fund outflows in response to weak fund performance.*

We illustrate the above effects in Figure 1. Here, we assume that each investor receives a noisy private signal (θ_i) about the future returns of the fund (see the appendix for details). If the signal is low (i.e., moving towards the left on the horizontal axis), the investor expects low future returns and predicts that a large number of investors will redeem their shares, which further reduces the expected payoff (shown on the vertical axis) due to dilution of the fund. The solid red line depicts the payoff that results from staying invested for the case of a non-swinging fund, given the investor's beliefs about the behaviour of all other invertors. The investor compares this payoff with the one resulting from withdrawing from the fund. The latter is given by the dashed red horizontal line, which highlights that future returns do not affect the investor's payoff if she redeems. If the investor receives the signal θ_A, she is exactly indifferent between withdrawing and remaining invested, as shown by the intersection of both red lines at point A. Swing pricing shifts this point based on the two effects discussed above. First, it lowers the payout to redeeming investors as shown by the downward shift in the horizontal line, moving the point of indifference to B. Second, it mitigates the dilution of the fund. This raises the expected payoff

to publish the NAV. This is for several reasons. For one, the cost of liquidating assets depends on the market conditions that prevail when the fund sells the assets. These costs can be hard to predict, particularly for less liquid assets and under strained or volatile market conditions. Second, the cost of transacting will also depend on future fund flows that may be equally difficult to predict. The fund manager may, for example, postpone asset sales and draw down cash balances if she expects future inflows to offset the need to sell assets as suggested by the empirical findings in Chernenko and Sunderam (2016). By contrast, fund managers may be selling assets in excess of net outflows as proposed by the results in Shek et al. (2015) and Morris et al. (2017). Incurring higher transaction costs today would be justified if the fund manager anticipated more outflows or worse market conditions in the future. As a result, the effective costs of selling assets may be difficult to allocate across individual orders on any particular day.

of remaining investors as depicted by the upward shift in the solid line, shifting the intersection of the two payoffs (black lines) to point C. The investor would thus remain invested even if her signal is lower than θ_A as long as her signal is at least θ^*. This implies that swing pricing reduces fund outflows for any given expected return of the fund. Note that the difference between the two payoffs from remaining invested (solid lines) increases as the signal becomes lower. This is because the dilution of the fund rises as a larger share of investors is expected to redeem due to the increasingly weak outlook on fund performance. The effect of swing pricing on fund outflows is thus expected to become stronger as the expected fund performance weakens. To the extent that past performance is a good predictor of future performance, we expect swing pricing to dampen outflows in response to weak fund performance as stated in Hypothesis 1.

Our second hypothesis is concerned with the effectiveness of swing pricing as a financial stability tool given its current application in practice:

Hypothesis 2. *Swing factors that are calibrated to normal market conditions may fail to offset investor first-mover advantages during periods of market stress.*

Since liquidation costs rise under stressed market conditions (e.g., Committee on the Global Financial System (2014)), fund managers would need to raise their swing factors to offset the first-mover advantage. In practice, however, swing pricing rules tend to be simple and swing factors to be confined to relatively low values.

We illustrate in Figure 2, based on a stylised example, the difference between how swing factors are typically calibrated in practice and how they would need to be set in order to fully offset the first-mover advantage. The red (dotted) line shows an example of a typical swing pricing rule, where the swing factor is set to 1% of the NAV per share whenever net outflows exceed 2% of the fund's total net assets (TNA) and is zero otherwise.[7] The swing factor is calibrated so that it corresponds to the cost of liquidating 2% of the fund's TNA. At this level of outflows, the red line touches the black (dashed) line, which represents the cost of liquidating securities. This cost increases with the amount of outflows because of the adverse price impact the fund manager faces when having to sell large amounts of securities (Borkovec et al. (2016)).

The blue line, finally, depicts the swing factor that follows from an outflow-dependent policy. It ensures that investors withdraw if, and only if, they expect the fund returns to be negative (i.e., less than the outside option of holding cash). We derive this policy formally in the appendix. The main characteristic of this policy is that it fully offsets the first-mover advantage by reducing the payout to investors in response to larger outflows. We note that the swing factor is lower than corresponding liquidation costs. Thus, under this policy, outflows dilute the value of the fund. Yet because of the dual effect of swing pricing on investor payoffs, this swing factor still keeps investors that expect small positive returns from redeeming.

There are three regions of interest in Figure 2. The first one concerns outflows of up to

[7]The parameter choices of this stylised example tally with those reported in industry surveys (ALFI (2015b)) or by fund investment companies (e.g., Golub et al. (2014)).

2% of TNA. Here, the dilution effect is weak so that the two swing pricing rules generate very similar outcomes. The second region is for outflows equivalent to 2% to 8% of TNA. In this region, a fund that applies a 1% swing factor taxes redemptions by more than what would be necessary to address the first-mover advantage. As a result, there may be "captured" investors that (e.g., given private information) expect negative fund returns but remain invested because of the swing factor.[8] It is in this region of moderate outflows that we would expect swing pricing, as applied in practice, to have a relatively strong dampening effect on outflows if compared with funds that do not swing. The third region covers outflows exceeding 8% of TNA, where the outflow-dependent rule implies a swing factor above 1%. As outflows increase, the gap between the two rules widens, suggesting that a 1% swing factor becomes increasingly ineffective in addressing the first-mover advantage. As a result, fund flows would become more sensitive to expected fund returns.

Our third prediction relates to the effect of swing pricing on the fund's returns:

Hypothesis 3. *Swing pricing raises measured fund returns by reducing fund dilution, particularly during periods of large fund outflows.*

This is because the fund reduces the payout to redeeming investors by adjusting the NAV downwards. In addition, the fund incurs lower liquidation costs since it needs to sell fewer securities to service redemptions. The results in BlackRock (2011) indicate that such effects can be sizeable. For the period from July 2010 to June 2011, the study finds an increase in annual fund returns by up to 2.5 percentage points with funds swinging on up to 72 days.[9] While we expect swing pricing to support fund returns whenever the fund swings the NAV, the effect should be strongest when liquidation costs are high such as during stressed periods.

Our fourth hypothesis concerns the impact of swing pricing on the volatility of fund returns. There are two considerations in the context of swing pricing. The first one is its effect on the volatility of the published (i.e., swung) fund prices, often referred to as accounting volatility (ALFI (2015a)). The second, more indirect one, is the effect of swing pricing on the volatility of the fund's portfolio. The overall effect of swing pricing on the variance of the NAV per share is then given by:

$$Var[\tilde{p}_t] - Var[p_t^n] \;=\; Var[s_t\, p_t] - \; 2Cov(p_t, s_t p_t) \;+\; Var[p_t] - Var[p_t^n], \tag{2}$$

where we denote by p_t^n the (counterfactual) price per share that would prevail in the absence of swing pricing. The first two terms on the right-hand side of equation (2) summarise the effect of swing pricing on the variance of the NAV per share. $Var[s_t\, p_t]$ represents the additional

[8]The discussion in Greene et al. (2007) suggests that the desire to prevent investors from being captured in weak funds indeed determined the U.S. Securities and Exchange Commission's cautious stance on allowing U.S. funds to impose redemption charges.

[9]For the year 2015, a follow-up study (BlackRock (2016)) reports additional fund returns of up to 0.77 percentage points and funds swinging on up to 46 days.

variation in the NAV per share that is due to the up- and downward adjustment of the share price by the swing factor (s_t). The covariance term, in turn, captures the comovement of the swing factor with the NAV per share. The sign of this term depends on the contemporaneous correlation of net fund flows, which determine the sign of the swing factor, and the fund's (unswung) share price (p_t). If the price of the fund's portfolio is positively correlated with net fund flows, the covariance term will be negative, raising the accounting volatility of the swinging fund. In our empirical analysis (see Section 3.3), we provide some evidence to support this claim, by showing that weak fund performance induces fund outflows, which in turn may prompt the fund manager to swing the NAV downwards (i.e., $s > 0$).

The difference between the last two terms on the right-hand side of equation (2) represents the effect of swing pricing on the variance of the fund's underlying portfolio. It is difficult to sign this effect because of the hypothetical nature of the comparison. The two terms cancel out if swinging has no effect on the composition of the fund's portfolio. To the extent that swing pricing induces the fund to raise its holdings of risky assets (see below), we would expect the volatility of the underlying portfolio to increase. Taking the two effects together, we predict that:

Hypothesis 4. *Swing pricing raises a fund's accounting volatility.*

This effect is expected to be strongest during times of large net fund flows, when the swing factors are triggered most often.

Our last prediction relates to the effect of swing pricing on fund manager incentives to insure against liquidity risks. We argue that:

Hypothesis 5. *Swing pricing reduces funds' liquid asset holdings.*

Swing pricing, by discouraging investors from redeeming their shares, would allow the fund manager to take on more liquidity risk if compared with a non-swinging fund. Compensation schemes that are linked to fund performance, for example, provide a strong incentive to reduce the fund's holdings of low-yielding liquid assets.[10] In line with this hypothesis, Chernenko and Sunderam (2016) show that variable annuity funds hold less cash than similar open-end funds because their fund in- and outflows are less volatile. The flip side of reduced cash holdings is that they raise the average cost of liquidating the fund's assets. This raises the implied dilution of investor redemptions, which, in turn, could reduce the dampening effect of swing pricing on fund outflows, particularly under strained market conditions when liquidity concerns come to the fore.

[10] Ma et al. (2016), for example, document that roughly three quarters of fund managers received performance-linked bonuses for a sample of more than 5,000 U.S. open-end mutual funds over the period from 2006 to 2011.

3. Empirical analysis

This section presents the empirical analysis to test the five hypotheses that follow from our conceptual framework. The section starts with a description of the data. Guided by our predictions, we analyse the effect of swing pricing by comparing fund flow dynamics as well as other fund metrics of U.S. open-end bond funds with those of comparable Luxembourg funds. We consider developments for the entire period of observation (2012–16) before turning to developments during the taper tantrum, which was marked by significant fund outflows. To conclude, we assess how swing pricing affects funds' cash holdings.

3.1. Data

Our analysis builds on 1,719 mutual bond funds for which we gather monthly data from Lipper and daily data on funds' NAV from Bloomberg. To construct our sample, we first select all actively managed open-end mutual bond funds available from Lipper that are domiciled in the United States or Luxembourg. Data are available at the level of the individual fund's share classes. We keep only the primary share class of each fund to avoid bias from intra-fund reallocations or subsidisation. Hence, we can refer to each fund share class as representing a unique fund. Data coverage for Luxembourg funds improves significantly as of 2012, which is why we base our analysis on the period from January 2012 to May 2016.

All funds in the sample need to meet two criteria. First, based on the Lipper fund classification (henceforth referred to as the fund *style*), we keep only funds that can be allocated to a style for which we observe both U.S. and Luxembourg funds. This is to ensure that we are comparing funds with similar investment focus. Second, we exclude all funds that invest mainly in advanced economy sovereign debt for which liquidation costs are low and, as a result, the first-mover advantage should be small. Overall, our sample consists of 1,000 U.S. funds and 719 Luxembourg funds, split across ten different styles such as *Bond USD Corporates* or *Bond USD High Yield*.

Fund flows as well as other fund characteristics are fairly similar for the U.S. and Luxembourg funds, highlighting the similarity of their investment strategies and investor basis. Figure 3 depicts the aggregate fund flows as a percentage of TNA (left-hand panel), and TNA by country (right-hand panel). At this level, fund flows of U.S. and Luxembourg funds as well as their TNA are highly correlated, with correlation coefficients of 0.78 and 0.94, respectively.

The period from May to early July 2013, highlighted by the grey-shaded region, marks a clear break in the flow patterns for both countries. This period was characterised by a sharp increase in bond yields, following signs of a possible tapering of the U.S. Federal Reserve's monetary policy accommodation. During this taper tantrum, credit spreads on corporate bonds and emerging market economy debt increased significantly, resulting in sizeable valuation losses for the type of funds in our sample (Bank for International Settlements (2013)). This suggests that this period of strained market conditions be specifically accounted for in our empirical analysis.

Even though U.S. and Luxembourg funds share many common features, some notable differences exist. To provide a comprehensive comparison, we show the summary statistics of each country sample in Table 1. One apparent difference is the size of the funds, as measured by their TNA. U.S. funds, on average, are 5.4 times as large as their Luxembourg counterparts in the sample. Furthermore, U.S. funds exhibit somewhat higher and less volatile returns, on average, during the period of observation. Fund flows, by comparison, appear broadly similar across both groups, supporting the patterns shown in Figure 3. About 60% of the funds report a benchmark index to evaluate their performance. These funds tightly manage their performance against the benchmark, as is evident from the low standard deviation and small range of the reported *market-adjusted returns*, which are given by the difference between the funds' returns and those of the benchmark. We will exploit this fact when comparing the performance of funds during the taper tantrum (see Section 3.4 below). Finally, we note that only about one out of eight U.S. funds applies redemption charges, which is consistent with the results in Chernenko and Sunderam (2016). Luxembourg funds make even less use of redemption charges. This is not surprising, given the widespread use of swing pricing, which provides a similar means of levying liquidation costs on redeeming investors.

Other studies using the CRSP database, which only contains data for U.S. funds, provide a welcome benchmark for our sample selection. Our summary statistics, for example, tally with those presented by Goldstein et al. (forthcoming) for a sample of 4,679 fund share classes (1,660 corporate bond funds) from 1992 to 2014. For one, their study reports a median and standard deviation for cash holdings of 2.81% and 10.04, as compared with our values of 2.20% and 14.80, respectively. Likewise, they report the use of redemption charges only for the 80th percentile of U.S. funds (75th in our sample).

3.2. Methodological approach

Our methodological approach builds on the premise that investors subscribe to funds or redeem their shares based on the information they have about a fund at any given point in time. In this sense, we presume that investors in Luxembourg funds are aware of the risk of the NAV being swung and adjust their trading behaviour accordingly. This information, often supplemented by a commitment to a maximum swing factor, is available from the fund's prospectus. In some cases, investors may also know the swing factor that is currently applied if the fund manager swings the NAV, which is typically available at the request of the investor. That said, the threshold at which the swing factor kicks in is not disclosed by the fund, nor can investors observe whether the NAV was actually swung.

Investor expectations are a key determinant of investor behaviour. Yet the set of information that is used by individual investors to form their expectations is unknown. Recent information on past fund returns, however, is likely to be a pivotal component of investors' information set. Our empirical analysis thus builds on using past fund returns as a gauge of investors' return expectations, in line with the literature studying the relation of fund flows and past returns.[11]

Our empirical analysis also presumes that U.S. and Luxembourg funds are comparable across the main parameters of interest to investors. Indeed, with the exception of swing pricing, U.S. and Luxembourg fund managers can resort to the same set of policy tools to address redemption pressures (IOSCO (2015)).[12] At the same time, it appears unlikely that the ability to swing prices has any meaningful impact on the fund company's decision whether to register a fund in the United States or in Luxembourg. Other considerations, such as having established a renowned brand name in the region, are likely to be far more important. Thus, we can consider the ability of the fund to swing as largely exogenous. Controlling for other fund characteristics, we can therefore gauge whether differences in the fund performance of U.S. and Luxembourg funds are consistent with the predictions from the Section 2.2.

3.3. Differences in the flow-to-performance relation of U.S. and Luxembourg funds

We start with testing Hypothesis 1 by analysing whether Luxembourg fund flows are less sensitive to weak performance than those of their U.S. peers. To do so, we run several variants of the following baseline regression:

$$flow_{it} = X'_{it-1}\,\beta\,\delta + \alpha_i + \gamma_{ct} + \varepsilon_{it}, \tag{3}$$

where $flow_{it}$ represents the value of fund i's net inflows as a percentage of TNA in month t. X_{it-1} is the vector of p predictors, β is a $p \times 4$ matrix of coefficients, δ is the 4×1 vector of interaction dummies. Furthermore, α_i represents the time-invariant individual fund effect, whereas γ_{ct} captures country-month fixed effects to account for, e.g., tax-loss selling before year-end. ε_{it} is the error term.

X_{it-1} comprises all time-varying fund characteristics based on those shown in Table 1. In addition, we construct a variable of returns interacted with an indicator variable that is equal to one if returns are negative. This allows us to account for the potential non-linearity in the flow-to-performance relation, following the approach proposed by Goldstein et al. (forthcoming). That is, we control for the possibility that flows respond differently to negative returns than to positive ones. Our main results are based on the first lag of monthly fund returns (annualised, in per cent). This performance metric is available to investors when taking their decision whether to sell or buy shares. It also addresses potential endogeneity concerns that would be associated with using current returns. Furthermore, relying on nominal returns is consistent with the findings in, e.g., Fulkerson et al. (2013), who make the case that investors focus on simple return measures, largely neglecting any risk adjustment. All that said, we consider a variety

[11] See Chevalier and Ellison (1997) or Sirri and Tufano (1998) for early contributions to this literature as well as Clifford et al. (2011) for a recent discussion of the literature.

[12] We note that Luxembourg funds, in principle, are also allowed to charge anti-dilution levies on an individual transaction basis. These levies are generally applied to large orders of individual clients. They are thus less relevant for the investor coordination problem studied in our paper.

of alternative return measures to confirm the robustness of our results (see below). Other fund-level controls are the first lag of (log) TNA, (log) age, flow value and of the expense ratio.

The interaction vector, δ, consists of four indicator variables, allowing us to distinguish the impact of the predictors for four different cases: (i) U.S. funds (the reference case); (ii) Luxembourg funds (indicated by LUX); (iii) U.S. funds during the taper tantrum (TT); and (iv) Luxembourg funds during the taper tantrum ($TT \times LUX$).

As a reference point, we consider a fund fixed-effect regression based on using only U.S. funds and omitting any interaction terms for the taper tantrum.[13] We highlight the slope coefficients on returns and negative returns in Column 1 of Table 2. The estimates support the findings in Goldstein et al. (forthcoming): inflows into bond funds are less sensitive to good performance than outflows are to weak performance as indicated by the much larger coefficient on negative returns than the one on (all) returns. Based on the point estimates in Column 1, a U.S. fund with annualised returns of +10% in the preceding month (roughly equivalent to the 75th percentile of the U.S. funds' returns in our sample) would experience additional inflows of only 0.01% of TNA in the current month, with the effect not being statistically significant. Had the fund, by comparison, returned −10% (roughly equivalent to the 10th percentile of the U.S. fund returns, Table 1) it would have been subject to additional net outflows of 0.52% of TNA ($10 \times (0.001 + 0.051)$). To put these numbers into perspective, we recall that average cash holdings of U.S. funds were 1.75% of TNA.

The relation of fund flows and past returns differs for U.S. and Luxembourg funds, supporting Hypothesis 1. As we move from Column 1 to Column 2 in Table 2, we include the Luxembourg funds to assess the differences with their U.S. peers. What stands out is the Luxembourg funds' lower sensitivity to negative returns, which more than compensates for their higher sensitivity to performance more generally.[14] Our point estimates in Column 2 suggest that, on average, a Luxembourg fund with a pre-month return of −10% witnessed additional net outflows of 0.25% of TNA ($-10 \times (0.001 + 0.053 + 0.021 - 0.050)$). The same fund, by comparison, received additional net inflows of 0.22% of TNA ($10 \times (0.001 + 0.021)$) if its annualised pre-month return was +10%. The reduction in outflows that can be linked to swing pricing follows from the sum of the slope coefficients on returns and negative returns of Luxembourg funds ($0.021 - 0.050$). Conditional on returns being negative, outflows are reduced by nearly 0.03% of TNA for every percentage point decline in returns.

[13] Alternative estimation procedures, such as OLS or the widely applied GMM estimator proposed by Arellano and Bond (1991), do not appear preferable to the fixed-effect regression for our purposes. Clearly, the OLS estimation is expected to be biased in a dynamic panel setup, as is confirmed by a much higher coefficient estimate for lagged flows (not reported) compared with the estimate of the fixed-effect regressions. The GMM estimator, in turn, may overidentify the model given the large number of instruments that result from using a sample with up to 54 monthly observations per fund. Indeed, the length of the sample argues in favour of using the fixed-effect regression in our case.

[14] We can reject the hypothesis that the sum of the two slope coefficients, Return$_{t-1}\times$ LUX and Negative return$_{t-1}\times$ LUX, is zero for the usual confidence levels.

As a next step, we control for additional fund characteristics that may affect investor redemptions. First, we take account of redemption charges, which, similar to swing pricing, should disincentive investor redemptions. Column 3 in Table 2 reports the coefficients estimates that result from excluding all funds with redemption charges, which predominantly reduces the number of U.S. funds in the sample. Following this adjustment, the absolute value of the coefficient on negative returns interacted with the Luxembourg dummy increases. Thus, Luxembourg fund flows are, in relative terms, even less sensitive to past weak performance if we compare them only with U.S. funds that do not impose redemption charges.

Second, we account for differences in the funds' cash holdings in order to control for anticipated dilution costs. We recall from the conceptual framework that higher liquidation costs increase the dilution effect of investor redemptions, reducing investor incentives to stay with the fund. Cash holdings serve as a useful gauge of liquidation costs. As a direct effect, lower (higher) cash holdings raise (reduce) the average costs of liquidating the fund portfolio. Second, funds with lower cash holdings may have to respond more promptly to net outflows, suggesting that they have less leeway in timing their sales and may need to make higher price concessions when liquidating securities. Column 4 in Table 2 presents the slope coefficients for the return measures based on including lagged cash holdings in the set of predictors. We consider the changes in the estimates line by line. First, our estimates reinforce the earlier finding of a concave flow-to-performance relation for bond funds. Positive returns induce a modest net inflow into funds, with the coefficient estimate now being statistically significant. Negative returns, however, prompt much larger net outflows – to the tune of four times more (in absolute value) than the response to positive returns.

Once controlling for differences in cash holdings, we also find that net flows into Luxembourg funds are as responsive to positive returns as for their U.S. peers, with the slope coefficient ($\text{Return}_{t-1} \times$ LUX) becoming close to zero and statistically insignificant. One interpretation of this result is that Luxembourg fund managers have little incentive to dampen inflows into their funds by making active use of swing pricing (i.e., by adjusting the NAV per share upward).

The reaction of fund flows to negative returns, by contrast, differs across the two groups. Consistent with our earlier findings and the predicted impact of swing pricing, Luxembourg funds that yield negative returns are less susceptible to outflows than their U.S. peers. The difference is not only significant statistically, but also in terms of its magnitude. The marginal effect of negative returns on outflows is reduced by roughly 0.04% of TNA per percentage point of return.

Hypothesis 2 suggests that swing pricing, given its current design, is unlikely to offset investor first-mover advantages if markets are under stress. The taper tantrum interaction terms, indicated by TT in Table 2, allow us to indirectly test this prediction, even though we cannot measure such advantages directly. We focus on the specification in Column 4, discussed above, which includes controls for cash holdings and excludes funds with redemption charges. We take the sum of all eight slope coefficients for returns and negative returns reported in

Column 4, including those interacted with the taper tantrum interaction term, to calculate the flow-to-performance relation for Luxembourg funds during the taper tantrum. This yields 0.06% of TNA per percentage point change in (negative) returns, more than twice the value we found for normal market conditions. Had swing pricing policies fully offset first-mover advantages during the taper tantrum, there should have been no significant increase in the flow-to-performance relation. Our finding thus lends some indirect support to Hypothesis 2 and tallies with the results of Malik and Lindner (2017), who study first-mover advantages for a small sample of individual funds. We note, however, that the additional impact on Luxembourg fund flows during the taper tantrum is not statistically significant (see the coefficient estimates in the last two rows of Table 2), given the comparatively large standard errors.[15]

We assess the robustness of our results by considering alternative return measures. As a first check, we regress fund flows on the same set of predictors as in Column 4, Table 2, but vary the measure of fund returns. Specifically, we consider the impact of using cumulative returns over the preceding three months (Column 5) and six months (Column 6), respectively. This adjustment assumes that investors not only factor in the most recent returns to assess future fund performance, but also consider the fund's medium-term performance in their assessment. One rationale for such an approach is the presumption that skilled fund managers perform well on average, but may nevertheless fail to generate returns in individual months (Kacperczyk et al. (2014)).

Our main takeaway from the results shown in Columns 5 and 6 is that they lend further support to Hypothesis 1. First, we find additional evidence that negative returns induce fewer outflows from Luxembourg funds than from their U.S. peers. Intuitively, the difference becomes larger as we lengthen the range of returns that we assume investors are factoring into their decisions. Comparing a U.S. and Luxembourg fund with negative returns over the past three months, we find that the Luxembourg fund benefits from reduced outflows of about 0.08% of TNA per percentage point change in (negative) returns (Column 5). If, by comparison, the return of both funds was negative, on average, over the past six months, the benefit amounts to as much as 0.16% of TNA (Column 6).[16]

As a second robustness check, we consider whether potential differences in investors' currency of account affect our results. One concern with the above regressions could be that investors from different regions evaluate fund performance based on their home currency. Since an appreciation (depreciation) of the USD against the investor's home currency raises (reduces) the fund's return in home-currency terms, investors using different currencies of account could respond differently to past fund returns. While information on investors' currency of account is generally not available, a rough approximation is that investors are more likely to evaluate U.S. fund performance in USD terms and Luxembourg fund performance in euro (EUR), for

[15] Standard tests can also not reject the null hypothesis that the sum of both coefficients is zero.

[16] These results follow from adding the slope coefficients of $\text{Return}_{t-1} \times$ LUX and Negative $\text{return}_{t-1} \times$ LUX in Columns 5 and 6 of Table 2, respectively.

example, because investors are biased towards investing in funds domiciled in their home region. In Columns 1 to 3 of Table 3, we show the slope coefficients for Luxembourg funds based on measuring U.S. fund returns in USD (as throughout the paper), but swapping Luxembourg fund returns into EUR terms based on spot exchange rates shown in the left-hand panel of Figure 4.[17] As before, we consider results based on using monthly returns (Column 1), three-month (Column 2) and six-month returns (Column 3). We find that the estimates are little changed if compared with the corresponding estimates in Columns 4 to 6 in Table 2.

Finally, we consider alternative measures of investors' opportunity costs. Thus far, we have implicitly assumed that investors respond differently to negative returns than to positive returns because a natural alternative to investing in funds – at least in the short term – is to hold cash, which yields zero nominal return. In Columns 4 to 6 of Table 3, we alter this assumption and consider how our results change if we assume that investors benchmark fund returns against the corresponding risk-free rates. Columns 4 to 6 show the coefficient estimates for Luxembourg funds based on using monthly returns, three-month and six-month returns, respectively, subtracting the euro-currency market interest rates with the corresponding term for Luxembourg funds, while using the corresponding yields on the U.S. Treasury bills for US funds.[18]

Overall, the impact of these changes is fairly limited. This is not surprising since risk-free rates hovered around zero throughout most of the period of observation, as shown for the example of three-month rates in the right-hand panel of Figure 4. If anything, the results lend further support to accepting the hypothesis that swing pricing dampens fund outflows in response to negative returns during normal times. During the taper tantrum, by contrast, we find no evidence of a meaningful reduction in the sensitivity of fund flows to weak performance. To shed more light on this issue, we study fund flows, returns and volatility during the taper tantrum in more detail in Section 3.4.

3.4. Fund performance during the taper tantrum

We assess differences in fund performance between U.S. and Luxembourg funds to gauge the effects of swing pricing during the taper tantrum. Complementing the previous analysis on the flow-to-performance relation, we match individual Luxembourg funds with U.S. funds based on a variety of fund characteristics available to investors in the run-up to the taper tantrum. Overall, we detect little evidence of systematic differences in net fund flows of U.S. and Luxembourg funds during this episode. That said, our results suggest that Luxembourg funds which were subject to outflows benefitted from higher market-adjusted returns than their U.S. peers. This is consistent with the anti-dilution effect of swing pricing (Hypothesis 3). Furthermore, we find signs of increased (accounting) volatility for Luxembourg funds, supporting Hypothesis 4.

[17] We omit the coefficient estimates for U.S. funds because these remain the same as in Columns 4 to 6 of Table 2.

[18] We do not report the coefficient estimates for U.S. funds which change only at the level of the third digit if compared with the estimates in Column 4 to 6 of Table 2. These estimates are available upon request.

We estimate the average treatment effect of Luxembourg funds, the *treated* funds (ATET), to identify the effects of swing pricing. We consider the ATET of three different measures. The top rows of Table 4 present results for the cumulative net fund flows from May to June 2013.

The rows in the middle report estimates for market-adjusted returns. These are calculated as the difference between each fund's annualised returns and those of the fund's benchmark from May to June 2013. We use this measure, rather than nominal returns, to account for differences in the riskiness of fund portfolios. We recall that the funds in our sample deviate very little from their benchmarks (see also Table 1), suggesting that this adjustment provides a useful control for differences across fund returns that are not related to swing pricing.

The bottom rows, finally, report the ATET for the annualised volatility of daily fund returns based on the reported NAV per share. We calculate the volatility for the period from 2 May to 5 July 2013, which represents the beginning and end of the 2013 bond market sell-off (Adrian and Fleming (2013)). Because we expect funds to swing only if they experience large outflows during this period, we compare the returns and volatility based on using only funds that experience net outflows. In all specifications, we exclude funds that impose redemption charges to support the precision of measuring the impact of swing pricing on fund performance.

We apply several alternative matching algorithms to evaluate the effect of swing pricing. Columns 1 to 3 in Table 4 report the ATET using nearest-neighbour matching. We match each Luxembourg fund with four U.S. funds, using the number of neighbours recommended in Abadie and Imbens (2011). For the results in Column 1, we match funds based on their age as well as their average returns, net flows and total assets in the three months preceding the taper tantrum (February to April 2013). To account for differences between funds that cater more to retail than to institutional investors, we also include an indicator variable that is equal to one if the minimum required investment is below USD 10,000. In addition, we require that funds are only matched with funds that have the same fund style.

Luxembourg funds do not appear to have experienced fewer outflows than their U.S. counterparts during the taper tantrum. The first row of Column 1 depicts the ATET for cumulative net fund flows during the taper tantrum. We find no statistically significant impact.

Because investors' incentives to redeem depend on the liquidation costs of the fund, high (low) cash holdings in the run-up to the taper tantrum should dampen (amplify) net outflows. We thus refine our matching by including an indicator variable in the set of covariates which indicates whether the fund, in April 2013, had cash holdings below or above the median of funds that use the same benchmark. This takes into account that funds investing in different asset classes may be exposed to different liquidation costs and, as a result, will generally hold different cash buffers. The downside of this refinement is that it reduces the number of observations because data on cash holdings are not available for all funds. Column 2 in Table 4 shows the results, with the coefficient estimate turning out to be even lower, but remaining statistically insignificant.

Funds manage their performance tightly against the benchmark they commit to. Matching funds based on the same benchmark thus provides a very close match. Column 3 presents the results when using the same set of covariates as before (including cash holdings) and matching benchmarks exactly. For this specification, the ATET turns positive indicating reduced outflows from Luxembourg funds when compared with their U.S. peers. The number of available observations, however, becomes too small to draw any statistical inference, highlighting the trade-off between selecting a close match and the number of matchable funds.

To gain some further insights into the ATET, we develop an alternative matching algorithm based on the correlation of daily fund returns. This approach builds on the presumption that funds with similar portfolio allocations should be characterised by a high correlation of their returns. For each Luxembourg fund, we calculate the pairwise correlation coefficient of daily returns with each individual U.S. fund over the three months preceding the taper tantrum. Since Luxembourg funds experienced relatively steady inflows during these months (see also the left-hand panel of Figure 3), we do not expect their measured returns to be much affected by swing pricing activity. To further increase the precision of our comparison, we keep only correlation coefficients that are based on at least 30 observations per fund during this period, which gives us a maximum of 390 Luxembourg funds. Next, we match each Luxembourg fund with the U.S. fund for which we observe the highest correlation.

The corresponding ATET for the funds' net flows provides no evidence of a significant effect on Luxembourg fund outflows during the taper tantrum as shown in Column 4 of Table 4. While the effect points to a reduction in outflows, it is neither statistically significant nor of meaningful magnitude.

To assess the robustness of this matching algorithm, we also show the ATET that follows from matching each Luxembourg fund with the four U.S. funds that exhibit the highest correlation with this fund in Column 5. This specification confirms our earlier results, suggesting that, overall, Luxembourg funds were as exposed to outflows during the taper tantrum as their U.S. peers. These findings lend some support to Hypothesis 2, suggesting that swing factors, as applied in practice, are too low to have a meaningful impact on investor decisions during episodes of market stress.

We now turn to the assessment of market-adjusted returns to test whether Luxembourg funds managed to mitigate the dilution implied by fund outflows. Consistent with Hypothesis 3, we find evidence that Luxembourg funds generated higher returns than their U.S. peers during the taper tantrum. Columns 1 to 3 (centre rows) report the ATET based on using nearest-neighbour matching. These estimates point to additional returns in a range of about 37 to 52 basis points on an annualised basis – a sizeable effect, given that average market-adjusted returns hovered around zero when considering the entire period of observation (see Table 1). Matching funds based on their daily returns yields qualitatively similar results, although suggesting a somewhat lower effect at around 17 to 30 basis points (Columns 4 and 5).

We test whether the difference in market-adjusted returns is not an artefact of matching generally more profitable Luxembourg funds with less profitable U.S. funds. To do so, we estimate the ATET for the matched funds for each month over the entire period of observation based on comparing (annualised) market-adjusted returns for the latest two months. The left-hand panel of Figure 5 depicts the corresponding ATET as well as its 95% confidence interval based on the matching approach applied for the results in Column 2 of Table 4, which appears to strike a good balance between the number of matched funds and the stringency of the matching requirements. We find that the ATET tends to hover around zero, but spikes during the taper tantrum (highlighted by the grey-shaded region). This lends further support to our interpretation that swing pricing helped Luxembourg funds to contain dilution during the taper tantrum.

Finally, we evaluate whether Luxembourg funds that experienced outflows also exhibited higher volatility of their daily returns during the taper tantrum. The bottom rows of Table 4 show the ATET for each of our five specifications. Overall, the estimates support Hypothesis 4 that swing pricing raises the fund's accounting volatility, particularly when considering the narrowly matched specifications in Columns 2 and 3. As for the comparison of returns, we consider to what extent the difference between U.S. and Luxembourg funds is specific to the taper tantrum episodes. The right-hand panel in Figure 5 illustrates the ATET and corresponding 95% confidence interval, using the matching approach as in Column 2 of Table 4 for each month in our sample. For consistency, we calculate the annualised volatility based on two-month rolling intervals of daily returns. The results indicate a positive ATET on average, at around 1.5 percentage points of annualised volatility. Yet during the taper tantrum (highlighted by the grey-shaded region) we record a spike in the ATET, with the estimate rising significantly above its average value. One interpretation is that, consistent with the predicted impact, swing pricing tends to raise funds' accounting volatility, with the effect being amplified during periods of market stress.

3.5. Cash holdings in the presence of swing pricing

We conclude this section by comparing U.S. and Luxembourg funds' cash holdings to gauge their exposure to liquidity risks and test Hypothesis 5. Our conceptual framework highlighted that swing pricing could encourage fund managers to reduce cash holdings in order to raise returns. At first glance, the summary statistics of funds' cash holdings in Table 1 provide no support for this prediction. The picture changes, however, once we control for differences in fund characteristics. Indeed, we find evidence that Luxembourg funds hold less cash than their U.S. peers. This is consistent with fund manager incentives to insure less against redemption risks if the fund can discourage investor withdrawals by committing to swing the NAV when facing outflows.

We run several regressions to estimate the differences in funds' cash holdings as reported in Table 5. Column 1 presents the main coefficient estimates for a regression of cash holdings (as a percentage of fund value) on a variety of lagged time-varying (X_{it-1}) and time-invariant

(Z_i) fund controls:

$$cash_{it} = X'_{it-1}\,\beta_1\,\delta + \; Z'_i\,\beta_2\,\delta + \; \gamma_t \; + \; \gamma_b \; + \; \varepsilon_{it}, \tag{4}$$

where $cash_{it}$ measure fund i's cash holdings as a percentage of TNA in month t. We include a full set of country and taper tantrum interaction terms (summarised in δ), as in equation (3), as well as fixed effects for the respective month (γ_t) and the reported benchmark (γ_b) of the fund (not reported). One issue with funds' reported cash holdings is that highly levered funds or those with significant derivative positions, which tend to exhibit cash holdings in the tail ends of the sample distribution, could drive the results. To control for this, we winsorise cash holdings at 20% which excludes all funds with negative reported cash holdings.

Our main interest is in the coefficient on the indicator variable for funds domiciled in Luxembourg (LUX, Table 5, Row 1). We find that Luxembourg funds, on average, hold 0.98 percentage points less cash than those domiciled in the United States. The difference is large if compared with the funds' average cash holdings of 3.3% of TNA in the winsorised sample.

To further investigate the robustness of our results, we define an indicator variable that is equal to one whenever a fund has cash holdings above the median of those of other funds using the same benchmark and zero otherwise. Applying the comprehensive set of fund controls mentioned above, Columns 2 and 3 of Table 5 show the marginal effects (at the means) for a logit and probit regression based on using this indicator variable. Column 4, in turn, provides the marginal effects for a logit regression if we exclude all fund observations with negative reported cash holdings. For each of these specifications, the predicted probability of above-median cash holdings is lower for Luxembourg funds, in a range of 45% to 47%. This lends further support to Hypothesis 5 that Luxembourg funds hold less cash than comparable U.S. funds.

Table 5 provides several additional insights into the drivers of funds' cash management decisions. For one, we find that funds accommodate past flows by adjusting their cash positions, supporting the results in Chernenko and Sunderam (2016). Net outflows in the previous month, for example, are associated with lower cash holdings, suggesting that fund managers run down cash buffers to meet redemptions. Furthermore, funds with low annual charges (i.e., below the sample median) hold less cash on average. This is consistent with the predictions in the models of Chordia (1996) or Nanda et al. (2000), suggesting that fund managers attract long-term investors by charging low annual fees, which, in turn, allows the fund to hold less cash.

4. Concluding remarks

In this paper, we develop a conceptual framework to explore the effects of swing pricing. This framework yields several predictions to guide our empirical analysis of how swing pricing affects investor behaviour and fund manager incentives. Our identification strategy is based on comparing Luxembourg funds, which are allowed to apply swing pricing, with similar funds from the United States, where swing pricing is not yet available to fund managers. To this end, we construct a sample of 1,719 actively managed open-end mutual bond funds. Next to considering a comprehensive set of fund controls, we apply different matching approaches to ensure the comparability of Luxembourg funds with their U.S. peers.

Our main findings can be summarised as follows. Consistent with the predictions from the conceptual framework, we observe that negative returns prompt larger outflows from U.S. funds than from their Luxembourg counterparts. This observation holds during normal market conditions. Yet during the 2013 U.S. taper tantrum, a period of marked declines in bond prices, U.S. and Luxembourg funds appear to have been equally exposed to investor redemptions. This supports the view that current swing pricing rules, which tend to apply a constant swing factor if outflows exceed a certain threshold, fail to offset investor first-mover advantages in more stressed markets.

In terms of the effect of swing pricing on other fund performance measures, we show that Luxembourg funds generated higher returns during the taper tantrum. This tallies with the predicted anti-dilution effect of swing pricing, which is based on the redistribution of liquidation costs from remaining investors to those deciding to redeem their shares. In addition, we document that Luxembourg funds, relative to their U.S. counterparts, experienced an increase in the volatility of daily returns during the taper tantrum. This finding is consistent with our framework's prediction that swing pricing increases funds' accounting volatility.

Finally, we find evidence that Luxembourg funds hold less cash than comparable U.S. funds. By reducing redemption risks, at least under normal market conditions, the introduction of swing pricing encourages funds to seek higher returns by lowering their cash buffers. This weakens any stabilising effect of swing pricing on the underlying markets. Regulatory responses to address vulnerabilities in the mutual fund industry can thus be enhanced by taking the interaction of policy tools into account, such as combining swing pricing with minimum liquidity requirements for funds or liquidity stress testing. That said, more research is needed to assess the underlying risks in this industry in order to inform the design of risk management tools and regulatory frameworks.

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Figures and Tables

Figure 1: How swing pricing reduces the threshold signal

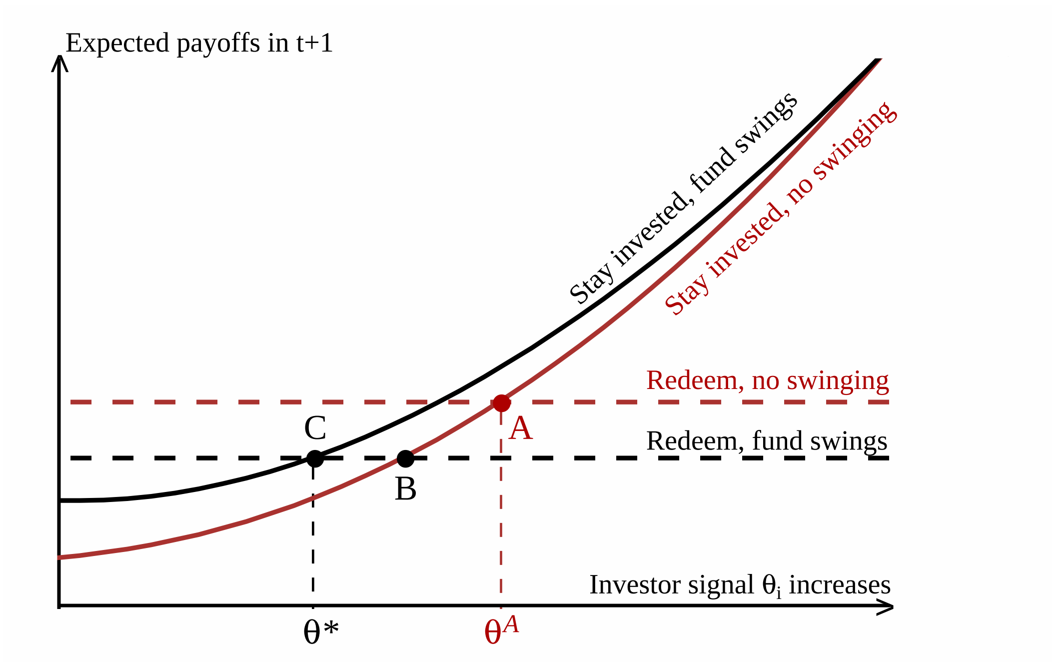


Figure 2: Swing pricing in practice – varying impact

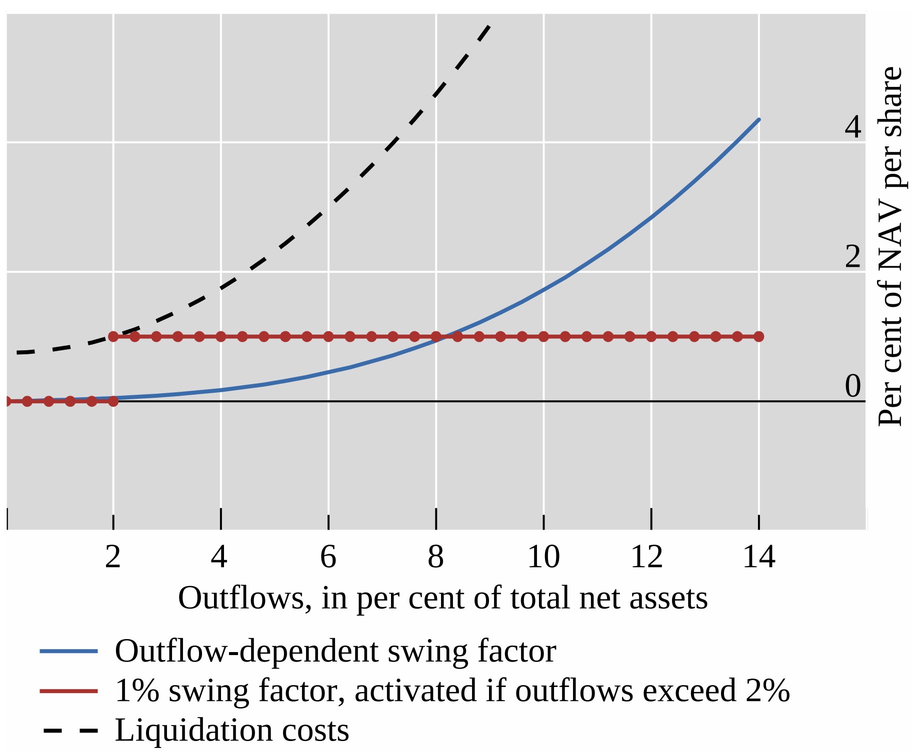
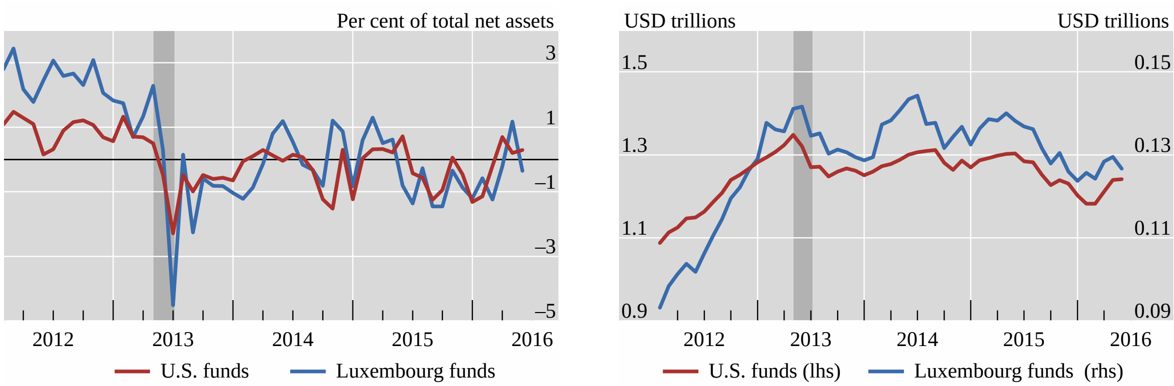


Figure 3: Aggregate fund flows and net assets by country

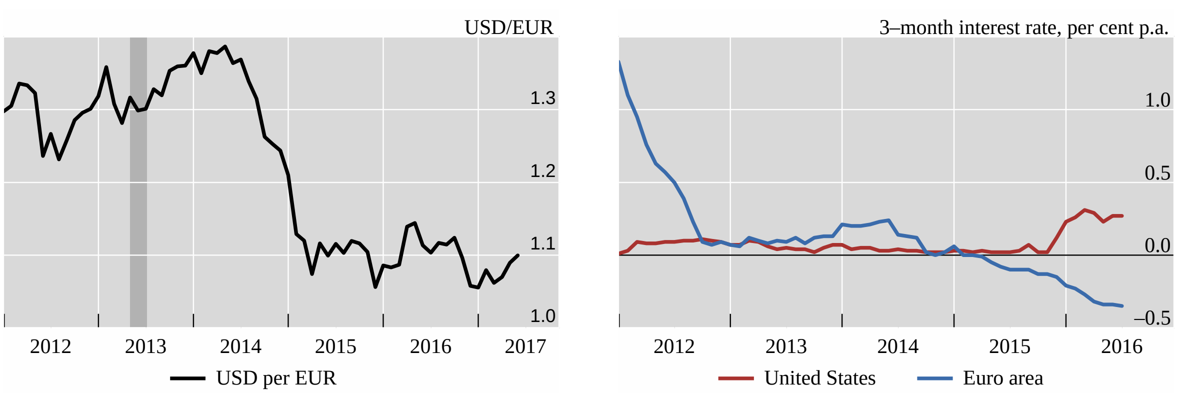
(a) Fund flows (b) Total net assets



Sample comprising 1,000 U.S. funds and 719 Luxembourg funds. The grey-shaded region indicates the period from 2 May to 5 July 2013 (taper tantrum).

Figure 4: Interest rates and exchange rates

(a) USD/EUR exchange rate (b) 3–month interest rates



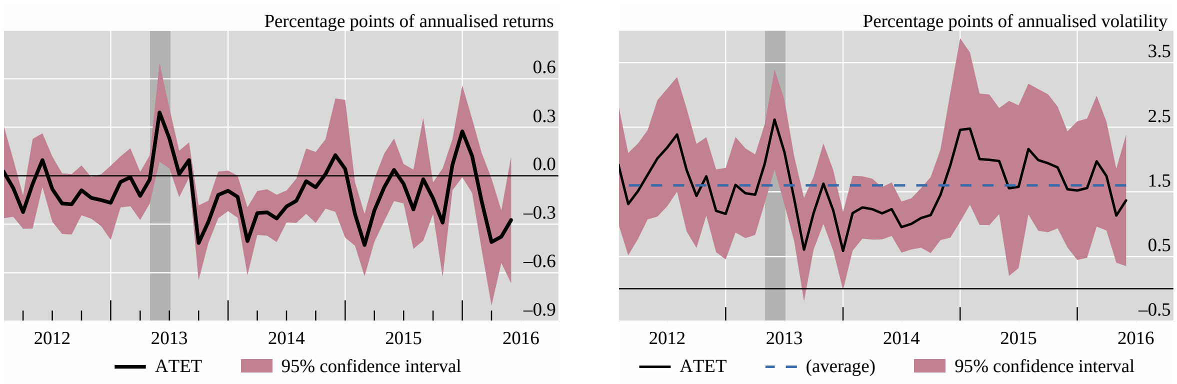
The USD/EUR exchange rate is in U.S. dollars (USD) per euro (EUR) based on spot exchange rates (noon, New York). For the U.S., 3–month interests rates are equal to the yield on 3–month U.S. Treasury bills based on dealers' closing bid rates. For the euro area, they are equal to the 3–month euro-currency market bid rates.

Sources: Bank for International Settlements; Federal Reserve Bank of New York; Federal Reserve Bulletin.

Figure 5: Monthly ATET estimates for Luxembourg funds

(a) Market-adjusted returns

(b) Volatility of daily returns



Estimates based on 82 matched Luxembourg funds. The grey-shaded region indicates the period from 2 May to 5 July 2013 (taper tantrum).

Table 1: Summary statistics

	U.S. funds					Luxembourg funds				
Variable	10%	50%	90%	St Dev	Mean	10%	50%	90%	St Dev	Mean
Total net assets	25.60	318.10	3,361	5,681	1,476	2.92	62.28	543.06	926.13	272.03
Flows	−3.51	−0.07	4.39	6.03	0.44	−4.92	−0.03	6.48	9.11	0.85
Returns	−12.53	2.83	21.41	16.65	4.28	−27.81	1.57	35.82	28.60	3.83
Market-adjusted returns	−0.51	0.01	0.57	0.68	0.02	−0.90	−0.05	0.74	0.96	−0.08
Daily return volatility	1.10	3.00	5.68	1.96	3.30	2.24	6.23	10.26	3.70	6.60
Cash holdings	−6.43	2.20	9.93	14.80	1.75	−0.25	4.44	14.70	30.61	2.86
Expense ratio	0.30	0.73	1.15	0.35	0.74	0.63	1.28	1.90	0.54	1.29
Annual charges	0.15	0.40	0.67	0.21	0.41	0.40	0.91	1.40	0.40	0.91
Redemption charges	0.00	0.00	2.00	0.82	0.54	0.00	0.00	0.00	0.28	0.04
Age	30.00	168.00	336.00	134.76	179.08	17.00	74.00	236.00	88.67	103.31
Minimum investment	0.50	2.50	1,000	11,552	1,136	0.00	0.50	100.00	6,581	817.62

Notes: Unbalanced sample comprising 1,000 U.S. and 719 Luxembourg mutual open-end bond funds with up to 70,009 month-fund-share observations per variable. *Total net assets*: value of total net assets (TNA) at the fund share-class level, in millions of U.S. dollars (USD); *Flows*: monthly net fund inflows as a percentage of TNA; *Returns*: annualised monthly returns in USD terms, in per cent; *Market-adjusted returns*: difference between monthly returns and the corresponding return of the fund's benchmark, in per cent (annualised); *Daily return volatility*: annualised volatility of daily returns in %, based on the published price per share; *Cash holdings*: cash in % of TNA; *Annual charges*: annual fund charges as a percentage of TNA; *Redemption charges*: redemption charges as a percentage of TNA; *Expense ratio*: monthly expenses as a percentage of TNA (annualised); *Age*: months since launch of the fund; *Minimum investment*: minimum subscription amount in thousands of USD.

Table 2: Flow-to-performance relation: U.S. vs. Luxembourg funds

	[1]	[2]	[3]	[4]	[5]	[6]
Return$_{t-1}$	0.001	0.001	0.002	0.016***	0.042***	0.098***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.012)	(0.016)
Negative return$_{t-1}$	0.051***	0.053***	0.055***	0.048***	0.103***	0.081**
	(0.008)	(0.009)	(0.010)	(0.017)	(0.029)	(0.035)
Return$_{t-1}$ × LUX		0.021***	0.022***	0.009	0.019	−0.017
		(0.006)	(0.007)	(0.011)	(0.021)	(0.029)
Negative return$_{t-1}$ × LUX		−0.050***	−0.057***	−0.045*	−0.103**	−0.146***
		(0.012)	(0.014)	(0.026)	(0.041)	(0.051)
Return$_{t-1}$ × TT		−0.001	−0.002	0.503*	−0.143**	−0.193***
		(0.005)	(0.006)	(0.265)	(0.070)	(0.070)
Negative return$_{t-1}$ × TT		−0.008	0.002	−0.547**	0.149*	0.215**
		(0.018)	(0.019)	(0.266)	(0.087)	(0.104)
Return$_{t-1}$ × TT × LUX		0.480	0.501	0.094	0.477**	0.260
		(0.332)	(0.362)	(0.492)	(0.201)	(0.182)
Negative return$_{t-1}$ × TT × LUX		−0.435	−0.462	−0.016	−0.397*	−0.222
		(0.338)	(0.368)	(0.498)	(0.222)	(0.260)
Cash holdings				yes	yes	yes
Excl. funds with redemption charges			yes	yes	yes	yes
Return measure	1m	1m	1m	1m	3m	6m
R-squared	0.083	0.075	0.076	0.063	0.062	0.066
Number of funds	1,000	1,719	1,432	1,243	1,233	1,219
Observations	44,930	70,009	58,983	29,046	28,322	27,342

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Fund fixed-effect regressions with robust standard errors, clustered by fund, in parenthesis. Dependent variable: flows in % of total net assets (TNA). All regressions include country-month fixed effects. Sample: Column [1] only U.S. funds; [2] all funds; [3] to [6] all funds without redemption charges. Independent variables: lagged returns, lagged negative returns, lagged log TNA, log age, lagged expense ratio; in regressions [4] to [6] lagged cash holdings are also included, which reduces the number of available funds. Interaction terms for all independent variables: none in regression [1]; Luxembourg (LUX) dummy, taper tantrum (TT) dummy and TT × LUX dummy in regressions [2] to [6]. Return measure: monthly returns in regressions [1] to [4]; cumulative returns over the past 3 months and 6 months (annualised, in %) in [5] and [6], respectively. Negative returns: returns interacted with an indicator variable, which is equal to one if returns are negative and zero otherwise.

Table 3: Flow-to-performance relation: accounting for exchange rates and investor opportunity costs

	[1]	[2]	[3]	[4]	[5]	[6]
$\text{Return}_{t-1} \times \text{LUX}$	0.010	0.018	−0.016	0.010	0.018	−0.016
	(0.011)	(0.021)	(0.029)	(0.011)	(0.021)	(0.029)
$\text{Negative return}_{t-1} \times \text{LUX}$	−0.046*	−0.103**	−0.150***	−0.046*	−0.102**	−0.151***
	(0.025)	(0.041)	(0.050)	(0.025)	(0.041)	(0.050)
$\text{Return}_{t-1} \times \text{TT} \times \text{LUX}$	0.084	0.455**	0.249	0.085	0.452**	0.241
	(0.487)	(0.204)	(0.187)	(0.488)	(0.206)	(0.188)
$\text{Negative return}_{t-1} \times \text{TT} \times \text{LUX}$	−0.006	−0.367	−0.218	−0.007	−0.364	−0.206
	(0.493)	(0.225)	(0.260)	(0.494)	(0.226)	(0.259)
Return measure	1m	3m	6m	1m	3m	6m
(− risk free rate)				1m	3m	6m
R-squared	0.063	0.062	0.066	0.067	0.067	0.072
Number of funds	1,243	1,233	1,219	1,362	1,352	1,336
Observations	29,046	28,322	27,342	32,191	31,390	30,318

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Fund fixed-effect regressions with robust standard errors, clustered by fund, in parenthesis. Dependent variable: flows in % of total net assets (TNA). All regressions include country-month fixed effects. Funds with redemption charges are excluded. Independent variables: lagged returns, lagged negative returns, lagged log TNA, log age, lagged expense ratio and lagged cash holdings. Interaction terms for all independent variables: Luxembourg (LUX) dummy, taper tantrum (TT) dummy and TT × LUX dummy. Return measure: Luxembourg fund returns are converted from U.S. dollars (USD) into euro (EUR) based on monthly USD/EUR exchange rates. In regressions [1], [2] and [3], we measure returns based on 1–month, 3–month and 6–month annualised nominal returns, respectively. In regressions [4], [5] and [6], returns are given by the 1–month, 3–months and 6–months annualised nominal returns less the risk-free rate of return with the corresponding term. For U.S. funds, risk-free rates are approximated by the yield on U.S. Treasury bills. For Luxembourg funds, risk-free rates are approximated by euro-currency market interest rates. Negative returns: returns interacted with an indicator variable, which is equal to one if returns (less the risk-free rate for regressions [4] to [6]) are negative and zero otherwise.

Table 4: Average treatment effect of Luxembourg funds during the taper tantrum

	[1]	[2]	[3]	[4]	[5]
Net fund flows	-1.510	-2.385	1.947	0.368	0.175
	(1.338)	(1.784)	(2.427)	(0.561)	(0.592)
Matched LUX funds	421	126	32	390	390
Obs	1,128	623	264	534	714
Market-adjusted returns†	0.515***	0.392**	0.367	0.167*	0.302***
	(0.199)	(0.156)	(0.347)	(0.090)	(0.071)
Matched LUX funds	109	82	15	115	106
Obs	322	273	144	188	221
Volatility of daily returns†	1.459***	2.416***	3.099**	0.493**	0.208
	(0.283)	(0.390)	(1.408)	(0.223)	(0.214)
Matched LUX funds	217	82	15	230	228
Obs	501	273	142	324	425
Matching	Nearest neighbour	Nearest neighbour	Nearest neighbour	ρ of daily returns	ρ of daily returns

Notes: † Based on funds with net outflows during the period from May to June 2013 (taper tantrum). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parenthesis. [1] to [3]: Nearest-neighbour matching with four neighbours. In [1] and [2] fund styles are matched exactly; in [3], the fund benchmarks are matched exactly. The following covariates are used for matching funds: average fund returns, net flows and (log) total assets in the three months preceding the taper tantrum (February to April 2013) and (log) fund age in April 2013. For [2] and [3] an indicator of whether the fund had cash holdings above or below the median of those of other funds using the same benchmark in April 2013 (last observation before the taper tantrum) is also included. [4] each Luxembourg fund is matched with the U.S. fund with the highest correlation based on daily returns over the three months preceding the taper tantrum; [5] same as [4], but using the four U.S. counterparts exhibiting the highest correlation; to calculate potential outcomes for Luxembourg funds, we weigh the observations for the four U.S. funds by the relative size of their correlation coefficients.

Table 5: Fund cash holdings

	[1]	[2]	[3]	[4]
LUX	-0.984^{**}	-0.450^{***}	-0.449^{***}	-0.467^{***}
	(0.391)	(0.084)	(0.083)	(0.099)
Flows_{t-1}	0.036^{***}	0.006^{***}	0.005^{***}	0.007^{***}
	(0.004)	(0.001)	(0.001)	(0.001)
Return_{t-1}	0.006^{***}	0.001^{*}	0.001^{*}	0.000
	(0.002)	(0.000)	(0.000)	(0.001)
Log TNA_{t-1}	-0.078^{***}	-0.029^{***}	-0.028^{***}	-0.021^{***}
	(0.014)	(0.003)	(0.003)	(0.003)
Log age	-0.112^{***}	-0.037^{***}	-0.038^{***}	-0.037^{***}
	(0.032)	(0.006)	(0.006)	(0.007)
Expense ratio_{t-1}	-0.017	0.038^{**}	0.037^{**}	0.011
	(0.098)	(0.019)	(0.019)	(0.021)
Log min investment	-0.025^{***}	-0.004^{***}	-0.004^{***}	0.002
	(0.006)	(0.001)	(0.001)	(0.001)
Low charges	-0.009	-0.026^{**}	-0.026^{**}	-0.011
	(0.061)	(0.013)	(0.012)	(0.014)
Cash measure	cash	indicator	indicator	indicator
Winsorised	20%			cash ≥ 0
Regression	OLS	logit	probit	logit
R2	0.184			
Observations	12,524	20,097	20,097	14,020

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. OLS coefficient estimates in [1], estimated marginal effects at the means in [2] to [4]. Robust standard errors in parenthesis. All regressions include month and benchmark fixed effects as well as country and taper tantrum interaction terms. Funds with redemption charges are excluded. Cash measure used as dependent variable: [1] cash holdings, winsorised at 20% to exclude funds reporting negative cash holdings; [2] to [4] indicator of value one if the fund's cash holdings are above the median of those of other funds using the same benchmark in the respective month and zero otherwise; [4] includes only funds with at least zero cash holdings. Independent variables: as defined in Table 1; and *LUX*: an indicator variable that identifies Luxembourg funds; *Low charges*: a dummy variable equal to one (zero otherwise) if the fund has lower annual charges than the median of funds in the sample.

Appendix A. Swing pricing model

This appendix formalises the five hypotheses that we test in the paper. Our model builds on the one developed in Chen et al. (2010). We assume there is one fund and a continuum of risk-neutral investors $[0, 1]$. Each investor initially holds one share of the fund, and we normalise the total amount of investment to 1. There are two periods: 1 and 2. In period 1, a fraction $\bar{X}$ of the investors decide whether to redeem their shares or whether to stay invested in the fund until period 2. All other investors remain with the fund and there are no inflows. Following Chen et al. (2010), we assume the fraction $\bar{X}$ is sufficiently small to rule out the possibility of the fund going bankrupt.[19]

The investor compares the returns that result from withdrawing in period 1 and remaining invested until period 2. If she withdraws, she receives the NAV per share R_1 but will be charged the swing factor $s > 0$. In this case, she invests the proceeds in a riskless outside investment opportunity yielding $R = 1$ (e.g., cash). Her payoff in period 2 is thus given by $(1-s)R_1$, which we assume to be known to the investor before she makes her decision in period 1.

Liquidation costs motivate the existence of the swing factor. Specifically, we assume that the fund needs to sell $(1 + \lambda)$ worth of securities to raise one unit of cash. λ represents the cost of liquidating assets. To match the cost structure with empirical findings (e.g., Borkovec et al. (2016)), we assume that $\lambda = \bar{\lambda} + x^{\eta}$, where x is the share of investors that withdraw in period 1. This setup accounts for the price impact of the fund manager's sales. The term $\eta > 1$ measures the elasticity of the fund's cost of liquidating assets with respect to the amount of assets being sold. Accordingly, the larger the amount of assets the fund manager needs to sell, the worse the terms at which she can transact. $\bar{\lambda}$, in turn, represents other costs of trading that are directly proportional to the amount traded, such as commissions or fees.

If the investor chooses to stay with the fund in period 1, her expected payoff in period 2 depends on two factors. The first one is the expected return of the fund portfolio $R_2(\theta)$. As in Chen et al. (2010), we assume the return depends on the realisation of the fund fundamental θ in period 1, with R_2 being an increasing function of θ and the latter being drawn from a uniform distribution on the real line.

The second determining factor is the share of investors that choose to redeem in period 1. Since redemptions dilute the value of the fund, strategic complementarities among investors arise. To see this, we note that the investor is exactly indifferent between remaining invested in the fund and withdrawing in period 1 if the expected return on her fund share is equal to the return she yields from redeeming her share and investing the proceeds in the outside opportunity:

$$R_2(\theta)\,\frac{1-\left(1+\bar{\lambda}+x^{\eta}\right)(1-s)\,x}{1-x} \;=\; 1-s. \tag{A.1}$$

Equation (A.1) highlights the investor coordination problem, which may give rise to multiple equilibria. To restore a unique equilibrium, we resort to the techniques of the global games literature (see Morris and Shin (2003) and the literature reviewed therein). Specifically, we assume that each investor i receives a private but noisy signal $\theta_i = \theta + \sigma\,\varepsilon_i$ in period 1 which informs her decisions whether or not to redeem. ε_i is an idiosyncratic noise term drawn from the distribution $g(\cdot)$, with cumulative distribution function $G(\cdot)$. The parameter $\sigma > 0$, in turn, indicates the noisiness of the signal. Both σ and the distribution are common knowledge.

[19] The fund is bankrupt when the amount of funds needed to pay out redeeming investors exceeds the amount of funds available to the fund, which can occur in the presence of liquidation costs.

A key result of the global games literature is that the assumed information structure leads to a unique equilibrium in which all investors apply a threshold strategy: if the private signal is below the threshold θ^* the investor withdraws from the fund, whereas she remains invested if her signal is above θ^*. Morris and Shin (2003) present and explain the proof for the general case of a symmetric binary action global game like the one presented here. For the sake of brevity, we do not restate the proof here.

We note that ensuring uniqueness of the equilibrium requires some restrictions on the swing pricing rule, $s(\cdot)$, if we allow the rule to depend on investor outflows. In particular, the swing pricing rule needs to preserve action monotinicity so that the investor's expected payoff gain from remaining invested as opposed to withdrawing, $\pi(x, \theta_i)$, is non-increasing in x. This means that the incentive to withdraw from the fund (weakly) increases with the share of investors that also decide to withdraw (i.e., there are strategic complementarities between players' actions). Intuitively, this assumes that the swing pricing rule does not reverse the first-mover advantage, which is implied by the effect of dilution, by making it more profitable for an investor to remain with the fund when an increasing share of investors decides to withdraw.

Rewriting the indifference condition in (A.1) in terms of the investor's expected payoff gain, it must hold that for the investor receiving signal $\theta_i = \theta^*$:

$$\pi(x,\theta^*) \;=\; \int_{\theta=-\infty}^{\infty} \frac{1-\left(1+\bar{\lambda}+x^{\eta}\right)(1-s)\,x}{1-x} R_2(\theta)\frac{1}{\sigma}g\left(\frac{\theta^*-\theta}{\sigma}\right)d\,\theta \;-\;(1-s) \;=\; 0. \tag{A.2}$$

Here, $(1/\sigma)g\left((\theta^*-\theta)/\sigma\right)$ is the posterior distribution of θ conditional on having received the signal θ^*, that is, the signal of the investor who is exactly indifferent between withdrawing and remaining with the fund. Since $x = G((\theta^*-\theta)/\sigma)\bar{X}$ is the proportion of investors who withdraw, the above indifference constraint can be written as:

$$\pi(x,\theta^*) \;=\; \int_{x=0}^{1} \frac{1-\left(1+\bar{\lambda}+x^{\eta}\right)(1-s)\,x}{1-x} R_2\Big(\theta^*-\sigma\, G^{-1}\Big(\frac{x}{\bar{X}}\Big)\Big)dx \;-\;(1-s) \;=\; 0, \tag{A.3}$$

which implicitly characterises the threshold signal θ^*. In the limiting case when the investor signal becomes increasingly precise, (A.3) converges to:

$$R_2(\theta^*) \;=\; (1\;-\;s)\left[\int_0^1 \frac{1-\left(1+\bar{\lambda}+x^{\eta}\right)(1-s)\,x}{1-x}dx\right]^{-1}. \tag{A.4}$$

This equation motivates Hypothesis 1. A positive swing factor (i.e., a downward adjustment of the NAV) reduces the cutoff signal and, as a result, reduces the fraction of investors who withdraw from the fund (i.e., lowers x). This is due to the two effects discussed in Section 2.2 and illustrated in Figure 1.

The model also enables us to derive swing pricing rules that would address the potential coordination failure among investors.[20] A particularly interesting rule is $s^* = \lambda x/(1+\lambda x)$, which yields $\theta^* = R_2^{-1}(1)$. With this rule, investors always withdraw if they expect the fund portfolio to return less than their outside option and remain invested otherwise. In addition, the investor's decision whether or not to withdraw in period 1 is independent of the choices of

[20] An assessment of what constitutes an optimal swing pricing rule from a welfare perspective requires a general equilibrium framework, which is beyond the scope of this paper. We present such a framework in a companion paper – see Lewrick and Schanz (2017) – focussing on some of the main mechanisms of swing pricing in a stylised multi-period model.

the other investors, thereby offsetting any first-mover advantage. In Figure 2, we compare this rule (blue line) with one that is representative of swing pricing rules used in practice (red line).

We derive Hypothesis 2 from this comparison. If the fund manager chooses $s < s^*$, as is the case for outflows greater than 8% of TNA in the numerical example, the threshold signal increases such that $\theta^* > R_2^{-1}(1)$. This means that investors receiving a signal $\theta_i \in [R_2^{-1}(1), \theta^*]$ redeem their shares because of strategic complementarities, i.e., the swing factor no longer offsets the first-mover advantage. As the share of redeeming investors increases, e.g., because of a decline in the fund fundamentals θ during stressed markets, the effect of a constant swing factor on investor incentives would weaken further, making the fund outflows more responsive to expected returns.

Hypothesis 3 follows directly from the expected payoff of remaining investors, as given by the left-hand side of equation A.1. For any given x, the swing factor raises the payoff by $R_2(\theta)[(1+\lambda)x]/(1-x)$. This additional payoff is increasing in x, suggesting that swing pricing raises fund returns particularly during times of large outflows.

Hypothesis 5 can be motivated by a slight expansion of the model. We assume that the return of the fund portfolio increases with the liquidity costs that are proportional to the transaction amount, so that $R_2(\theta^*, \bar{\lambda})$ with $\partial R_2(\cdot)/\partial\bar{\lambda} > 0$. This reflects, for example, the higher yield earned on more risky securities, which tend to be traded less frequently and at a higher cost. Since $\bar{\lambda}$ and s affect the threshold signal in opposite directions, swing pricing allows the fund manager to pick a less liquid portfolio with higher returns, while maintaining the same redemption risk (i.e., keeping θ^* unchanged).

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