Prime Time for Prime Funds: Floating NAV, Intraday Redemptions and Liquidity Risk During Crises

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Abstract

This paper offers a first look at a recent innovation, namely, mutual funds offering intraday share redemptions. This novel design feature emerged following the adoption of floating net asset values by prime institutional money market funds in October 2016. Consistent with a theoretical model, we find that funds offering multiple intraday NAVs and redemption windows maintain higher liquidity buffers but are exposed to significantly larger outflows during periods of stress, compared to funds offering end-of-day NAVs/redemptions. Our analysis covers (1) the COVID-19 shock of March 2020, and (2) the near-default of U.S. debt during the debt ceiling crisis of 2018.

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The recent COVID-19 pandemic illustrated yet again the critical role of money market funds as a vital source of short term credit for financial markets. Following several days of investor outflows from money market funds, on the evening of March 18, 2020 the Federal Reserve Board announced the establishment of a Money Market Mutual Fund Liquidity Facility (MMFLF). According to the Fed, the purpose of the MMFLF was to "assist money market funds in meeting demands for redemptions by households and other investors, enhancing overall market functioning and credit provision to the broader economy."

The investor outflows and the resulting stress on money market funds during March 2020 provide a unique opportunity to examine the effectiveness of the series of regulatory reforms that have been implemented since the global financial crisis of 2008. Following the latest rule changes implemented by the SEC in October 2016, prime institutional money market funds are required to price and transact their shares using floating net asset values (NAVs) instead of a constant NAV of $1.00 per share. A number of important questions are as yet unanswered in the wake of these reforms. For example, what are the liquidity management policies of funds with floating NAVs and how do funds calibrate their liquid asset holdings in order to meet expected redemption demands of investors? And, are the liquidity buffers maintained by the funds adequate in view of the recent, as well as potential future crises? Furthermore, an interesting byproduct of the reforms of 2016 is the adoption of multiple intraday NAVs and redemption windows (multiple 'strikes') by several prime institutional funds (hereafter, PIFs). The choice of the multiple strikes vs. the single strike design is likely to have non-trivial implications for the liquidity management policies, risk-taking incentives, and performance of the affected funds, and a better understanding of these issues is clearly important.

In this study we carry out a comprehensive analysis of the implications of the key reforms with a view to assessing their effectiveness in mitigating the risks to financial markets associated with the money market fund investors' run-like behavior. We use a simple model of investor redemption behavior in single-strike and multi-strike funds in order to derive testable implications. Using data on daily fund NAVs of PIFs, we provide new evidence on the redemption-related liquidity risk facing single-strike and multi-strike funds. Importantly, since the 2016 SEC reforms required institutional funds to offer their shares exclusively to institutional investors, our findings apply to a homogenous group of sophisticated investors who have strong incentives to monitor the daily and intraday NAVs of funds. By exploiting the rich cross-sectional variation in the liquidity provision policies of PIFs (reflected in the single- vs. multi-strike design), we are able to directly quantify the extent to which the redemption-related liquidity risk affects the daily and weekly liquidity buffers of PIFs. To our knowledge, this is the first study to examine how PIFs calibrate their liquid asset holdings on a daily basis in order to meet expected intraday redemption demands of investors. We believe this study is also the first to estimate the likelihood of funds' liquidity shortfalls under different stress test scenarios involving unexpected, though foreseeable, next-day net cash outflows.

Our analysis covers two episodes during which prime institutional funds were subjected to exogenous shocks. These include the COVID-19 induced outflows during March 2020, and a period of congressional inaction regarding the suspension of the U.S. debt ceiling which led to a near-default of U.S. government debt in early 2018. Consistent with our theoretical model we find that multi-strike funds have a significantly higher flow-related liquidity risk as evidenced by the more severe outflows experienced by such funds during periods of stress. As an illustration, Figure 1 shows the fund flows experienced by PIFs during March 2020. Panels A and B of the figure depict the daily and cumulative flows respectively, while Panel C illustrates the significant impact on the average net asset values of the funds.[1] The cumulative net cash outflows experienced by multi-strike funds during March 2020 represent about 37% of the total net assets of these funds as of the end of February 2020.

Figure 2 provides a more detailed illustration of the distribution of the percentage

[1] The 17-basis point reduction (from 1.0007 on March 10th to 0.9990 on March 19th) in the four-digit floating NAV of multi-strike PIFs illustrated in Panel C of Figure 1 equates to an average dilution cost of about $13 million, which is $3 million higher than that experienced by the average single-strike fund.

daily net cash flows experienced by multi-strike and single-strike funds. Panel A depicts the pattern of outflows for funds with weekly liquid assets (WLA) below the respective median levels while Panel B illustrates the corresponding pattern of outflows for funds with above median level of WLA. It is evident that multi-strike funds are more susceptible to outflows during such episodes. Furthermore, the difference in the outflows in Panel A is qualitatively similar to that in Panel B. This suggests that the higher outflows suffered by multi-strike funds during the crisis were not simply in response to poor liquidity in the funds with the attendant fears of potential redemption restrictions being put in place.[2] At the same time as we subsequently document, multi-strike funds are on average more conservative in their liquidity management policies and carry larger liquidity buffers. Consistent with the theoretical prediction, compared to single-strike funds, money market funds offering multiple strikes have portfolios with significantly lower allocations to riskier assets such as bank obligations, asset backed securities and commercial paper. Overall, the heightened sequential feature of investor fund flows in a multi-strike fund increases the fragility of the PIF's funding. Such self-imposed fragility commits the PIF to a more conservative liquidity strategy and in turn attracts investors who prefer intraday access to liquidity.[3]

We examine and rule out a number of alternative explanations for the heightened sensitivity of investor flows to adverse economic shocks in the case of multi-strike funds. In particular, we find that the contrasting results between multi-strike and single-strike PIFs cannot be explained by the possibility that the exogenous economic shocks have a more negative impact on the future performance of multi-strike funds compared to single strike funds. The results are also not due to a difference in the degree of sophistication on the part of investors in multi-strike funds compared to their single-strike counterparts, or a difference in the degree of specialization of fund sponsors in the prime money market fund

[2]As we subsequently discuss, PIFs are required to maintain their WLA above 30% to avoid incurring the risk of imposing a liquidity fee of up to 2%, or a temporary suspension of investor redemptions.

[3]In the banking literature, fragility has been argued as a commitment device (Diamond and Rajan (2001a,b)). With fragility in its capital structure, a bank is committed to not engaging in certain activities (Calomiris and Kahn (1991)).

segment. Our analysis also controls for the likely difference in the liquidity preferences of the investors in the two groups of funds. We confirm that the higher flow-related liquidity risk of multi-strike funds is related to the degree of portfolio illiquidity. It is well recognized that fund NAVs can reflect stale market prices, especially in periods of diminished market liquidity. In turn, this can create an incentive for investors to preemptively exit the fund, even in the presence of floating NAVs. Our results suggest that this early exit incentive is more pronounced in the case of multi-strike funds which allow multiple intraday redemption opportunities in contrast to single-strike funds.

A question of obvious interest is whether the liquidity buffers of PIFs are sufficient given the magnitude of redemption risk they face. To answer this question we subject the funds to a stress test following the SEC guidelines. We find that even though PIFs carry a high proportion of liquid assets, the liquidity buffers are not adequate given the observed distribution of investors' redemption demand during periods of market stress. In particular, multi-strike funds are especially prone to liquidity shortfalls.

Overall, our results suggest that the introduction of floating NAVs has not eliminated the strategic complementarities in the redemption decisions of institutional investors—investors still have an incentive to redeem early, especially during periods of low secondary market liquidity. Our findings regarding the early redemption incentive for fund investors even in the presence of floating NAVs are broadly consistent with the theoretical implications of the model analyzed by Parlatore (2016).[4] Our results also complement earlier evidence on the risk of severe payoff complementarities in the prime institutional funds segment that subjects them to run-like behavior (Schmidt, Timmermann, and Wermers (2016)), and more generally, among open-end mutual funds (see e.g., Chen, Goldstein, and Jiang (2010), and Goldstein, Jiang, and Nguyen (2017)).[5] Importantly, our findings on the new (intraday) NAV striking system of PIFs

[4]In the model analyzed by Parlatore (2016), adverse shocks to asset quality lead to asset sales and potential fund liquidations in the absence of any support provided by the fund sponsor. This dynamic in which asset sales depress prices making sponsor support costly, gives rise to strategic complementarities in sponsor support decisions leading to a run on asset markets by the money market funds.

[5]Kacperczyk and Schnabl (2013) document that the sensitivity of fund flows to yield differentials created strong incentives for money market funds to chase higher yields by increasing risk at the start

are also related to recent empirical evidence on the economic implications of alternative NAV pricing rules (known as *swing pricing*) for the fragility of open-end funds arising from costly liquidity provision (Jin et al. (2021)).

Our paper also contributes to the recent literature that examines the behavior of money market funds in the wake of the money market reforms implemented in 2016. Cipriani and La Spada (2021) use the money market fund reforms and the subsequent fund outflows from prime funds to government funds as a quasi-natural experiment, to quantify the premium that fund investors are willing to pay for money-like assets. Li et al. (2021) examine the outflows from money market funds during the COVID-19 crisis of March 2020 and document that the MMFLF was instrumental in stemming the outflows. A key distinguishing feature of our paper is that it provides a first look at an industry innovation in response to recent reforms including floating NAVs, namely, multi-strike funds. In this context we provide empirical evidence, consistent with a theoretical model, that offers important insights into the investor flow-related risk facing funds that offer intraday redemptions.

1. Industry Background

1.1 Innovation in Share Pricing: The Intraday Mark-to-Market NAV

Institutional money market funds are those whose shares are sold primarily to institutional investors or institutional accounts. The funds primarily invest in corporate debt securities including commercial paper. In the wake of the financial crisis of 2008 the Securities and Exchange Commission (SEC) implemented a series of regulatory changes designed to shore up the stability and resilience of money market mutual funds in the face of financial stress. The first set of regulatory changes imposed restrictions on the maturity and liquidity of fund portfolio securities via an amendment to Rule 2a-7 of the Investment Company Act. Following a second set of reforms implemented in October 2016, institutional prime money market funds and institutional municipal

of the financial crisis in August 2007. Funds that took on more risk suffered stronger outflows in the aftermath of Lehman Brothers default in September 2008.

money market funds are required to price and transact their shares using a floating NAV based on the market value of the securities in their portfolios. Specifically, all prime institutional money market funds (PIFs) are now required to float their portfolio NAV to the fourth decimal place.[6] The reform aims to address the susceptibility of PIFs to heavy redemptions in times of stress and increase the transparency of portfolio valuation, while preserving, as much as possible, their benefits as a cash-management vehicle.

The new NAV pricing system has altered the traditional money-like nature of PIFs as institutional investors may now need to redeem funds on a prior-day basis, for next-day value. For example, an investor placing a redemption order at 8:00 A.M. with a PIF which prices (or strikes) its NAV at 3:00 P.M. would not receive final trade confirmation and money wires until 5:00 P.M. If the same investor submitted an identical order at 3:01 P.M., i.e., one minute after the fund's 3:00 P.M. redemption deadline, she would only be able to access liquidity on the following day (i.e., T+1 settlement). To cater to investors with intraday liquidity needs, several PIFs have started offering sequential intraday trading sessions (e.g., at 8:00 A.M., 12:00 P.M., and 3:00 P.M.) to allow investors to trade fund shares frequently during the day at the prevailing mark-to-market NAV. Since they "strike" their portfolio NAV multiple times during a trading day, these PIFs are often referred to as "multi-strike funds."

Figure 3 illustrates the time-series variation in the end-of-month total assets under the management of multi-strike funds and single-strike funds during the period from 14 October 2016 to 5 June 2020. The figure highlights a clear segmentation of institutional investors' demand between intraday liquidity provision of multi-strike funds and the end-of-day (or next-day) liquidity provision of single-strike funds. On average, multi-strike funds manage about 59% of the total assets in the prime segment, with the remaining 41% of these assets being managed by single-strike funds. This evidence confirms a preference

[6] By contrast, government money market funds and retail money market funds (funds that limit ownership of the funds to natural persons) are allowed to use the amortized cost method of pricing or penny rounding to maintain a stable $1.00 share price.

of the average institutional investor for more frequent access to liquidity provided by multi-strike funds.

Multi-strike funds represent an unprecedented innovation in the pricing of open-end mutual fund shares as they provide investors with convenient access to intraday liquidity (i.e., T+0 settlement) even under a floating NAV pricing system. Without proper daily liquidity management, however, this convenience could worsen NAV dilution as redemption-motivated trades of a fund would be reflected in subsequent intraday NAV strikes. Consider for instance a large unanticipated redemption shock suffered by a multi-strike fund early in the day, e.g., at 8:00 A.M.. Such redemption demand could materially lower the mark-to-market NAV of the fund as quoted in the subsequent intraday striking sessions (e.g., at 10:00 A.M., 12:00 P.M., and 3:00 P.M.) if the fund lacked sufficient daily liquid assets to honor the redemptions, and was forced to sell other non-maturing, illiquid assets. In turn, this could heighten redemption risk among multi-strike funds, as institutional investors can react to other investors' redemption decisions within the same day. By comparison, a more traditional PIF which strikes its NAV once at the end of the day (e.g., at 5:00 P.M.) would be less exposed to redemption risk since investors would condition their redemption decisions on actions of all other investors during the previous trading day, or two trading days prior under a T+1 settlement scheme. Thus, more frequent redemption opportunities ("strikes") offered by the funds, combined with greater uncertainty surrounding the estimation of sequential intraday NAVs, are likely to incentivize funds to hold larger precautionary liquidity buffers.

Figure 4 provides a simple illustration of the intraday redemption timeline of a typical multi-strike PIF pricing its NAV daily at 8:00 A.M., 12:00 P.M., and 3:00 P.M.. In this example, an institutional investor who lodged a redemption request before the first strike time of 8:00 A.M., would be able to receive the cash wires by 10:00 A.M. on that same trading day (i.e., T+0 settlement). Even if the investor missed the first 8:00 A.M. redemption deadline, as long as the order is placed before 12:00 P.M., she would still be able to receive cash by 2:00 P.M. to support her daily operating activities. Thus, a multi-strike NAV pricing system has the potential to offer not only frequent (multiple sessions), but also rapid (within 2 hours) access to cash to institutional investors on the same trading day.

1.2 Daily and Weekly Internal Liquidity Requirements for PIFs

While an equity mutual fund is likely to sell marketable portfolio securities to generate enough cash to meet investors' redemption demands by the settlement period, money market funds are typically "hold-to-maturity" vehicles as they rarely sell their non-maturing assets to meet redemption requests. This means that a money market fund relies primarily on three sources of internal liquidity: cash on hand, cash from investors purchasing shares, and cash from maturing securities.[7] The role of internal liquidity management is therefore important to reduce the likelihood that a PIF might be forced to prematurely sell money market securities such as commercial paper and bank obligations, with the risk of diluting its portfolio NAV if the secondary market for such securities is not sufficiently liquid.[8]

To prevent the dilution of the value of outstanding fund shares, Section 22(e) of the Investment Company Act 1940 requires funds to assess and manage liquidity risk, continuously. Furthermore, the SEC imposes specific minimum requirements on the amounts of daily and weekly liquid assets a PIF must hold, as well as specific remedies for restoring liquidity in cases where a fund has breached these minimum liquidity levels. In particular, whenever a fund's daily liquid assets (DLA) account for less than 10% of its total net assets, the fund is prohibited from acquiring any new assets other than those classified as daily liquid assets. Under Rule 2a-7, daily liquid assets are defined as any

[7] A recent study by the Institutional Money Market Association shows that for a sample of about 37 U.S. money market funds, the monthly value of securities sold before maturity averaged at only 0.33%. Interestingly, during the period from April 2008 to May 2009 the monthly percentage of fund's portfolio value resold prior to maturity varied between 0.2% (in May 2008) and 2.4% (in September 2008, at the peak of the global financial crisis). Please refer to "The use of amortised cost accounting by MMF" available through https://www.immfa.org.

[8] As a possible remedy to an internal liquidity shortfall, a money market fund could also resort to external liquidity sources such as cash injections from the fund sponsor. Such sponsor support though requires full public disclosure and therefore comes with a high reputational risk.

of the following: cash, direct obligations of the U.S. Government (irrespective of their time to maturity), securities that will mature or are subject to a demand feature that is exercisable and payable within one business day, and receivables scheduled to be paid within one business day pending sale of portfolio securities.

The SEC also sets minimum thresholds for the level of a fund's weekly liquid assets (WLA) which include the following: daily liquid assets, U.S. government agency discount notes with remaining maturities of 60 days or less, securities that will mature or are subject to a demand feature that is exercisable and payable within five business days, and receivables scheduled to be paid within five business days pending sales of portfolio securities. Specifically, PIFs are required to maintain their percentage WLA above the threshold of 30% to avoid incurring the risk of imposing a liquidity fee of up to 2%, or temporarily suspending redemptions (that is, "gate") for up to 10 business days in a 90-day period.[9] Importantly, should the WLA fall below 10% of its total assets, a fund would be required to impose a 1% liquidity fee on all redemptions, unless such fee is considered by the fund's board to not be in the best interest of current shareholders.[10]

The recent money market fund reforms have also led to enhanced transparency with respect to a fund's liquidity by requiring all PIFs to disclose on their website, on a daily basis, the percentage level of their DLA and WLA, net shareholder inflows or outflows, market-based NAVs per share, any imposition of fees and redemption gates, and any use of affiliate sponsor support. In addition, PIFs are also required to promptly disclose on a new Form N-CR certain events such as the imposition or removal of liquidity fees or redemption gates, and the primary considerations or factors taken into account by a

[9]The fund's board of directors—including a majority of its independent directors—could decide against imposing a fee or gate if it is not in the best interest of current shareholders. Importantly, the SEC describes a number of "guideposts" that a board may wish to consider in determining whether the imposition of fees or gates is in a PIF's best interests. These guideposts include: (i) relevant indicators of liquidity stress in the markets; (ii) the current and expected liquidity profile of the fund; (iii) the make-up of the fund's investor base and previous investor redemption patterns; and/or (iv) the fund's past experience, if any, with the imposition of fees and gates.

[10]Prior to the recent money market fund (MMF) reforms, Section 22(e) under the 1940 Act allowed MMFs to suspend the right of redemption or postpone the date of payment or satisfaction upon redemption of any redeemable security for up to 7 days. Under the new reform, MMFs are now able to gate redemptions for up to 10 days. Importantly, Rule 22c-1(a)(3) under the 1940 Act does not allow MMFs (and ETFs) to apply "swing pricing" factors to mitigate redemption risk.

fund's board in its decision related to such fees and gates.

2. Testable Hypotheses

To guide our empirical analysis, we develop a simple model of investor redemption behavior in the context of two kinds of prime institutional money market mutual funds. The model is described in more detail in the Appendix. Below we discuss the essential intuition underlying the model and the resulting testable hypotheses.

We consider two types of funds that are distinguished by the frequency with which they price and transact shares during the day. Specifically, the multi-strike fund allows investors to buy and sell the fund's shares at an interim mid-day stage as well as at the end of the day, using the fund's NAV determined at each of these points in time. By contrast, the single-strike fund allows investors to invest in or redeem shares only at the end of each day using the end-of-day NAV.

The model allows for the possibility of two types of institutional investors who differ in their "attentiveness," i.e., their ability or willingness to continuously monitor the posted NAV as well as the fundamental value of a fund's portfolio of securities. As noted by Hanson, Scharfstein, and Sunderam (2015), since secondary markets for commercial paper and CDs tend to be illiquid, a fund's floating NAV is based at least partially on accounting or model-based estimates. They argue that in this respect money market funds are more like banks which need to make accounting-based assessments of loan portfolio value, rather than equity mutual funds. As such, the authors note that given the sluggishness in the adjustment of mark-to-market portfolio valuations, the adoption of floating NAVs would not eliminate investor incentives to run during market turmoil. Given the staleness in the market prices of relatively illiquid securities, the fund's NAV can deviate substantially from the true per share value during periods of crises, and the gap is potentially larger, the greater the illiquidity. Accordingly, in our model the more attentive investor (termed the "informed" investor for convenience) is better informed about the difference in NAV and fundamental value, and has a natural incentive to redeem shares whenever the value declines below the fund's posted NAV.

We show that the multi-strike feature allows the informed investor to capitalize on her information advantage by preemptively exiting the fund when conditions warrant.[11] Intuitively, the redemption incentive is potentially more pronounced during a declining market when adjustments in market prices and fund NAVs are likely to lag behind changes in asset fundamental values. The model also implies the existence of a strategic complementarity in the investors' redemption decisions – share redemptions by the informed investor also prompt the uninformed investor to redeem their shares. Accordingly, we have the following testable hypotheses.

Hypothesis 1 From the Proposition (in the Appendix), it follows that a multi-strike fund that allows for intraday redemptions (a) experiences larger (in absolute terms) and more volatile fund flows, and (b) optimally adopts a more conservative portfolio investment strategy.

Hypothesis 2 Based on Corollaries 1 and 2 to the Proposition (in the Appendix), the difference in fund flow volatility between multi-strike and single-strike fund is stronger during times of rapidly changing market conditions. The strategic complementarity in the investors' redemption decisions magnifies the effect. Further, the strategic complementarity among investors is directly related to the illiquidity of a fund's portfolio.

3. Data and Methodology

3.1 Data and Summary Statistics

Our sample covers the universe of U.S. taxable prime institutional money market mutual funds during the period from October 14, 2016 (the implementation date for the latest SEC reforms) to June 5, 2020. We obtain daily information on fund and fund sponsor characteristics from iMoneyNet, and complement the sample with data on fund sponsors'

[11] The information advantage is short-lived and is eliminated by the end of the day when the single-strike fund prices and transacts its shares.

assets under management from the CRSP Survivor-Bias-Free Mutual Fund Database. Importantly, to our knowledge, our study is the first to use daily data on the funds' NAV striking systems which have been available in iMoneyNet since October 14, 2016. We identify multi-strike prime institutional funds using the *Strike Time* and *Strike Price* variables available in the iMoneyNet database.[12] Our sample of prime institutional funds includes 22 multi-strike funds and 12 single-strike funds.[13]

Panel A of Table 1 displays the descriptive statistics for our sample of PIFs. The average PIF has $7.3 billion in assets under management, and has been in operation for almost 18 years. The average fund has an annualized gross-of-fee income yield (*GYIELD*) of 1.75% and net operating expenses of 0.15% (*OPEX*), resulting in an average annualized after-fee income yield of 1.60%. On average, PIFs are sponsored by fund families managing totals assets of $569 billion, with 97% of these assets allocated to asset management products other than PIF products.

Panel B of Table 1 reports the descriptive statistics of the monthly PIF portfolio holdings. Typically, PIFs invest in an array of money market securities, including U.S. Treasury securities (*USTR*), U.S. government agency obligations (*AGENCY*), collateralized repo contracts (*REPO*), domestic and foreign bank obligations (*BNKOB*), asset-backed commercial paper (*ABCP*), and unsecured commercial paper (*CP*). Over our sample period, the average PIF invested almost 60% of its portfolio in more risky and less liquid securities (*RISKY*) comprising *ABCP* (15%), *CP* (23%), and *BNKOB* (23%). On the other hand, about 23% of a PIF portfolio is allocated to safe and highly-liquid asset classes (*SAFE*) which includes U.S. treasury obligations (10%), and tri-party repo contracts collateralized by U.S. Treasury securities (14%).[14]

[12]PIFs started offering multi-strike NAV pricing on the implementation date of the floating NAV on 14 October 2016. During our sample period, no (existing or newly-launched) PIF has altered the initial decision to opt for either a multi-strike or a single-strike pricing and settlement mechanism.

[13]These PIFs represent 158 unique NASDAQ tickers, and about $309 billion in aggregate total net assets (TNA) as of December 2019. Of this amount, the aggregate TNA for the multi-strike funds amounted to $242 billion, with single-strike funds accounting for the remaining aggregate TNA. These figures are similar to the total net assets of all prime institutional MMFs aggregated by the Investment Company Institute (ICI) in Table 36 of its 2020 Investment Company Fact Book. Year-end figures from the ICI are identified by circle markers in Figure 3.

[14]In the money market for repurchase agreements, money market funds invest primarily in tri-party

3.2 Measurement of Liquidity Buffers

In this study, we employ several proxies for the liquidity buffer held by PIFs. Our first (ex-ante) proxy is the percentage of daily liquid assets (*DLA*) held by the fund. A decline in the *DLA* of a fund due to an increase in the weighted average maturity *WAM* of risky assets beyond one business day would impair its ability to cover next-day net cash outflows with internal liquidity.[15] For robustness, we also employ the percentage of weekly liquid assets (*WLA*) held by the fund as a proxy for its liquidity buffer.

Since having a high percentage of portfolio securities maturing within one business day does not necessarily guarantee that the fund's liquidity is "deep" enough to cover heavy redemptions of institutional investors on the following day, we construct a third proxy, the (ex-post) daily liquidity buffer, $LBD_{i,t}$, as follows:

$$LBD_{i,t} = DLA_{i,t} + NFLOWS_{i,t+1} - MINLIQ, \tag{1}$$

where $DLA_{i,t}$ is the percentage of assets in the form of daily liquid assets held by fund i on day t, $NFLOWS_{i,t+1}$ is the percentage net cash flows of fund i on the next day $t+1$, and *MINLIQ* is the minimum liquidity threshold of 10% required by the regulator. Similarly, we construct a proxy of the weekly liquidity buffer of fund i on day t, $LBW_{i,t}$, as the percentage of assets in the form of weekly liquid assets held by fund i on day t ($WLA_{i,t}$) net of the fund's next-day net cash flows ($NFLOWS_{i,t+1}$), and the minimum liquidity threshold of 30%.

Panel C of Table 1 provides summary statistics related to the maturity and liquidity characteristics of the prime institutional funds' portfolios. On average, PIFs hold 38% of the portfolio in the form of daily liquid assets (*DLA*) and about 55% of the portfolio as

repo contracts intermediated by two clearing banks, J.P. Morgan Chase and the Bank of New York (BNY) Mellon. The majority of these repo contracts comprise overnight investments, in which securities are repurchased by the seller on the next business day. Only a minority of tri-party repo contracts mature later than the next business day (i.e., term repos), with the clearing banks readjusting the collateral value of these contracts daily. Given the overnight nature of these collateralized contracts, repos are typically deemed safe investments.

[15] On the other hand an increase in the maturity of safe assets such as cash and U.S. Treasury securities would not reduce the *DLA* as such assets are considered daily liquid assets *irrespective* of their maturity.

weekly liquid assets (*WLA*). Importantly, they hold securities with a weighted average maturity (*WAM*) and weighted average life (*WAL*) of 28 days and 60 days, respectively.[16] Interestingly, the 5th percentiles of the distribution of the funds' *DLA* (22%) and *WLA* (42%) are both well above the required minimum thresholds of 10% and 30%, respectively. Panel C of Table 1 also presents statistics related to the funds' daily liquidity buffer (*LBD*) and the weekly liquidity buffer (*LBW*). The average PIF carries a very conservative daily (weekly) liquidity buffer of 24% (19%).

Figure 5 illustrates the 50-th (*P50*), 10-th (*P10*), and 1-st (*P1*) percentiles of the distribution of funds' daily liquidity buffer, *LBD* (top subplot), and weekly liquidity buffer, *LBW* (bottom subplot), over the sample period from October 14, 2016 to June 25, 2020. For ease of illustration we cap the range of the observations at 35%. We also highlight (shaded area) the high uncertainty period surrounding the COVID-19 pandemic outbreak from 1st March 2020 to 23rd March 2020, when the FED established the MMFLF. The figure shows several instances in which *LBD* and *LBW* fall below the minimum thresholds of 10% and 30%, respectively.[17] This evidence suggests that sudden liquidity shortfalls are not just confined to periods of market stress, as PIFs seem to breach the minimum thresholds even during normal times. In economic terms, the negative realizations of the daily liquidity buffer, *LBD*, vary between a mild liquidity shortfall of –0.2% and a more severe liquidity shortfall of about –13% (on 17 and 18 March 2020). In most of these instances, however, PIFs were able to restore a positive *LBD* by the next day, possibly due to regulatory restrictions preventing PIFs who are in breach of the 10% threshold from purchasing any new assets, other than daily liquid assets.

The bottom subplot of Figure 5 shows that the median (*P50*) of the distribution of

[16]When calculating the *WAM* under Rule 2a-7, a money market fund is permitted to use the interest rate reset date for floating-rate securities. By contrast, the *WAL* of a security is typically longer than the *WAM* as it reflects the stated final maturity date (or the next demand feature date, if lower than the final maturity date).

[17]We note that the thresholds apply specifically to a fund's daily liquid assets (DLA) and weekly liquid assets (WLA). Our measures of the (ex post) daily and weekly liquidity buffers, LBD and LBW, are more conservative as they reflect the adequacy (or lack thereof) of a fund's liquid assets to absorb the impact of the following day's net cash flows without breaching the minimum thresholds.

the weekly liquidity buffer, *LBW* remains well above the minimum liquidity threshold of 30%. However, when we consider the first percentile (*P1*) of the distribution of *LBW*, we uncover as many as 786 fund-day instances where the *LBW* breaches this minimum threshold, with the extent of the shortfall varying between –0.04% and –48.24% (on 18 March 2020). Importantly, none of such daily negative realizations of *LBW* resulted in the discretionary imposition of liquidity fees or, worse, the suspension of investors' redemptions during our sample period.[18]

4. Fund Characteristics and NAV Striking System: A Preliminary Analysis

In this section, we begin with a preliminary analysis of the differences in fund and fund sponsor characteristics conditional on the number of NAV strikes offered by a fund. To this end, we first separate our sample of PIFs into single-strike funds and multi-strike funds. For each of these two groups, we then average fund and fund sponsor characteristics and report the descriptive statistics in Panel A of Table 2. The evidence presented in Panel A suggests that there is no significant difference in the assets under management (*FNDTNA*) of multi-strike funds and single-strike funds. Interestingly, multi-strike funds are affiliated with smaller fund sponsors, as judged by the sponsor fund family TNA (*FAMTNA*). Multi-strike fund sponsors are also 21% more likely to be registered as a banking institution (*BNKFND*), and manage assets of larger institutional investors as indicated by the \$69 million larger minimum initial investment required for a new client to open an account with the fund. On average, multi-strike funds are less likely to reach for yield as indicated by their 3 basis points lower daily annualized (gross and net) income yield. They also experience a 0.65% higher 30-day volatility of daily percentage net cash flows (*FLOWVOL*) than single-strike funds. This finding is confirmed by the evidence of Figure 6 where the average multi-strike fund faces a much higher exposure to daily flow-related liquidity risk, a result which is consistent with Hypothesis 1(a).

[18]We use the two iMoneyNet variables of liquidity fees and redemption gates to identify any such instances. We confirmed this using the SEC-EDGAR historical archive of form N-CR and found no evidence of liquidity fees (Items E of form N-CR) or suspension of redemptions (Items F of form N-CR) during our sample period.

In Panel B of Table 2, we take a closer look at the difference in the portfolio compositions of multi-strike funds and single-strike funds. Multi-strike funds hold, on average, 3% more U.S. Treasury securities (*USTR*), 1.6% more U.S. government agency securities (*AGENCY*), and about 3% more collateralized short-term (overnight) repurchase agreements (*REPO*) than single-strike funds. By contrast, single-strike funds tend to hold a significantly higher percentage of foreign bank obligations (*FBNKOB*), asset-backed commercial paper (*ABCP*), and financial and non-financial commercial paper (*CP*), than multi-strike funds.

Overall, the evidence in Panel A and Panel B of Table 2 suggests that the ex-ante choice of the intraday NAV striking system drives the cross-sectional variation in risk-taking incentives of single-strike and multi-strike funds. We explore this issue in Table 3 by examining in detail the liquidity holdings and maturity risk of PIFs, conditional on the actual number of NAV strike times per day offered to their institutional investors. In Panel A of Table 3, we begin with an analysis of the percentage of liquid assets and the percentage liquidity buffer of PIFs. After separating multi-strike funds based on whether they offer two (*Multi: 2 Strikes*) or three (*Multi: 3 Strikes*) intraday redemption windows, we compute the average of several portfolio liquidity measures.[19] Consistent with our expectations, the greater the number of intraday strikes offered by a fund the higher its *DLA* and *WLA*. To wit, PIFs offering 3 strikes per day tend to hold 9% (3%) more daily (weekly) liquid assets, on average. Since multi-strike funds could also be associated with greater next-day percentage net cash outflows, we report the average daily liquidity buffer (*LBD*) values as well. On average, multi-strike funds offering 3 strikes (*Multi: 3 Strikes*) have 4% higher liquidity holdings than single-strike funds (*Single-strike*). The results are similar when we consider the alternative liquidity proxy of weekly liquidity buffer (*LBW*) in Panel A of Table 3.

In Panel B of Table 3, we repeat the analysis of Panel A of the table using proxies

[19]Since there are only 21 daily observations for one PIF offering four intraday strikes in our sample, we decided not to report the descriptive statistics of four-strike funds in Table 3. These 21 observations are included however in the variable *NSTRIKES* in all other tables.

of the portfolio-level and asset-level maturity risk of the PIFs.[20] The statistics related to the portfolio weighted average maturity, *WAM*, in Panel B suggest that multi-strike funds that offer three redemption windows during the day have portfolios with weighted average maturity that is on average about 8 days shorter than that of single-strike funds. Importantly, multi-strike funds seem to reduce their *WAM* mostly among riskier assets (i.e., *BNKOB*, *ABCP*, and *CP*) as indicated by the 6-day shorter asset-level maturity of risky assets, *WAM_RISKY*, for such funds compared to single-strike funds.

5. Daily Liquidity Buffers and Intraday Striking Systems

5.1 An Analysis of the Determinants of Funds' Daily Liquid Holdings

Our first hypothesis is that multi-strike funds face less predictable net cash flows, and optimally adopt a more conservative portfolio investment strategy. The resulting empirical observation should be that multi-strike funds hold a higher percentage of daily liquid assets to minimize the risk of being unable to meet next-day redemptions. In this section, we test this prediction by examining the relationship between the daily liquidity buffer of PIFs and several fund and fund sponsor characteristics. To this end, we estimate one of the regression specifications of Table 4 as follows:

$$\begin{aligned}
LIQ_{i,t} = {} & \alpha + \beta_0 \times NSTRIKES_i + \beta_1 \times NSTRIKES_i \times H_INVSOPH_{i,t-1} \\
& + \beta_2 \times NSTRIKES_i \times H_STAKES_{i,t-1} \\
& + \beta_3 \times NSTRIKES_i \times H_INVSOPH_{i,t-1} \times H_STAKES_{i,t-1} \\
& + \beta_4 \times H_INVSOPH_{i,t-1} + \beta_5 \times H_STAKES_{i,t-1} \\
& + \beta_6 \times H_INVSOPH_{i,t-1} \times H_STAKES_{i,t-1} + \boldsymbol{\Gamma' X_{i,t-1}} + \mu_d + \mu_s + \epsilon_{i,t},
\end{aligned} \tag{2}$$

where the dependent variable, $LIQ_{i,t}$, is a generic variable corresponding to one of our two proxies of a fund's daily liquidity buffer, namely, the daily liquid assets (*DLA*) in Panel A of Table 4, and the daily liquidity buffer (*LBD*), in Panel B of Table 4. Our primary

[20]The difference in total number of observations between Panel A and Panel B of Table 3 is due to 51 fewer observations available for the maturity variables of *WAM* and *WAL*.

independent variable of interest is the number of daily redemption windows offered by a fund, $NSTRIKES_i$. In all models we include—but do not report for brevity—the vector $\boldsymbol{X_{i,t-1}}$ comprising the following lagged fund and fund sponsor characteristics: the logarithm of the assets under the management of the fund (*LFNDTNA*); the logarithm of the assets under the management of the fund sponsor (*LFAMTNA*); the logarithm of the number of days since fund inception (*LFNDAGE*); the proportion of a fund sponsor's assets under management that are not related to PIFs, i.e., the sponsor's non-PIF assets (*NOPRMBUS*); total operating expenses charged by the fund (*OPEX*); the percentage of net cash flows (*NFLOWS*); and the fund's daily gross annualized income yield (*GYIELD*). In all models we include fund sponsor fixed effects (μ_s) and day fixed effects (μ_d), with standard errors clustered by both fund and time.[21] The use of fund sponsor fixed effect is consistent with the evidence of Kacperczyk and Schnabl (2013) on the primary role of fund sponsors when choosing the fund's portfolio composition, risk, and overall liquidity.[22] To examine the effect of managerial skill on the liquidity management of PIFs, we also estimated a version of Equation 2 with fund manager fixed effects (μ_m).[23] In an unreported result, we reached qualitatively similar conclusions on the positive relationship between a fund's liquidity and the number of strikes after controlling for fund manager fixed effects (μ_m) in Equation 2. This finding is consistent with the Kacperczyk and Schnabl (2013) argument that in the MMF industry "there is limited scope for fund manager skill in portfolio choice."

The results of the analysis of the determinants of funds' daily liquid holdings are presented in Table 4. The dependent variable in Panel A of Table 4 is the fund's daily liquid assets, *DLA*. The estimated loading of 2.001 on the variable *NSTRIKES* in column (i) confirms that multi-strike funds carry a higher percentage of daily liquid assets than

[21] We do not include fund fixed effects because *NSTRIKES* is time invariant.

[22] Please note that the use of sponsor fixed effects accounts for cross-sectional differences in fund-sponsor registration as a banking institution (*BNKFND*).

[23] If the intraday liquidity provision of multi-strike PIFs requires fund managers with superior liquidity management skills, we could then expect more experienced managers to sort into these funds. To the extent that differences in liquidity buffers between single- and multi-strike funds are driven by time-invariant manager characteristics, introducing manager-fixed effects should isolate the effect of different NAV striking systems.

single-strike funds, on average. In economic terms, a fund offering three intraday strikes tends to hold a level of daily liquid assets that is 4% higher than a fund offering a single end-of-day redemption window, on average. We reach similar conclusions in Panel B of Table 4 when our dependent variable is the fund's *LBD* which is computed as in Equation 1. The evidence confirms that our findings in column (i) are not explained by differences in next-day net cash (out-)flows between multi-strike funds and single-strike funds.[24]

A potential concern about our identification strategy is that the difference in the liquidity holdings between multi-strike and single-strike funds might be driven by differences in investors' liquidity preferences across the two types of funds. We address this issue by explicitly controlling for several institutional investor characteristics in Table 4. One could argue that more sophisticated institutional investors are likely to monitor more closely intraday NAV changes experienced by multi-strike funds, and run faster at early signs of a sudden liquidity shortfall. Schmidt, Timmermann, and Wermers (2016) show that funds charging an operating expense ratio below 15 basis points experienced the heaviest redemptions from more attentive institutional investors during the crisis week of September 15-19, 2008. They argue that the level of operating expenses paid by institutional investors is a reliable proxy of their degree of sophistication, and the likelihood of heavy redemptions during periods of market stress. They also find that more sophisticated investors residing in low-expense-ratio funds are those holding larger accounts, have more skin in the game, and, thus, greater incentives to continuously monitor the fundamentals of the MMFs in which they invest. Following this evidence, we construct the variable *H_INVSOPH* to identify institutional investors with high degree of sophistication. This variable is equal to 1 if institutional investors pay an operating expense ratio below the median value of 15 basis points, and 0 otherwise. We expect multi-strike funds to hold more liquid assets if their institutional

[24]In an unreported test—available in the Internet Appendix—we also examined the relationship between the NAV striking system and our measures of weekly liquid assets and liquidity buffer, *WLA* and *LBW*, and obtained qualitatively similar results to those presented in Table 4.

investor base is likely to be more responsive to a sudden drop in a fund's intraday liquidity.

We augment our measurement of investors sophistication by also controlling for the size of a fund's stake held by institutional investors, *H_STAKES*. This variable is equal to one if the minimum investment for institutional investors to open an account with the fund is greater than \$10 million (50-th percentile), and 0 otherwise. We expect larger sophisticated institutional investors, with more "skin in the game" to have stronger incentives to closely monitor the daily liquidity holdings of multi-strike funds.[25] This effect should be captured by the coefficient of the interaction term, *NSTRIKES* × *H_INVSOPH* × *H_STAKES*, in the results reported in Table 4.

It is also plausible that institutional investors with less predictable intraday liquidity demand sort into multi-strike funds offering intraday redemptions thus leading such funds to hold more liquid securities. Accordingly, we isolate the effect associated with the degree of predictability of institutional investors' liquidity demand using the variable *LIQDEM* which is computed as the past 30-day volatility of a fund's percentage daily net cash flows.[26] We expect funds whose net cash flows are relatively more predictable in terms of size and frequency to be able to foresee next-day net cash flows more accurately, and hence hold lower liquidity buffers than peer funds with more volatile net cash flows, all else equal. We also expect that a less predictable demand of highly sophisticated investors with a greater (minimum) investment in the fund (*LIQDEM*×*H_INVSOPH*×*H_STAKES*) is likely to strengthen a fund's economic incentives to increase its daily liquidity buffer. Levels of *H_INVSOPH*, *H_STAKES*, and *LIQDEM*, as well as their first-order interactions, as regressors are omitted for brevity in Table 4.

The estimated coefficient of 1.482 of the interaction variable *NSTRIKES* × *H_INVSOPH* in column (ii) in Panel A of Table 4 indicates that multi-strike funds markedly increase their *DLA* when institutional investors are likely to

[25]In our sample, the correlation between operating expense ratios and the (logarithm of the) minimum account size is –0.24 (–0.38).

[26]We tested the robustness of our findings to the use of 60-day and 90-day net cash flow volatility, and obtained similar results to those presented here.

be more responsive to a liquidity shock. For the same level of investor sophistication, PIFs offering 3 strikes per day hold 3% more daily liquid assets than single-strike funds, a result which is both economically and statistically significant. Consistent with the findings of Schmidt, Timmermann, and Wermers (2016), the significant estimated coefficient in column (iii) on the interaction term *NSTRIKES* × *H_INVSOPH* × *H_STAKES* suggests that multi-strike funds increase their holdings of daily liquid assets by an additional 1.5% in the presence of highly sophisticated investors with more "skin in the game". This finding is driven primarily by large sophisticated investors with less predictable daily liquidity demand as confirmed by the significant estimated coefficient (29.46) of the interaction term (*NSTRIKES* × *H_INVSOPH* × *H_STAKES* × *LIQDEM*) in column (iv) of Panel A of Table 4. We reach similar conclusions in Panel B of Table 4 when we consider *LBD* as our dependent variable. Since our dependent variables in Table 4 are level variables, we also control for lagged values of these variable in column (v) of Panel A (*LAGGED_DLA*) and column (v) of Panel B (*LAGGED_LBD*). The results are qualitatively similar to those illustrated in column (iv).

Overall, the higher preemptive daily liquidity buffer carried by multi-strike funds in Table 4 suggests that their intraday liquidity provision feature exposes them to greater flow-related liquidity risk than single-strike funds. This result is consistent with Hypothesis 1, and it is not explained by the cross-sectional variation in the funds' risk-taking incentives, differences in (next-day) net cash (out-)flows, differences in institutional investors' sophistication, liquidity preferences or heterogeneity in managerial attributes. The evidence presented in this section also highlights that PIFs seem to comply with the adoption of "know your customer" policies and procedures outlined by the SEC to assure that they: (i) undertake appropriate efforts to identify risk characteristics of their shareholders, and (ii) plan their holdings of liquid assets accordingly.[27]

[27] The "know your customer" policies are regulated by Rule 38a-1 under the Act of 1940.

5.2 Liquidity Buffers and Intraday Redemptions: Identification Strategy

In this section, we conduct a robustness test to address the potential endogeneity in the relationship between fund liquidity buffers and intraday redemptions. To this end, we use an instrumental variables approach. We exploit the empirical evidence provided by Cipriani and La Spada (2021) on the ability of fund sponsors offering government MMFs to recapture the net cash outflows experienced by prime MMFs following the introduction of the 2016 MMF reform. They show that between November 2015 and October 2016, investors flew out of a sponsor's prime MMFs and into the *same* sponsor's government MMFs.[28] This is consistent with the fact that investors responded to the loss of money-like feature and conversion from intraday to end-of-day (or even next-day) liquidity of their prime MMF shares because of the new regulation.[29]

The heterogeneity across fund sponsors in the ability to recapture investors' outflows from prime funds can be interpreted as a cross-sectional determinant of a fund sponsor's decision to adopt a multi-strike system for its PIF(s) that allows us to estimate the liquidity buffer equation. For instance, a fund sponsor offering mostly PIFs would be significantly less likely to recapture investors' net cash outflows from PIFs following the new regulation. Such a fund sponsor would have strong incentives to opt for a multi-strike system to preserve the same-day (T+0) liquidity benefit and rapid (within 2 hours) access to cash that PIFs had historically offered prior to the new reform.[30] In other words, a multi-strike system would allow the fund sponsor to minimize out-of-family net cash outflows from PIFs by providing investors with multiple intraday redemption points thus mimicking closely the intraday liquidity features of government MMFs.

We directly model the choice of a multi-strike pricing system and then use this

[28]Reasons behind investors' decision to reallocate capital *within* rather than *across* fund sponsors include, among others: (i) the possibility of moving money in and out of funds belonging to the same fund sponsor at very low cost (Massa, 2003); and (ii) investors' incentive to minimize the information acquisition costs when searching for a new fund sponsor (Huang, Wei, and Yan, 2007).

[29]See also Fishman and Hughes, Why it's prime time to rethink prime funds, Goldman Sachs, 2016.

[30]Alternatively, a fund sponsor could decide to (i) convert its PIFs into government institutional MMFs or (ii) launch one or more new government institutional MMFs to help increase within-sponsor asset retention. We account for these alternative options in our regression models in this section.

specification as the first stage of a two-stage least-squares estimation procedure. Based on the preceding discussion, we use a fund sponsor's product offering of government institutional MMFs from a pre-sample period in 2012 and 2013 as our main identifying restriction to instrument for the endogenous decision of the fund sponsor to offer multi-strike or single-strike PIFs.[31] Specifically, our proxy of a fund sponsor's ability to recapture intra-sponsor net cash outflows from PIFs between November 2015 and October 2016—and therefore its incentives to later opt for intraday multi-strike pricing—is the percentage share of its government institutional MMF business relative to its total institutional MMF business in the pre-sample period. To have a good instrument, we need our proxy measure of a fund sponsor's incentives to offer multi-strike NAV pricing to be correlated with whether the PIF of that fund sponsor subsequently adopted a multi-strike system.[32] That is, we need a strong first-stage regression.

Importantly, we need to assume an exclusion restriction for our baseline specification in the second-stage regression. Our exclusion restriction is that, controlling for other variables, our proxy measure of a fund sponsor's incentives, namely, the pre-reform percentage share of its government institutional MMF business, affects the liquidity buffer of a PIF after the reform implementation date only through its effect on the intraday NAV striking system that the fund sponsor decided to adopt on 14 October 2016. We believe our exclusion restriction assumption is a plausible one given that most MMF sponsors started their business and decided on their product offerings long before the MMF reform implementation date.

We proceed with a two-stage least-squares estimation procedure where the first stage regression models the choice of the number of NAV strikes for the PIF by the fund sponsor at the time of the reform implementation on 14 October 2016—or at the time of fund

[31]Our instruments are constructed one and two years before the transition period from July 2014 to October 2016 because a fund sponsor's decision to offer a multi-strike system and investors' within-sponsor substitution between prime and government institutional MMFs could be jointly determined.

[32]The Spearman correlation coefficient between a fund sponsor's average percentage share of government institutional MMFs (relative to its total institutional MMFs) in the pre-sample period and its percentage of total assets in—or number of—multi-strike PIFs offered is -0.55.

inception if the fund is offered after that date. We define *GOVSHARE* as the time-invariant average percentage share of government institutional MMFs offered during the pre-sample period by the fund sponsor as a proportion of the total institutional MMF business. Panel A of Table 5 illustrates the findings of the first stage estimation while Panel B of Table 5 reports the results of the second-stage estimation for our baseline specification. All model specifications include time fixed effects with standard errors clustered by fund and time.

The coefficient on *GOVSHARE* in Panel A of Table 5 is negative and statistically significant. This is consistent with our identification hypothesis that fund sponsors with a higher percentage share of government institutional MMFs during the pre-sample period of 2012 ($GOVSHARE_{2012}$) or 2013 ($GOVSHARE_{2013}$) are less likely to opt for an intraday multi-strike system. The precision of the estimate in column (i) on *GOVSHARE* (t-stat $= -22.73$) also suggests that we do not have a problem with a weak instrument. The strength of the instrument is also confirmed by a large Olea and Pflueger's (2013) effective first-stage F-statistic of 88, which is well above the two-stage least-squares critical value of 37 for a 5% worst case relative bias. Unsurprisingly, the decision to offer a multi-strike PIF is negatively associated with the fund sponsor's number of PIFs converted to government institutional MMFs (*PIF_TO_GOV*) and the number of new government institutional MMFs launched by the fund sponsor (*NEW_GOV*) during the period from November 2015 to October 2016. Also, the number of intraday NAV strikes is positively related to the presence of more sophisticated investors (*H_INVSOPH*) and investors with greater liquidity needs (*LIQDEM*), consistent with a preference for multiple intraday redemption windows on the part of such investors.

Based on the first-stage regression, we derive the implied (estimated) intraday striking system as the expected value of *NSTRIKES* projected on the instrument and other explanatory variables that determine the choice of the NAV pricing mechanism. The estimated coefficients in the second stage on the independent variable *NSTRIKES* in Panel B of Table 5 are stronger in economic magnitude than those reported in

Table 4 for our daily liquidity proxies of *DLA* and *LBD*.[33] Furthermore, the estimated coefficients on *NSTRIKES* are strongly significant, even after all of the control variables for investor liquidity preferences, fund and fund sponsor characteristics are included in the regressions. The relationship between daily liquidity buffers and number of strike times holds across all the specifications, regardless of the instrument used to project *NSTRIKES*. Importantly, the Hansen's *J test* of over-identification provides evidence of the lack of residual correlation of the instruments with the second-stage residuals.

Overall, the findings of our baseline and IV specifications in this section suggest that multi-strike PIFs hold higher percentages of daily liquid assets than their single-strike peers as a result of greater flow-related liquidity risk. In the next section, we quantify the flow-related liquidity risk exposure of multi-strike funds using an exogenous adverse shock.

6. COVID-19 Shock, Funds' Redemption Risk and the Illiquidity Cost of Multiple Intraday NAV Strikes

In this section we estimate the investors' flow response to the growing uncertainty during the weeks of March 2020 surrounding the COVID-19 pandemic outbreak, and the stabilizing impact of the Money Market Mutual Fund Liquidity Facility (MMFLF) on the funds' net cash outflows.[34] We use the cross-sectional variation in the liquidity provision policies of PIFs to contrast the behavior of investors' net cash (out-)flows conditional on the expected illiquidity cost of intraday versus end-of-day (or next-day)

[33]It is worth noting that if we include the instrument based on the percentage share of government institutional MMFs among the explanatory variables in Panel B of Table 5, it is not significant. This result is in line with the fact that a good instrument should correlate with the endogenous explanatory variable and should not be related to the dependent variable other than through its effect on the explanatory variable. It also suggests that the degree of fund sponsors' specialization in the prime MMF business (i.e., 1-*GOVSHARE*) does not explain differences in the liquidity management policies of PIFs.

[34]Under this facility, the Federal Reserve Bank of Boston (FRBB) provides loans available to eligible financial institutions secured by high-quality assets purchased by the financial institution from money market mutual funds. The MMFLF was established on March 23, 2020 with the aim of helping prime money market funds meet the redemption demand of investors, and enhance overall market functioning and credit provision to the broader economy. As of May 31 2020, the total value of the collateral pledged to secure the FRBB's loans to money market mutual funds was $32.5 billion.

redemptions. The analysis helps establish that (a) multi-strike funds were subject to larger outflows during the crisis, and (b) the heightened sensitivity of flows in multi-strike funds is related to the higher illiquidity costs associated with multiple intraday redemption opportunities offered by such funds. Importantly, our results are based on the use of high-frequency (daily) net cash outflows thus allowing us to more closely examine the time series dynamics of investors' behavior during the crisis period.

6.1 Net Cash Outflows and Daily Liquidity Buffers of Prime Institutional Funds

We begin with an analysis of the sensitivity of daily net cash flows to the number of intraday NAV strike windows offered by a fund, *NSTRIKES*, in Panel A of Table 6. In particular, we estimate the following regression model in column (i):

$$\begin{aligned} NFLOWS_{i,t} = \alpha + \beta_0 \times NSTRIKES_i + \beta_1 \times NSTRIKES_i \times I_{\textit{9-18 March}} \\ + \beta_2 \times NSTRIKES_i \times I_{\rightarrow \textit{31 March}} + \mathbf{\Gamma' X_{i,t-1}} + \mu_d + \mu_s + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where the dependent variable $NFLOWS_{i,t}$ is the fund's daily percentage net cash flows which are computed as $(TNA_t - TNA_{t-1} \times (1 + r_t))/TNA_{t-1}$ and then winsorized at top and bottom 0.5% tails of the net cash flow distribution. In all models in Panel A, the coefficients on the variable *NSTRIKES* measure the marginal impact of a fund's multi-strike pricing system during the pre-crisis week from March 2 to March 6, 2020. In columns (i), (iii) and (iv) of Panel A, we interact our main independent variable of interest, $NSTRIKES_i$, with (a) the dummy variable $I_{\text{9-18 March}}$ which equals 1 during the crisis period from March 9 to March 18, 2020, prior to the 11:30 P.M. announcement by the Federal Reserve of the establishment of the Money Market Mutual Fund Liquidity Facility (MMFLF); and (b) the dummy variable $I_{\rightarrow \text{31 March}}$ which equals 1 during the period from March 19 to March 31, 2020. In column (ii) of Panel A, we interact *NSTRIKES* with: the dummy variable $I_{\text{9-20 March}}$ to identify the period from March 9 to March 20, 2020, prior to the launch of the MMFLF on 23 March 2020; and the dummy variable $I_{\rightarrow \text{31 March}}$

which equals 1 during the period from March 23 to March 31, 2020, and zero otherwise.

In columns (iii) and (iv), we include the variable *WLA* which is the share of WLA in the total assets of a fund i on day $t - 2$ to account for investors' response to lagged values of a fund's WLA (see e.g., Li et al., 2021). In column (iv), we account for differences in investors' liquidity preferences by including the variable *LIQDEM_FEB* which is computed as the daily volatility of percentage net cash flows over the past 30 days ending on 28 February 2020. To isolate the crisis period, we also interact *LIQDEM_FEB* and *WLA* with the dummy variable $I_{\text{9-18 March}}$. The vector of fund and fund sponsor characteristics, $\boldsymbol{X_{i,t-1}}$, is identical to that in Table 5. In all models, we include fund sponsor (μ_s) and day (μ_d) fixed effects, with standard errors clustered by both fund and time.

The coefficient of the interaction variable $NSTRIKES \times I_{\text{9-18 March}}$ in column (i) of Panel A of Table 6 is consistent with the illustrative evidence of Figure 1. On average, a fund offering three strikes suffered from 2% (–0.998×3 + 0.998×1) greater daily percentage net cash outflows than a single-strike fund during the period from 9 March to 18 March, before the Federal Reserve's announcement regarding the establishment of the MMFLF.[35] The greater daily net cash outflows of multi-strike funds decreased by about a third over the next two days following the 11:30 P.M. announcement of the establishment of the MMFLF on 18 March, as indicated by the lower negative coefficient (–0.647) of the interaction term $NSTRIKES \times I_{\text{9-20 March}}$ in column (ii). As expected, the establishment of the MMFLF contributed to substantially reducing the difference in net cash flows between multi-strike and single-strike funds, as indicated by the estimated coeffcients (0.599 and 0.593, respectively) of the interaction term $NSTRIKES \times I_{\to\text{31 March}}$ in columns (iii) and (iv). By March 31st, 2020, multi-strike funds did not seem to experience markedly greater net cash outflows compared to single-strike funds.

Interestingly, the economic impact of the NAV striking system on net cash outflows

[35]During the period March 9-18, 2020, six PIFs experienced large net cash outflows causing their daily liquidity buffers to become negative, meaning their percentage daily liquid assets—net of next-day investor redemptions—dropped below the 10% threshold. Among these six funds facing severe daily liquidity shortfalls lasting in some cases as long as 4 days, only one was a single-strike fund.

remains large and significant after controlling for the two-day-lagged percentage weekly liquid assets (*WLA*) held by PIFs, in columns (iii) and (iv). Consistent with the evidence of Li et al. (2021), the coefficient of the interaction term between $I_{\text{9-18 March}}$ and *WLA* is positive and highly significant in both columns (iii) and (iv) suggesting a heightened sensitivity of fund flows to a possible deterioration in the level of a fund's WLA during the crisis period. For instance, the coefficient (0.164) of the interaction term $WLA \times I_{\text{9-18 March}}$ in column (iv) implies that a one-standard-deviation (6.6%) decrease in fund's *WLA* is associated with a 1.1% (=0.164×6.6%) increase in daily net cash outflows during the crisis period from 9 March to 18 March, 2020.[36] Importantly, this impact of a fund's *WLA* on daily net cash (out-)flows during the crisis period is similar—in economic terms—to the 1.5% (=0.751×3–0.751×1) greater average daily net cash outflows experienced by a three-strike fund compared to a single-strike fund. By contrast, net cash flows do not seem to respond to changes in a fund's WLA outside of the crisis period as indicated by the insignificant coefficients (–0.012 and 0.006, respectively) of the variable *WLA* in columns (iii) and (iv).

As shown in Panel A of Table 5, the number of NAV strikes (*NSTRIKES*) of a fund is positively related to the presence of investors with greater liquidity needs (*LIQDEM*). The difference in investor liquidity demand across single- and multi-strike funds can potentially lead to a difference in fund flows between the two groups of funds during the crisis period. To account for this possibility, in column (iv) we add several *LIQDEM_FEB*-related terms to the regression specification, where *LIQDEM_FEB* is computed as the daily volatility of percentage net cash flows over the past 30 days ending on 28 February 2020. We note that the estimated coefficient of $NSTRIKES \times I_{\text{9-18 March}}$ in column (iv), after controlling for investor liquidity demand (*LIQDEM_FEB*), remains comparable in magnitude to that reported in column (iii). This finding suggests that the difference in investor fund flows between multi-strike funds and single-strike funds around the crisis

[36] Our estimates are very close to those of Li et al. (2021) who find that a one-standard-deviation (6.5%) decrease in the two-day-lagged *WLA* is associated with a 0.9-percentage-point increase in daily outflows during the crisis period from 9 March to 20 March, 2020.

period is not solely due to the difference in the liquidity preferences of their investors.

6.2 The Effect of Illiquid Holdings and Intraday Liquidity Provision on Investors' Flows during the Crisis Period

Hypothesis 2 predicts that multi-strike funds face stronger strategic complementarities in investor redemption decisions during periods of heightened market volatility, and that this effect is directly related to the illiquidity of a fund's portfolio. Accordingly, in this section we quantify the differential response of daily net cash flows to the proportional illiquid portfolio holdings of PIFs to examine how investors' expectation of the funds' portfolio illiquidity costs affected their redemption behavior during the crisis. To this end, we employ a pooled time series cross section regression design in which a fund's daily net cash flow during the peak of the crisis (March 9-18, 2020) is regressed on the two-month lagged percentage illiquid holdings as reported by the fund in January 2020.[37] Hanson, Scharfstein, and Sunderam (2015) argue that the secondary market for commercial paper and bank obligations held by PIFs tends to be highly illiquid. We should then expect PIFs reporting higher percentage holdings of such securities to face more severe net cash outflows during periods of higher market illiquidity when it would be more costly to trade commercial paper and bank obligations.

To identify the impact of illiquid holdings on institutional investors' flows during the peak of the crisis, we estimate the following regression and report the results in Panel B of Table 6:

$$\begin{aligned} NFLOWS_{i,t} = {} & \alpha + \beta_0 \times ILLIQUID\_HLD_i + \beta_1 \times ILLIQUID\_HLD_i \times NSTRIKES_i \\ & + \beta_2 \times GYIELD_{i,t-1} \times NSTRIKES_i + \beta_3 \times NSTRIKES_i \\ & + \beta_4 \times GYIELD_{i,t-1} + \boldsymbol{\Gamma' X_{i,t-1}} + \mu_d + \mu_s + \epsilon_{i,t}. \end{aligned} \tag{4}$$

[37] We also used the 1-month-lagged (i.e., February 2020), three-month-lagged (i.e., December 2019), and the average of the past three-month (i.e., December 2019 to February 2020) percentage illiquid holdings, and obtained results that were qualitatively similar to those presented in this section. It is important to note that investors could only observe past portfolio holdings to formulate expectations about a fund's illiquidity costs. Daily NAV variations are unlikely to reflect the asset-side liquidity of a PIF if its portfolio holdings are highly illiquid. In this case, a floating NAV would represent an incorrect proxy of the expected illiquidity cost of a fund's redemption-motivated trades since daily mark-to-market NAVs would adjust only sluggishly to changing market conditions.

In the above expression, the dependent variable $NFLOWS_{i,t}$ is the percentage net cash flow of a fund i in day t; the variables $NSTRIKES_i$, $GYIELD_{i,t-1}$ and the vector $\boldsymbol{X_{i,t-1}}$ are defined as in Table 5; μ_d and μ_s identify day and fund sponsor fixed effects, respectively; and $ILLIQUID\_HLD_i$ is a generic name for one of the following proxies of the two-month lagged percentage holdings of less liquid securities of fund i: unsecured commercial paper issued by financial institutions (*FINCP*) in column (i); foreign bank obligations (*FBNKOB*) in column (ii); asset-backed commercial paper (*ABCP*) in column (iii); and risky securities (*RISKY*) comprising bank obligations (*BNKOB*), financial and non-financial commercial paper (*CP*), and asset-backed commercial paper (*ABCP*) in column (iv).

The evidence of Panel B in Table 6 confirms that PIFs reporting a higher percentage of illiquid portfolio holdings experienced more severe net cash outflows. In economic terms, the coefficient of *ILLIQHLD* in column (i) of –0.479 indicates that each 1% increase in holdings of financial commercial paper (*FINCP*) is associated with about 0.5% lower daily net cash flows. The negative impact on net cash flows of the illiquidity cost of redemption-motivated trades worsens among PIFs holding more foreign bank obligations, *FBNKOB*. In this case, a fund reporting a 1% higher exposure to *FBNKOB* suffered about 1.4% higher net cash outflows during the crisis week, on average.

In all models in Panel B of Table 6 we also exploit the rich cross-sectional variation in intraday NAVs of multi-strike funds and include the interaction term *ILLIQUID_HLD* $\times$ *NSTRIKES*. Our aim is to quantify the conditional effect of multiple intraday NAV quotations on investors' expectations of the likely illiquidity cost of redemptions during the crisis period. For instance, the estimated loading (–0.174) of *NFLOWS* on the interaction term *ILLIQUID_HLD* $\times$ *NSTRIKES* in column (i) suggests that intraday liquidity provision exposed multi-strike funds holding less liquid assets to a 36% (–0.174/–0.479) higher flow-related daily liquidity risk compared to single-strike funds. This effect becomes particularly severe among multi-strike funds holding more foreign bank obligations, as shown in column (ii). In economic terms, a 1% increase in the portfolio holdings of foreign bank obligations (*FBNKOB*) exposed the average three-strike fund to net cash flows that were lower by about 1.6% $(1 \times (-0.819) \times (3-1))$ compared to the average single-strike fund.

A potential concern with these findings is that multi-strike funds might experience worse outflows because of cross-sectional differences in investors' flow-performance sensitivities. If investors were much more sensitive and alert to poor performance among multi-strike funds during the crisis, then the findings of Panel B of Table 6 could also be explained by the possibility that institutional investors perceived them as an asset class with potentially larger downside risk (i.e., flow-performance sensitivity is steeper among multi-strike funds). The insignificant coefficients on the interaction variable *GYIELD* × *NSTRIKES* in columns (i) to (iv) of Table 6, together with our previous evidence in Table 2 on the average higher percentage holdings of safe assets among multi-strike funds, cast doubts on the plausibility of this alternative explanation.[38]

Another potential explanation for the higher outflows experienced by multi-strike funds is the possibility that such outflows reflect preemptive exit decisions by investors who may fear the imposition of redemption gates by funds with low liquidity levels (see, e.g., Li et al. (2021)).[39] To address this possibility, in Figure 2 we examine the normalized cumulative net cash outflows during the March 2020 crisis period for funds with above median as well as below median level of weekly liquid assets (WLA). We find that within each group of funds multi-strike funds have higher proportional outflows, and the difference in aggregate outflows relative to single-strike funds is nearly identical in each group. Consistent with the statistically insignificant coefficients on the interaction term *WLA* × *NSTRIKES* in columns (iii) and (iv) of Panel A of Table 6, these findings

[38] La Spada (2018) argues that gross yields tend to be very compressed among MMFs and suggests regressing fund flows on percentiles of gross yields normalized over the interval [0, 1]. Our estimated coefficients of the interaction variable *GYIELD* × *NSTRIKES* in Panel C of Table 6 remain insignificant when we replace the raw gross yield with the normalized rank of fund i's gross yield. These results are available in the Internet Appendix.

[39] In this context, Voellmy (2021) shows that while redemption fees can be quite effective at preventing runs, the imposition of redemption gates can in fact create runs on funds with floating NAVs.

suggest that the differential outflows suffered by multi-strike funds are not simply due to concerns related to worsening liquidity conditions.

To summarize, consistent with Goldstein, Jiang, and Nguyen (2017), the evidence in Panel B of Table 6 supports the view that a higher portfolio concentration in less liquid assets contributed to heightened strategic complementarities among PIF investors' redemption decisions during the crisis. This was particularly true for multi-strike funds that offer multiple intraday redemption windows, thereby exacerbating the illiquidity costs related to redemption-motivated trades. These results are broadly consistent with Hypothesis 2.

6.3 Changes in Fund Portfolio Holdings around the COVID-19 Shock

If multiple intraday redemption windows allow institutional investors to monitor more frequently—and at very low cost via the fund's website—any intraday NAV dilution of the fund portfolio, multi-strike funds would have strong incentives, even during normal times, to limit their holdings of relatively illiquid assets (see, e.g., Covitz and Downing (2007), Duygan-Bump et al. (2013), and Hanson, Scharfstein, and Sunderam (2015)). For instance, a large unexpected redemption request received in the first strike session at 8:00 A.M. could force a fund to sell its illiquid assets at heavily discounted, "fire-sale" prices, thus increasing the first-mover advantage of attentive institutional investors in subsequent intraday strike sessions. It follows that proper liquidity management by multi-strike funds would require reducing their portfolio allocation to relatively less liquid securities such as (asset-backed) commercial paper compared to single-strike funds.

In this section, we use portfolio holdings data from iMoneyNet over the period from October 14, 2016 to June 5, 2020 to examine the changes in the funds' portfolio allocations, particularly around the COVID-19 shock. By exploiting the cross-sectional variation in the intraday NAV sessions, we can directly quantify the implication of investors' redemptions on the funds' incentives to hold assets for which there is a relatively less liquid secondary market. Since the 2016 SEC reforms required PIFs to offer their shares exclusively to institutional investors, our findings apply to a homogenous group of sophisticated investors. Importantly, we examine how the growing uncertainty concerning the COVID-19 outbreak in the weeks of March 2020 affected the funds' decisions to alter their portfolio allocations within, and across risky and safe assets.

Table 7 reports the results of weekly regressions of fund's percentage portfolio holdings of risky assets on the number of redemption windows offered by a fund, *NSTRIKES*.[40] The regression model is specified as:

$$\begin{aligned} HOLDINGS_{i,t} = \alpha + \beta_0 \times NSTRIKES_i + \beta_1 \times NSTRIKES_i \times COVID19_t \\ + \boldsymbol{\Gamma' X_{i,t-1}} + \mu_w + \mu_s + \epsilon_{i,t}, \end{aligned} \tag{5}$$

where the dummy variable $COVID19_t$ equals 1 during the three weeks from 11 March to 31 March 2020, and the variable $NSTRIKES_i$ and the vector $\boldsymbol{X_{i,t-1}}$ are defined as in Table 5. In all models we include fund sponsor fixed effects (μ_s) and week fixed effects (μ_w). In Panel A of Table 7, our dependent variable $HOLDINGS_{i,t}$ identifies one of the following proxies of a fund's percentage risky holdings: the aggregate percentage of risky holdings in a fund portfolio (*RISKY*) comprising bank obligations (*BNKOB*), financial and non-financial commercial paper (*CP*), and asset-backed commercial paper (*ABCP*). In column (ii), we follow Di Maggio and Kacperczyk (2017) and use the holdings risk, *HR*, as our dependent variable. This variable is computed as the difference in a fund's allocations to foreign bank obligations and U.S. Treasury and government agency securities and collateralized repo contracts. Our dependent variables in columns (iii) to (v) are the percentage holdings of: financial and non-financial commercial paper (*CP*), asset-backed commercial paper (*ABCP*), and foreign bank obligations (*FBNKOB*).

For the sake of robustness we also consider changes in fund allocations to the holdings

[40] Since weekly holdings are available from iMoneyNet on the Tuesday of each week, we consider weekly reported holdings for the periods 11-17 March, 18-24 March, and 25-31 March.

of relatively safe assets in Panel B of Table 7. The dependent variable *HOLDINGS* in columns (i) to (v) of Panel B is, respectively, the percentage holdings of one of the following assets: aggregate safe assets (*SAFE*); U.S. Treasury securities (*USTR*); repo contracts collateralized by U.S. Treasury and government agency securities (*REPO*); U.S. government agency securities (*AGENCY*); and floating-rate notes (*OTHER*). In both panels of Table 7 we interact the variable *NSTRIKES* with the dummy variable $COVID19_t$. The aim is to quantify any change in the funds' weekly portfolio holdings in response to this exogenous shock.

Starting with the findings of Panel A of Table 7, the coefficients of –1.097 and –0.958 of *NSTRIKES* in columns (i) and (ii) are consistent with the view that multi-strike funds face weaker incentives from redemption risk to hold risky assets, *RISKY*, and expose their portfolio to higher holdings risk, *HR*. In economic terms, a fund offering three strike times per day has a 2.2% lower exposure to risky assets relative to a single-strike fund, on average. This result is mostly attributable to the multi-strike fund's lower percentage holdings of less liquid securities such as *FBNKOB* (–0.7%) and *ABCP* (–1.5%). Interestingly, in response to the heightened flow-related liquidity risk during the COVID-19 shock in March 2020, multi-strike funds shifted their portfolio holdings composition markedly away from illiquid and unsecured commercial paper to highly-liquid—mostly overnight—collateralized repo agreements. For instance, the coefficient of –1.754 of the interaction term *NSTRIKES*×*COVID19* in column (ii) of Panel A of Table 7 implies a 3.5% reduction in the net exposure of multi-strike funds to risky securities. This result is mainly attributable to a 2.3% reduction in their holdings of unsecured commercial paper, and a 2.4% simultaneous increase in their holdings of collateralized repo contracts. Contrary to the significant coefficients of *REPO* in column (iii), we find that multi-strike funds reduced their holdings of U.S. government agency securities (*AGENCY*) in column (iv) of Panel B. A possible explanation for this result is that while *USTR* and *REPO* always enter the calculation of the *DLA* irrespective of their time to maturity, *AGENCY* assets are included in the percentage daily liquid assets only if they mature within a day.

In summary, the evidence in Table 7 is consistent with our first hypothesis (Hypothesis 1(b)) that the average multi-strike fund follows a more conservative liquidity management policy compared to single-strike funds. It does so by shunning assets with potentially limited secondary markets, and maintaining an average portfolio time to maturity well in excess of the period over which an institutional investor run would occur. Importantly, the unfolding crisis in March 2020 strengthened the funds' incentives to promptly increase the daily asset liquidity of their portfolios through overnight repo contracts in an attempt to minimize the unprecedented negative shock to the floating NAVs.

7. The U.S. Debt Ceiling Crisis and Funds' Portfolio Rebalancing

In this section, we examine the response of PIFs to the exogenous shock represented by the adoption by the U.S. Treasury Department of "extraordinary measures" to meet all federal government obligations following the reinstatement of the U.S. debt ceiling on December 8 2017.[41] On 9th February 2018, about a month before the U.S. Treasury Department was expected to exhaust all "extraordinary measures" and risk a technical default on its outstanding debt, Congress authorized a one-year suspension of the debt ceiling until March 2, 2019.[42]

Prior to the debt ceiling suspension, the countdown towards the expected default date of March 1, 2018 sent shock waves through financial markets and contributed to a sharp rise in yields on U.S. Treasury securities. The debt ceiling crisis and its eventual resolution represents an ideal setting to examine how PIFs responded to the threat of

[41] The U.S. debt ceiling is a legislative limit on the total federal government debt beyond which the U.S. Treasury Department is not allowed to issue any new debt. Without authorization by Congress to raise or suspend the debt limit, the U.S. Treasury may engage in "extraordinary measures" by temporarily withholding payments to certain internal accounts to free up some additional borrowing capacity and limit the risk of technical default. These measures buy some time for Congress to reach a deal to raise or (re-)suspend the debt limit.

[42] The House of Representatives voted 240 to 186 and the Senate voted 71 to 28 in *favor* of the debt ceiling suspension (see report R41814 on https://crsreports.congress.gov). This spending and debt limit deal, dubbed the Bipartisan Budget Act of 2018 is the third—after the Bipartisan Budget Acts of 2013 and 2015—in a series of increasing spending caps. The delay in the passage of this bill caused a nine-hour funding gap. For context, see Thomas Kaplan, "Trump Signs Budget Deal to Raise Spending and Reopen Government", *New York Times*, February 8, 2018, https://www.nytimes.com/2018/02/08/us/politics/congress-budget-deal-vote.html.

technical default on U.S. Treasury holdings. In particular, the episode allows us to examine whether PIFs hedged against the possibility of default by altering their portfolio exposure to Treasury securities, before and after the exogenous event, namely, the debt ceiling suspension on February 9, 2018.

We assess the funds' decisions with respect to their holdings of U.S. treasury securities, and the portfolio maturity profile around the debt ceiling suspension date using the following regression model, and present the results in Table 8:

$$\begin{aligned} EXPOSURE_{i,t} = \alpha + \beta \times NSTRIKES_i + \boldsymbol{\Lambda' EVENT_t} \times NSTRIKES_i \\ + \boldsymbol{\Gamma' X_{i,t-1}} + \mu_m + \mu_s + \epsilon_{i,t}. \end{aligned} \tag{6}$$

In the above expression, the dependent variable $EXPOSURE_{i,t}$ is a generic name for either the percentage holdings of U.S. Treasury securities in the fund portfolio, *USTR*, in columns (i) and (ii) of Table 8, or the weighted average maturity (WAM) of U.S. Treasury securities held in the fund portfolio, *WAM_USTR*, in columns (iii) and (iv) of Table 8. The variable $NSTRIKES_i$ and the vector $\boldsymbol{X_{i,t-1}}$ are defined as in Table 5. In all models, we include fund sponsor fixed effects (μ_s) and month fixed effects (μ_m), with standard errors clustered by fund and time.[43] The main coefficients of interest are represented by the vector $\boldsymbol{\Lambda} = (\lambda_1, ..., \lambda_6)'$ on the interaction term $\boldsymbol{EVENT_t} \times$ *NSTRIKES*. The vector variable $\boldsymbol{EVENT_t}$=*(S–3M, S–2M,..., S+3M)* comprises dummy variables for each of the six months from November 2017 to April 2018 surrounding the debt ceiling suspension date (S) of 9 February 2018. For example, the dummy variable *S–3M* equals 1 for the month of November 2017, and 0 otherwise.

Consistent with our previous findings in Panel B of Table 2, the loading of the dependent variable *USTR* on *NSTRIKES* in column (i) of Table 8 suggests that multi-strike funds hold a much larger (5%) share of U.S. Treasury securities than single-strike funds, on average. The estimated coefficient of the interaction term *NSTRIKES* $\times$ *S–1M*

[43]The models of Table 8 are estimated monthly because the time to maturity of U.S. Treasury securities is only available in the reported monthly portfolio holdings.

in column (i) confirms that in January 2018 multi-strike funds decreased their demand for U.S. Treasury securities by 4% more than single-strike funds, and gradually increased again their demand for such securities in the month(s) after the resolution of the U.S. debt ceiling impasse on 9 February 2018, as indicated by the positive and significant coefficient on the interaction term $NSTRIKES \times S{+}1M$.

In columns (iii) and (iv) of Table 8 we also examine how PIFs changed their maturity risk exposure to U.S. Treasury securities, *WAM_USTR*, around the debt ceiling shock. The estimated coefficients on the interaction term $EVENT \times NSTRIKES$ in columns (iii) and (iv) of Table 8 identify a clear trend in the response of multi-strike funds to the increasing default risk posed by U.S. Treasury securities. To wit, multi-strike funds gradually reduced their *WAM_USTR* as the suspension date approached. For instance, the estimated coefficient of $NSTRIKES \times S\text{–}1M$ in column (iii) of Table 8 suggests that in January 2018 two-strike funds reduced the weighted average maturity (WAM) of their U.S. Treasury securities by about 12 days more than single-strike funds, on average. Importantly, the estimated coefficients of $NSTRIKES \times S{+}1M$ in columns (iii) and (iv) provide clear evidence of portfolio re-adjustment in the weighted average maturity of U.S. Treasury securities following the announcement of the debt ceiling suspension by Congress. These findings on the portfolio maturity adjustment of U.S. Treasury securities are also consistent with a pre-suspension decision of PIFs to let existing Treasury holdings mature, followed by a post-suspension decision to purchase new issues of such securities.

In summary, the findings in this section suggest that in response to the growing uncertainty caused by the U.S. debt ceiling impasse in 2018, multi-strike funds altered their portfolio holdings to limit their flow-related liquidity risk. Since the debt ceiling uncertainty was not about whether, but *when* money market funds would receive payments for interest and principal on U.S. Treasury securities, the evidence in Table 8 highlights the significant distortions caused by the exogenous debt ceiling negotiations in terms of the ability of the funds to meet investors' redemption demands by liquidating their maturing safe assets. At the same time, these findings highlight the greater financial fragility of multi-strike funds as confirmed by their pre-emptive efforts to curtail their redemption-related risk.

8. Liquidity Shortfall and Stress Testing of PIFs

An open-end PIF faces significant liquidity risk if it fails to meet redemption requests that are expected under normal market conditions, or could be expected under stressed market conditions, without *significant dilution* of remaining investors' interests in the fund.[44] This implies that when determining the appropriate level of liquidity buffer to maintain, a PIF must consider not only the expected net cash outflows—e.g., redemption requests due to seasonality or tax considerations—but also, and more importantly, any redemption requests that may not be expected, but are *reasonably foreseeable* based on historical net withdrawals under stressed conditions. To this end, the SEC advises PIFs to review historical purchases and redemptions of shares across a variety of market conditions in order to determine whether daily and weekly liquidity buffers are sufficient to minimize dilution costs.[45] In this section, we stress test the ability of PIFs to maintain their daily and weekly internal liquidity above the minimum thresholds in response to severe, though plausible, redemption shocks.

8.1 Descriptive Statistics of Fund's Liquidity Shortfall by Intraday Striking System

We begin by stress testing the adequacy of the liquidity buffers of PIFs using the historical distribution of their own percentage net cash flows across different market conditions. Specifically, for each fund in our sample we first calibrate a *severe* daily redemption shock based on the left tail of the fund's historical distribution of daily net cash flows, *NFLOWS*.[46] We then evaluate whether the fund would have been able to meet such

[44] Refer to Rule 22e-4(a)(7) and Rule 22e-4(a)(11) of the Investment Company Act of 1940.

[45] In addition to considering a fund's own historical distribution of percentage net cash flows, the SEC also advises PIFs to consider the historical distribution of net cash flows of peer PIFs. Such comparison is expected to improve the fund's ability to match the liquidity of its portfolio (assets) to the expected net cash outflows due to investor redemption demands.

[46] Our time series of funds' historical daily *NFLOWS* starts on January 1, 2009. Although the start date precedes the implementation of the MMF reform, a longer time window is likely to provide PIFs

redemption shocks with its daily and weekly liquid assets without breaching the minimum thresholds.[47] We should emphasize that our redemption-based stress tests provide only a conservative estimate of the ability of PIFs to withstand a redemption shock. In fact, redemption shocks heighten a fund's liquidity risk when combined with other major events such as sudden changes in interest rates, credit downgrades or defaults of the fund's portfolio securities, and a general deterioration in market liquidity conditions.

In Panel A of Table 9, we report the summary statistics of the daily liquidity shortfall of a fund, *LBD_NEGATIVE*, which is defined as the negative realization of the daily liquidity buffer, *LBD*. During the period of our analysis, we find 82 instances where the *DLA* breached the 10% threshold, with an actual shortfall averaging at –4.1%. In Panel A, we also present the statistics of the fund's simulated liquidity shortfall corresponding to different redemption shocks calibrated to the left-tail percentiles of the historical distribution of *NFLOWS*. For each percentile shock varying between 0 and 10%, we also separately report the statistics related to *LBD_NEGATIVE* for single-strike funds and multi-strike funds. A redemption shock calibrated on the first percentile of a multi-strike fund's historical distribution of net cash flows (*NFLOWS (left tail: 1pct)*) would be associated with an average *LBD_NEGATIVE* of –7.9%, which is 5.4% larger than the shortfall that would be experienced by the average single-strike fund. These findings highlight that the liquidity buffers held by some PIFs might not be enough to meet foreseeable investors' daily net cash outflows, and are consistent with the evidence of Table 6. This is particularly the case among multi-strike funds where the worst daily liquidity shortfall (*NFLOWS (left tail: Worst)*) would have averaged at about –54%, even before considering any other major event such as credit downgrades, or default of portfolio securities.[48]

with more data points on past institutional redemptions across a variety of market conditions.

[47] Our conclusion remains unchanged when the redemption shock is calibrated at the segment-level. Segment-level net cash flow shocks are typically less severe than fund-level shocks as some PIFs in the segment experience inflows while other funds experience outflows on the same day.

[48] In an unreported table—available in the Internet Appendix—we examined the descriptive statistics of a fund's weekly liquidity shortfall, *LBW_NEGATIVE*, which is defined as the negative realization of a fund's weekly liquidity buffer, *LBW*. Using simulated net cash outflows (based on historical distributions), we find that multi-strike funds would have suffered an average liquidity shortfall of –18%—i.e., 11% worse

8.2 A Multivariate Analysis of Simulated Liquidity Shortfall

The summary statistics presented in Panel A of Table 9 clearly show that the actual liquidity buffer carried by (some) PIFs might not be enough to withstand severe redemption shocks, and this is particularly true among multi-strike funds. In this section, we employ a multivariate regression framework to examine whether this result is explained by cross-sectional differences in the characteristics and incentives of PIFs. Specifically, we examine the determinants of funds' simulated liquidity shortfall using the following regression model, and present the results in Panel B of Table 9:

$$\begin{aligned} DSHORT_{i,t} = \alpha + \beta_0 \times NSTRIKES_i + \beta_1 \times NSTRIKES_i \times FEDRATE_{t-1} \\ + \boldsymbol{\Gamma' X_{i,t-1}} + \mu_d + \mu_s + \epsilon_{i,t}. \end{aligned} \tag{7}$$

In the above expression, $DSHORT_{i,t}$ is the simulated daily liquidity shortfall. This variable is computed as the sum of the percentage of assets in the form of daily liquid assets held by fund (*DLA*) and the simulated next-day net cash flows corresponding to different left-tail percentiles of the historical distribution of *NFLOWS*, net of the minimum liquidity threshold of 10%. We consider different simulated realizations of *DSHORT* based on the first percentile (*NFLOWS (left tail: 1%)*), 5-th percentile (*NFLOWS (left tail: 5%)*), and 10-th percentile (*NFLOWS (left tail: 10%)*) of the historical distribution of the percentage net cash flows of a fund. The variable $NSTRIKES_i$ and the vector $\boldsymbol{X_{i,t-1}}$ are defined as in Table 5. Di Maggio and Kacperczyk (2017) show that changes in the FED short-term nominal target rate influence the product offering and risk-taking incentives of (prime) money market funds. If illiquidity and riskiness move together, multi-strike funds would then be more subject to the "reach-for-yield" argument of Di Maggio and Kacperczyk (2017) than single-strike ones (i.e., risk-taking goes down as rates go up). The interaction variable $NSTRIKES_i \times FEDRATE_{t-1}$ in the above expression quantifies the economic

than single-strike funds—had their net cash outflows corresponded to their worst historical realization (*NFLOWS (left tail: Worst)*).

incentives of multi-strike funds to take more risk in response to exogenous monetary policy shocks. In all models we include fund sponsor fixed effects (μ_s) and day fixed effects (μ_d), with standard errors clustered by fund and days.

The coefficient of –0.475 of the variable *NSTRIKES* in column (i) of Panel B of Table 9 suggests that an unexpected daily redemption shock corresponding to the first percentile of a fund's historical distribution of net cash flows (*NFLOWS (left tail: 1%)*) is associated with a breach of the daily liquidity threshold by a multi-strike fund offering 3 'strikes' that is 1% greater than the liquidity shortfall suffered by a single-strike fund, on average. We reach qualitatively similar conclusions in column (iii) and column (v) when we simulate *DSHORT* based on the 5-th percentile (*NFLOWS (left tail: 5%)*) and 10-th percentile (*NFLOWS (left tail: 10%)*) of the historical distribution of net cash flows.

Since yields on assets in which PIFs invest, and consequently their portfolio returns, depend on the level of the Fed target rate, changes in the Fed target rate are likely to alter the risk-taking behavior (see e.g., Di Maggio and Kacperczyk (2017)) and hence the liquidity holdings of multi-strike funds.[49] In a tightening monetary policy environment, for instance, multi-strike funds could choose to either leave their liquidity buffer unaltered or exploit the opportunity offered by higher average income yields to minimize the risk of an intraday liquidity shortfall. We isolate the effect of the Fed annualized target rate, *FEDRATE*, on fund's liquidity shortfall by including the interaction term *NSTRIKES* $\times$ *FEDRATE*. This variable quantifies the differential incentives to reach for yield among multi-strike funds and single-strike funds. The coefficients of *NSTRIKES* $\times$ *FEDRATE* in columns (ii), (iv) and (vi) of Panel A of Table 9 are all positive and significant, suggesting that the Fed's monetary policy contributes to reducing by about 40% the risk of a daily liquidity shortfall among multi-strike funds.[50]

[49]During our sample period the upper limit of the Federal Funds target rate varied between 0.25% and 2.5%.

[50]The economic magnitude of the daily liquidity shortfall of multi-strike funds increased markedly when we considered *WSHORT* as our dependent variable. In that case, a redemption shock calibrated on the first percentile of a fund's historical distribution of *NFLOWS* would have caused a triple-strike fund to breach the threshold of 30% by about 2% more than a single-strike fund, on average. The frequency of such an event is also economically relevant as multi-strike funds would have experienced a breach of the minimum threshold almost 15% of the times—or 1,747 instances—during our sample

In summary, our findings confirm that the high liquidity buffers of PIFs may not be sufficient to absorb the full impact of unexpected—though foreseeable—redemption shocks even during periods characterized by relatively mild economic incentives of money market funds to reach for yields. The liquidity shortfall becomes particularly problematic among funds offering intraday liquidity provision to institutional investors, with direct implications for the overall financial stability of the entire money market fund segment.

9. The Cost of Liquidity Provision: Total Returns and Gross Income Yields

Our earlier findings clearly establish that multi-strike funds respond to the heightened flow-related liquidity risk of intraday redemptions by enhancing their portfolio (asset) liquidity. In this section, we complement our earlier analysis by examining what it costs investors, in terms of total returns, to be able to access intraday liquidity via multi-strike funds.

A floating NAV requires institutional investors to consider and track different metrics when evaluating the performance of a PIF. Following the flotation of the NAV, institutional investors must now consider the performance of a PIF in a total return framework. In particular, when forming estimates of a fund's performance investors must pay attention to not only its annualized gross income yield (*GYIELD*) but also any capital gains or losses accruing as a result of NAV fluctuations.[51] For example, an institutional investor who purchased shares of a PIF with an annualized gross yield of 1% at a floating NAV of \$1.0003, and subsequently resold those shares at \$0.9999 after 30 days, would earn a daily gross income yield of 8 basis points but suffer a capital loss of 4 basis points, resulting into a total return of only 4 basis points—or half of the total income yield. In other words, this investor would now need to wait as long as 15 (=(1.0003–0.9999)/1%×365) days for the floating NAV investment to return to the

period, up from the more trivial 3% frequency obtained using the *actual* next-day net cash out-flows.

[51] Several fund sponsors offer simulation tools on their websites to help investors in PIFs understand the impact of a change in the four-digit NAV on their immediate and short-term liquidity needs. See e.g., https://www.gsam.com/content/gsam/us/en/advisors/resources/investment-ideas/investing-in-a-floating-nav-world.html.

initial investment, all else equal. This simple example shows that fluctuations in the NAV could be very detrimental to investors' total return, with this effect becoming increasingly more apparent the shorter the horizon of their investment in PIFs. It also highlights the importance for PIFs to limit any variations in daily mark-to-market NAVs, and monitor on a daily basis the effect of such variations on investors' liquidity demand.

To identify the cost of intraday liquidity provision, we use the following regression specification, and present the daily estimated coefficients in Table 10:

$$PERF_{i,t} = \alpha + \beta_0 \times NSTRIKES_i + \mathbf{\Gamma' X_{i,t-1}} + \mu_d + \mu_s + \epsilon_{i,t}. \tag{8}$$

In the above equation, the dependent variable $PERF_{i,t}$ is a generic name for one of the following performance proxies: the daily total return of a fund (*TOTRET*) in column (i), which is computed as the sum of the daily annualized gross income yield (*GYIELD*) and the daily capital gain or loss on the four-digit transactional NAV ($YIELD1_{NAV}$); the fund's daily annualized gross income yield (*GYIELD*) in column (ii); the fund's daily annualized after-fee income yield (*NYIELD*) in column (iii); the daily capital gain or loss on the four-digit transactional NAV, obtained by iMoneyNet directly from the fund's website ($YIELD1_{NAV}$) in column (iv); and the daily capital gain or loss on the four-digit shadow NAV, as reported by a fund to the SEC in its form N-MFP ($YIELD2_{NAV}$) in column (v).[52] Since intraday liquidity provision could increase performance volatility and hurt a fund's ability to predict its NAV at future striking sessions, we also compute the daily variation of a fund's capital gains and losses as the absolute value of the daily change in a fund's transactional NAV, $|\Delta NAV|$. We then use $|\Delta NAV|$ as our dependent variable in column (vi). Our primary independent variable of interest is the number of daily redemption windows offered by a fund, $NSTRIKES_i$. The vector of lagged control

[52]For multi-strike funds, the daily transactional NAV corresponds to the last-traded NAV of the business day.

variables $\boldsymbol{X_{i,t-1}}$ includes: *LFNDTNA*; *LFAMTNA*; *LFNDAGE*; *NOPRMBUS*; *OPEX*; *NFLOWS*. In all models, we include fund sponsor fixed effects (μ_s) and day fixed effects (μ_d), with standard errors clustered by fund and days.[53]

The negative coefficient of the independent variable *NSTRIKES* in model (i) of Table 10 suggests that PIFs offering multiple daily NAV strikes show weaker incentives to search for yield. In economic terms, the significant coefficient of –0.798 of the variable *NSTRIKES* in model (i) suggests that investors pay an average premium of about 2 basis points to a PIF if they are allowed to access their daily liquidity multiple times a day rather than only once a day. The estimated coefficients in models (ii) and (iv) of Table 10 indicate that the higher daily liquidity buffers held by multi-strike funds impose a significant toll on both gross income yields and transactional NAV yields. Explicitly, the coefficient of $\textit{YIELD1}_{NAV}$ in column (iv) suggests that about half of the total return dilution experienced by multi-strike funds is attributable to an average *daily* capital loss of 1 basis point. Although trivial at first sight, this daily liquidity premium stretches the investment horizon of institutional investors as they would now need to wait 4 extra days for their income yield to cover the realized capital loss on the NAV if the multi-strike fund has an income yield of 1%. Apparently, this is a significant premium institutional investors are prepared to pay to access intraday liquidity provision. We reach qualitatively similar conclusions on the effect of the number of intraday strikes on fund performance when we measure this performance using the annualized after-fee income yield (*NYIELD*) in column (iii), and the four-digit shadow NAV, as reported by the fund in its form N-MFP ($\textit{YIELD2}_{NAV}$), in column (v). Importantly, the loading of the dependent variable $|\Delta NAV|$ in column (vi) confirms that liquidity provision poses a significantly greater challenge for multi-strike funds in terms of their ability to forecast their next-day portfolio NAV. This result is consistent with under-performing multi-strike funds playing the major role of liquidity providers to institutional investors.

Overall, the results in Table 10 highlight the trade-off between intraday liquidity

[53]Please note that the use of day fixed effects eliminates the impact of time series changes in the Federal Target Rate on our estimated coefficients in Table 10.

provision of multi-strike funds and the total return accruing to investors, and the effect of intraday redemption windows on (gross and net) income yield and transactional NAV.

10. Concluding Remarks

The global financial crisis of 2008 highlighted the fragile nature of the liquidity transformation provided by money market funds and the attendant risks to financial markets. In response, a series of reforms have been adopted by the SEC with the goal of enhancing the stability of money market funds. Chief among these is the introduction of floating NAVs beginning in October 2016 for prime institutional funds, designed to mitigate the investor run-like risks faced by the funds. This paper examines the effectiveness of the reforms by examining two recent episodes involving exogenous shocks that subjected prime funds to severe outflows. Additionally, the paper provides a first look at the nature of the liquidity risks faced by multi-strike funds which represent a recent innovation in the industry.

We introduce a simple theoretical model to better understand the incentives of investors in single- and multi-strike funds, and empirically test the model's implications for the flow related risks faced by the funds. By exploiting the rich cross-sectional variation in the liquidity provision policies of single- versus multi-strike funds, we are able to directly quantify the extent to which the redemption-related risk affects the daily and weekly liquidity buffers of prime funds. In doing so, we are also able to carry out a detailed analysis of the funds' potential liquidity shortfalls under different stress test scenarios.

Our analysis covers two episodes during which prime institutional funds were subjected to the shock of severe outflows. These include the COVID-19 related outflows during March 2020, and the congressional failure to suspend the U.S. debt ceiling leading to the near-default of U.S. government debt in early 2018. We document that multi-strike funds have a significantly higher flow-related liquidity risk as evidenced by the more severe outflows experienced by such funds during economic crises. Our results also suggest that the introduction of floating NAVs has not eliminated the strategic complementarities in the redemption decisions of institutional investors. Investors are still incentivized to redeem early, especially during periods of low market liquidity.

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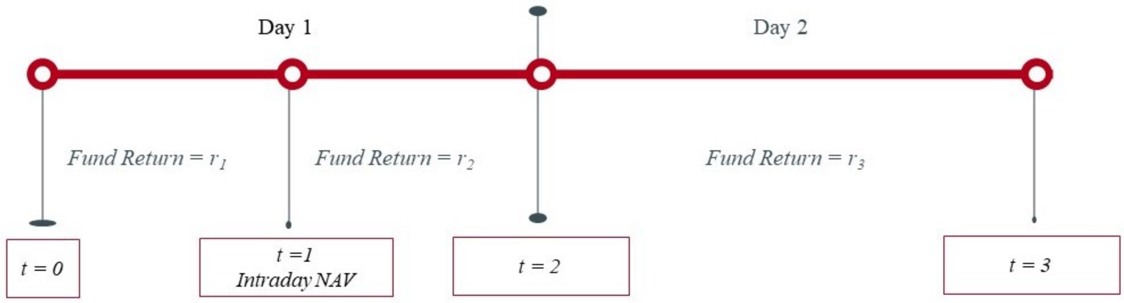
A. Appendix: Theoretical Model

1. The Model Setup

We consider a two-"day" timeline as depicted below. The key time points are marked as follows: $t = 0$ is the fund initiation time, and $t = 1$ is the middle of day 1 when the multi-strike fund has an intraday NAV "strike" which allows for potential redemption and purchase of shares by investors. Time $t = 2$ denotes the end of day 1, and $t = 3$ marks the end of day 2, which is also the time when the fund is liquidated. Below, we focus on the investors' actions on day 1.



We normalize the fund NAV at time 0 to \$1. We assume that the random time-additive fund investment returns of each time period, r_t, are mutually independent with zero mean. Specifically, the expected returns, $E(r_t) = 0$, for $t = 1, 2, 3$.[54] The return variances, $\sigma_t^2 = \lambda_t \sigma^2$, where σ^2 captures the overall fund risk level, and the coefficients λ_t translate it to the risk level in each period, t. We further assume that, at the liquidation date ($t = 3$), the fund's asset value suffers a loss of ϕl, representing the reduction in fund value due to the liquidity cost associated with investor redemptions, where the total redemption amount by the end of day 1 (i.e., by $t = 2$) is denoted by l. The term ϕ is related to the illiquidity of the fund's portfolio; the greater the illiquidity, the higher the liquidation cost associated with investor redemptions. Overall, given the time-additive investment returns ($r_t, t = 1, 2, 3$) and the investor-redemption induced loss (ϕl), the fund's terminal NAV is \$ $(1 + r_1 + r_2 + r_3 - \phi l)$ at $t = 3$.[55]

2. Fund Sponsor's Objective

The fund sponsor suffers a loss from the fund outflow l at the end of day 1, due to the reduction in assets under management, and due to the potential need for sponsor support in case of excessive outflows. We assume that such a loss to the sponsor is increasing and convex in l. The convexity reflects the asymmetric and nonlinear nature of the liquidity consequence of the fund flows. For simplicity, we assume the quadratic form for the cost

[54] All assets at all times are denominated in units of the contemporaneous risk-free bond that pays \$1 at time $t = 3$, and thus the nominal time discount rate is 0. Furthermore, the expectations here are to be understood as based on the market risk neutral probability. Thus, ex-ante all assets are expected to deliver zero mean return in all periods.

[55] By letting the redemption cost be reflected at $t = 3$, we incorporate a component of strategic complementarity among investors in our simple model.

function: $\alpha l + \beta l^2$.[56]

There are incentives for the fund sponsor to reach for yield. These incentives may naturally arise due to the existence of potential investors who will be attracted to funds with a high yield strategy. Given the absence of superior managerial skill in the model, the fund's realized performance, measured in the physical probability, rather than the risk neutral probability, is directly related to the fund's return volatility (under either probability), σ. Under the assumption that high σ leads to high fund yield under the physical probability, we simply bake in the fund's reach-for-yield incentive by assuming that the fund sponsor gets private benefits in the form of $(w\sigma - v\sigma^2)$, where the second term makes the profit function concave, and thus allows for an interior optimal solution.[57] Overall, the fund sponsor's objective is to maximize the private benefits while accounting for the expected costs due to fund flows:

$$\Pi = w\sigma - v\sigma^2 - E(\alpha l + \beta l^2). \tag{A1}$$

3. Investors' Decision

We assume there are two investors in the fund: the 'attentive' or 'informed' investor and the 'uninformed' one.[58] Both investors decide on their positions (i.e., their optimal trading demand) during day 1 in the model timeline based on their information sets. The attentive investor learns both r_1 and r_2 by time $t = 1$. The uninformed investor only learns the returns sequentially in time, i.e., learns r_1 by time $t = 1$ and learns r_2 by time $t = 2$.[59] Hence, note that by assumption, the informed investor's information advantage is perishable. We do not directly model the passive investors including investors whose trades are motivated purely by their liquidity needs, as they play a secondary role in our core story.

We use a reduced objective function for the investor's decision problem. Our modeling

[56] Based on a sample of mutual funds, Edelen (1999) find that fund flow shocks hurts fund performance because, as he argues, fund flows (in the form of either redemption or new fund sales) move the fund away from its initial efficient portfolio allocation.

[57] Our model captures the non-commitment nature of the fund sponsor's investment strategy to the fund's existing investors via the private benefit assumption. The fund may have attracted conservative investors by agreeing to implement an investment strategy that ensures safety and liquidity. Such an agreement is not binding. As a consequence, the fund may also have the competing agenda of engaging in riskier strategy in order to attract investors who seek high fund yield. Our specification of the private benefits as a quadratic function of σ leads to an internal optimal solution that balances the above two competing agendas.

[58] Our assumption regarding the existence of an 'informed' and an 'uninformed' investor is meant to simply capture the heterogeneity among investors in terms of their attentiveness to monitoring the value of the fund's portfolios assets, and its NAV. We purposely abstract from modeling the information costs involved in the monitoring, in order to focus attention on the key insights from the model with respect to single- versus multi-strike funds.

[59] We note that in practice the transaction decision is made *prior* to the time when the transaction price is determined. Therefore, the investor's assessment of the fund NAV at the time of the transaction is only the information-based expectation of the transactional NAV to be determined at a later time. As part of our strategy to simplify the analysis of information related trading, we assume away nonessential noise in the asset value. In particular, the public information perfectly reflects both r_1 and r_2 by the time that the investors are to make their transaction decisions either at time $t = 1$ or time $t = 2$. In the same spirit, the informed investor has perfect information at time $t = 1$ for the fund's next period NAV growth rate (r_2).

strategy allows us to deliver our key intuition based on the structure of the game, while bypassing the complexity involving the economics of information acquisition and processing—a topic that is examined extensively in the market microstructure and asset pricing literatures.

Specifically, we assume that investors view the discrepancy between the transactional NAV (A_t at time t) and the information based asset value ($A_{i,t}$, where the subscript i takes value of either a or u to indicate for the asset values based on the "attentive" and"uninformed" investors' information sets, respectively) as a potential arbitrage opportunity with the gain from the trading being $(A_t - A_{i,t})q_t$, where q_t is the investor's time t redemption demand, with the understanding that a negative q_t denotes a demand for share purchase rather than redemption. In the case of the multi-strike fund, the investor has the flexibility to redeem their shares either at $t = 1$ (in the middle of the day) or at $t = 2$ (i.e., at the end of the day). We further include an counterbalancing quadratic cost to the investor's redemption, resulting the investor's objective being:

$$\sum_{t=1,2} (A_t - A_{i,t})q_t - \gamma q^2, \text{ with } i = a \,\text{or}\, u. \tag{A2}$$

The quadratic term in the above objective reflects the fact that the investor's original position is unconditionally optimal and is an absorbing/stable equilibrium, and thus any deviation ($q = q_1 + q_2$) from that position due to the day's trading carries a direct penalty equal to γq^2. Later, we assume that the term γ is sufficiently large to produce a stable equilibrium.

4. The Benchmark Case with No Intraday Settlement

The benchmark case of the single-strike fund is purposefully made trivial for the sake of illustration and for easy comparison. In the benchmark case, while investors can submit their purchase/redemption request during the day, the investor redemption requests are settled at the end of day 1 (i.e., at $t = 2$) when the day's information is fully revealed. At the end of day 1, at time $t = 2$, the fund's NAV is given by: $A_2 = (1 + r_1 + r_2)$.

We now solve for the equilibrium trading of the informed and uninformed investors, q_s and q_u, respectively. Given that, at time $t = 2$, the informed investor no longer possesses any information advantage against the uninformed investor, there is no difference in the treatment of the two types of investors in our benchmark case.

Consider the attentive investor for example. The investor's expectation of the fund NAV at $t = 2$, is given by

$$A_{a,2} = E(1 + r_1 + r_2 + r_3 - \phi l) = A_2 - \phi q - \phi q_u, \tag{A3}$$

where q is the amount of her own redemption request to be decided by her optimally, and q_u is her anticipation of fund outflows due to the redemption demand from the uninformed investor. From Equation (A2), her objective function is given by $\phi q_u q - (\gamma - \phi)q^2$.

If $\gamma > \phi$, the optimization problem allows for a finite solution to the redemption demand for the informed investor: $q_a = \frac{\phi}{2(\gamma-\phi)} q_u = \theta q_u$, where the term $\theta = \frac{\phi}{2(\gamma-\phi)}$. In the same fashion, the uninformed investor's demand is given by: $q_u = \theta q_a$. From the above expressions for q_a and q_u we can clearly see the strategic complementarity in the two types of investors' trading demand, in that each investor's demand is directly proportional to the other's demand. Thus, one investor's redemption decision motivates the other investor to do the same. The strength of the strategic complementarity in the investors' trading demand is captured by θ. Recall that θ is directly related to the fund portfolio's illiquidity as captured by ϕ. Given that

$$\frac{\partial \theta}{\partial \phi} = \frac{\gamma}{(\gamma - \phi)^2} > 0, \tag{A4}$$

it follows that the higher the illiquidity of the fund's portfolio, the stronger the strategic complementarity.

We further assume that $\gamma > \frac{3}{2}\phi$, so that $\theta < 1$. With such an assumption, the feedback loop from the strategic complementary in the investors' redemption behavior does not lead to an explosive outcome. Rather, there is a unique equilibrium: $q_a = q_u = 0$. While ours is a stationary model, the strategic complementarity would indicate that any exogenous shock to the system in the form of positive outflow from, for instance, the informed investor ($q_a > 0$), leads to a positive but tempered response from the uninformed investor ($q_u = \theta q_a \in (0, q_a)$), which in turn leads to a positive but further tempered response from the informed investor. The feedback loop dies down eventually due to the condition of $\theta < 1$, leading back to the equilibrium of $q_a = q_u = 0$.[60]

Turning next to the fund sponsor, given the absence of any redemption demand by investors, his objective in this case can be expressed simply as: $\Pi = w\sigma - v\sigma^2$, which is optimized by choosing an appropriate risk level. Given this objective, he optimally chooses the fund return volatility as: $\sigma = \frac{w}{2v}$.

5. The Case of Intraday Settlement

We next examine the case of a fund which allows for intraday redemption at time $t = 1$. As a comparison to the benchmark case above, in the intraday settlement case, the investor's purchase/redemption request is settled in the middle of day 1 (i.e., at $t = 1$), if she submits her request by that time.

5.1 Informed Investor's Decision

At time $t = 1$, the fund's NAV is $(1 + r_1)$. The expected value of the fund's share at time $t = 1$ for the informed investor, who already knows the returns r_1 and r_2 by that time, is: $A_{a,1} = 1 + r_1 + r_2 - \phi q - \phi q_u$. Her objective is to maximize $(\phi q_u - r_2)q - (\gamma - \phi)q^2$.[61] This yields the optimal demand for the informed investor as: $q_a = \theta q_u - \frac{r_2}{2(\gamma - \phi)}$, where the

[60] For completeness, in the case of $\theta = 1$, the equilibrium solution is indeterminate: any pair of equal valued $\{q_a, q_u\}$ is a solution. In the case of $\theta > 1$, while $q_a = q_u = 0$ is the unique equilibrium solution, it is not stable—any shock to the system in the form of a positive outflow from either type of investors leads to ever larger outflows from them due to the feedback loop. This latter case can be viewed as describing an unstable system subject to a run in the face of any disturbance. We choose to focus on the case of $\theta < 1$, where the possibility of a destabilizing run is assumed away. The simplicity of this benchmark case with a definite stable equilibrium allows us to focus on the impact of the multi-strike feature. Furthermore, $\theta < 1$ is a necessary condition for the multi-strike case examined below to have a finite equilibrium.

[61] It is straightforward to see that the informed investor will only transact at $t = 1$ at a favorable price due to her information advantage. She has no incentive to transact at time $t = 2$ because she learns nothing new at time 2, while everyone else catches up with her information advantage.

first term representing the strategic complementary in the investors' behavior is the same as in the benchmark case. The second term in the above expression, not present in the benchmark case, reflects the redemption demand motivated by the informed investor's private information regarding the return, r_2. In our model, it is the combination of the NAV's sluggish adjustment to fundamentals, accentuated by the fund multi-strike feature, and the quick action of the informed investor that leads to a different equilibrium in the multi-strike case from that in the benchmark single-strike case.

5.2 Uninformed Investor's Decision

Turning next to the uninformed investor, at time $t = 2$ she observes the realized fund returns, i.e., r_1 and r_2, that are by now public knowledge, which allows her to infer the skilled investor's demand, q_a. So, her optimal demand will again be the same as in the benchmark case, i.e., $q_u = \theta q_a$. That is, the uninformed investor's trading is driven purely by the strategic complementarity with the informed investor's demand. Solving for the equilibrium quantities jointly, we have $q_u = -\frac{\theta}{(1-\theta^2)} \frac{r_2}{2(\gamma-\phi)}$ and $q_a = -\frac{1}{(1-\theta^2)} \frac{r_2}{2(\gamma-\phi)}$. Combining the two investors' demand, we have the total fund flow as: $l = q_s + q_u = -\frac{1}{1-\theta} \frac{r_2}{2(\gamma-\phi)}$. This expression represents the information-based flow, in the amount of $\frac{r_2}{2(\gamma-\phi)}$, multiplied by a magnifying factor that equals $\frac{1}{1-\theta}$. The larger the value of the term θ, the stronger the strategic complementarity in the investors' redemption decisions, and consequently the higher the magnification factor. This factor reaches a destabilizing level as θ approaches 1.[62]

5.3 Fund Sponsor's Decision

We now consider the fund sponsor's decision. The fund sponsor's objective function is

$$\Pi = w\sigma - v\sigma^2 - E(\alpha l + \beta l^2) = w\sigma - v\sigma^2 - u\sigma^2, \tag{A5}$$

where we define the notation $u = \frac{\beta}{(1-\theta)^2} \frac{\lambda_2^2}{4(\gamma-\phi)^2}$. The last term in the objection function, $u\sigma^2$, represents the loss due to the fund flow volatility generated by the informed investor's response to the timely private information, and the mutual response of both the informed and the uninformed investors given the strategic complementarity in their decisions. Interestingly, this potential loss provides a natural counterbalance to the fund's incentive to reach for yield. Accordingly, the fund sets the optimal fund return volatility at $\sigma = \frac{w}{2(u+v)}$. We summarize the analytical results of the model in the following proposition. Note that in the proposition and its corollaries that follow, we use the subscript s to indicate the benchmark case representing the single-strike fund that offers end-of-day settlement of investor orders, and the subscript m to indicate the multi-strike fund which offers intraday settlement.

Proposition 1. In the benchmark case with no intraday settlement, the aggregate fund outflow during day 1 is $l_s = 0$, and the fund volatility is given by: $\sigma_s = \frac{w}{2v}$. In the case of

[62]Note that at time $t = 1$, based on public information, $E(q_a) = E(q_u) = E(l) = 0$, and therefore, the uninformed investor's expectation of the asset value $E(1 + r_1 + r_2 + r_3 - \phi l) = 1 + r_1$, which is equal to the NAV at the time. Therefore, the uninformed investor has no incentive to transact at $t = 1$.

intraday settlement, the aggregate fund outflow is $l_m = -\frac{1}{1-\theta}\frac{r_2}{2(\gamma-\phi)}$, where $\theta = \frac{\phi}{2(\gamma-\phi)}$, and the fund volatility is given by $\sigma_m = \frac{w}{2(u+v)}$, where $u = \frac{\beta}{1-\theta}\frac{\lambda_2^2}{2(\gamma-\phi)}$.

From the proposition, it follows that a fund that allows intraday settlement (i.e., the multi-strike fund) (a) experiences larger (in absolute terms) and more volatile fund flows, and (b) optimally adopts a more conservative investment strategy, i.e., it chooses a lower fund volatility, $\sigma_m < \sigma_s$. The high fund flow volatility for the multi-strike fund translates to higher fund liquidity cost, everything else the same.

Based on the above proposition, we have the following corollary.

Corollary 1. Comparing the case of intraday settlement with the benchmark case, the increase in fund flow volatility is stronger during periods of high market daily volatility, ceteris paribus. That is:

$$\frac{\partial \sigma_m(l)}{\partial \lambda_2} > 0. \tag{A6}$$

The increase in fund flow volatility is also stronger among funds that choose a riskier strategy, ceteris paribus. That is:

$$\frac{\partial \sigma_m(l)}{\partial \sigma} > 0. \tag{A7}$$

Proof: We start by noting that

$$\sigma_m(l) = \frac{1}{1-\theta}\frac{\lambda_2 \sigma}{2(\gamma-\phi)}. \tag{A8}$$

It is then clear that

$$\frac{\partial \sigma_m(l)}{\partial \lambda_2} = \frac{\sigma_m(l)}{\lambda_2} > 0. \tag{A9}$$

Inequality (A7) follows similarly. □

We further note that the strategic complementarity in investor decisions serves as a magnification mechanism that exacerbates all of the effects noted in the above proposition and its corollary. From (A4), this translates into the effect of fund portfolio illiquidity. Specifically, we have the following corollary.

Corollary 2. When the fund portfolio is less liquid (thus higher ϕ), (a) the difference in fund flow volatility between the multi-strike fund and the single-strike fund is larger:

$$\frac{\partial \sigma_m(l)}{\partial \phi} > 0; \tag{A10}$$

(b) the disciplining effect on the fund's incentive to reach for yield is stronger:

$$\frac{\partial \sigma_s - \sigma_m}{\partial \phi} > 0; \tag{A11}$$

and (c) the increase in the fund's flow volatility is more sensitive to a deterioration in market conditions:

$$\frac{\partial^2 \sigma_m(l)}{\partial \phi \partial \lambda_2} > 0. \tag{A12}$$

Proof: From Equation (A8), we have $\frac{\partial \sigma_m(l)}{\partial \theta} = \frac{\sigma_m(l)}{1-\theta} > 0$. Combining with (A4), we have inequality (A10). Comparing fund volatilities (σ) across the single-strike fund and the multi-strike fund, we have $\sigma_s - \sigma_m = \frac{u}{u+v}\sigma_s$. Thus,

$$\frac{\partial \sigma_s - \sigma_m}{\partial \theta} = \sigma_s \frac{v}{(u+v)^2} \frac{\partial u}{\partial \theta} > 0, \tag{A13}$$

because $\frac{\partial u}{\partial \theta} = \frac{u}{1-\theta} > 0$. This then leads to inequality (A11). Finally, the inequality in (A12) follows directly from the equality in (A9) and inequality (A10). $\square$

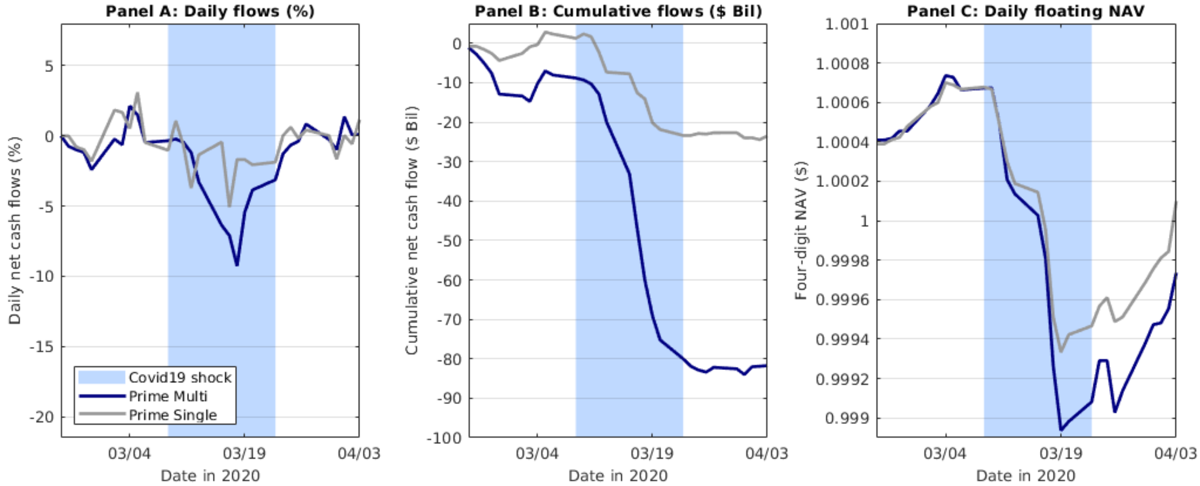


Figure 1. Exogenous Shock: The Effect of Covid-19 on Net Cash Flows of Multi-strike and Single-strike Funds. This figure illustrates the effect of the growing uncertainty surrounding the COVID-19 pandemic on prime institutional MMFs during March 2020, and the stabilizing role of the Money Market Mutual Fund Liquidity Facility announced by the Federal Reserve at 11:30 P.M. on 18 March 2020 and established on 23 March 2020. For the two categories of single-strike funds and multi-strike funds, we display the daily percentage net cash flows in Panel A, and the cumulative flows (in billions of dollars) in Panel B. Panel C presents the average fluctuations of the end-of-day four-digit NAV of single-strike funds and the last intraday four-digit NAVs of multi-strike funds. The shaded area in each Panel identifies graphically the COVID-19 uncertainty period from 9 March to 23 March 2020.

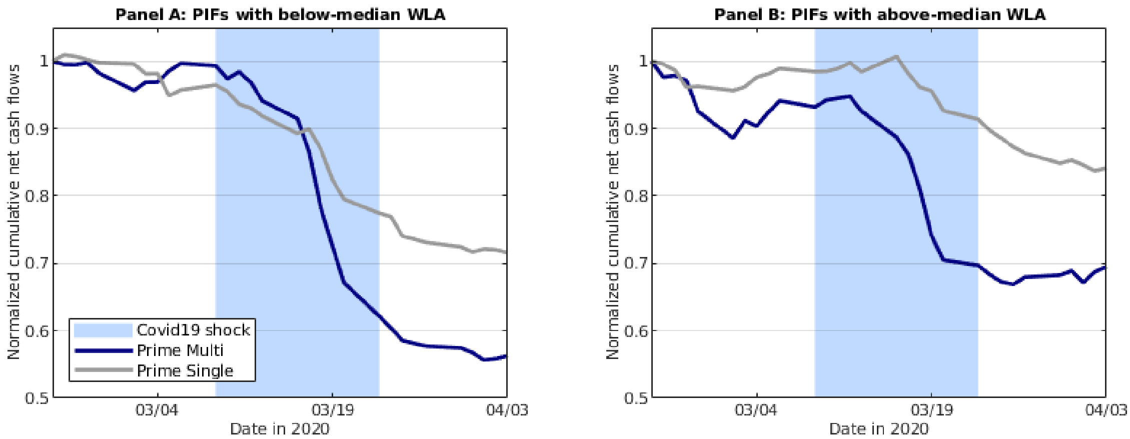


Figure 2. Normalized Cumulative Net Cash Flows of Multi-strike and Single-strike Funds by WLA Level. This figure illustrates the effect of the COVID-19 shock on normalized assets of multi-strike funds and single-strikes funds during March 2020 conditional on their pre-crisis percentage WLA level being above or below the median WLA. For illustrative purposes, we normalize to 1 the cumulative net cash flows of the two categories of single-strike funds and multi-strike funds. The shaded area in each Panel identifies graphically the COVID-19 uncertainty period from 9 March to 23 March 2020, when the FED established the Money Market Mutual Fund Liquidity Facility.

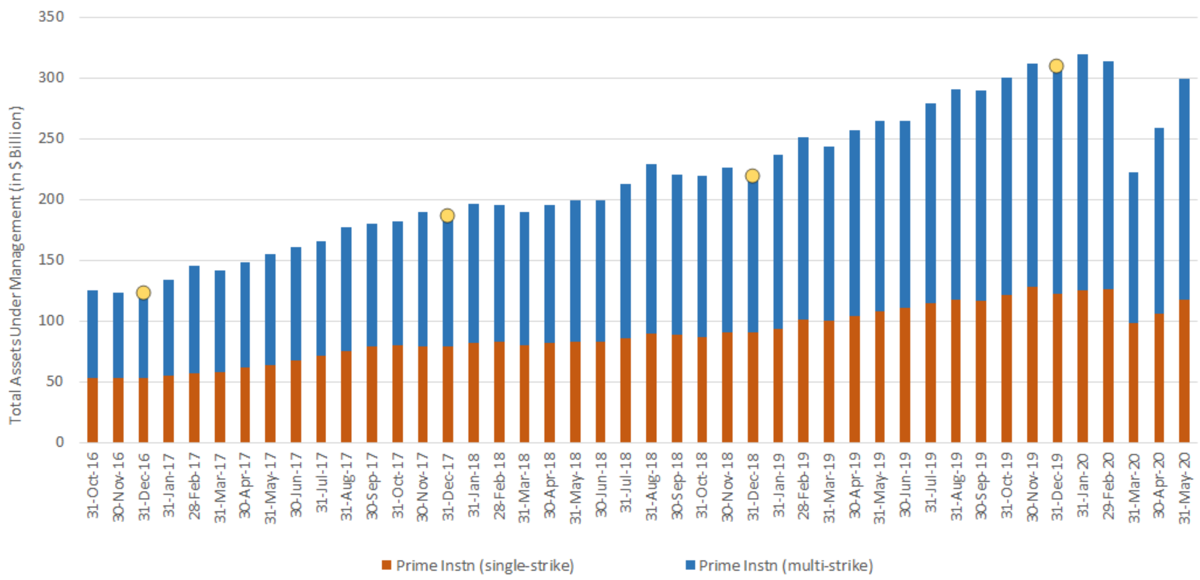


Figure 3. Total Net Assets of Prime Institutional Money Market Mutual Funds. This figure illustrates the end-of-month total net assets under the management (in $ billion) of prime institutional money market funds during the period from October 14, 2016 to May 31, 2020. We separately report the total assets under management of prime institutional money market funds offering one end-of-day redemption window (*Prime Instn (single-strike)*) and multiple intraday redemption windows (*Prime Instn (multi-strike)*). For comparison, the figure also illustrates—with yellow circle markers—the year-end total net assets of prime institutional money market funds as aggregated by the Investment Company Institute (ICI) in the 2020 Investment Company Fact Book.

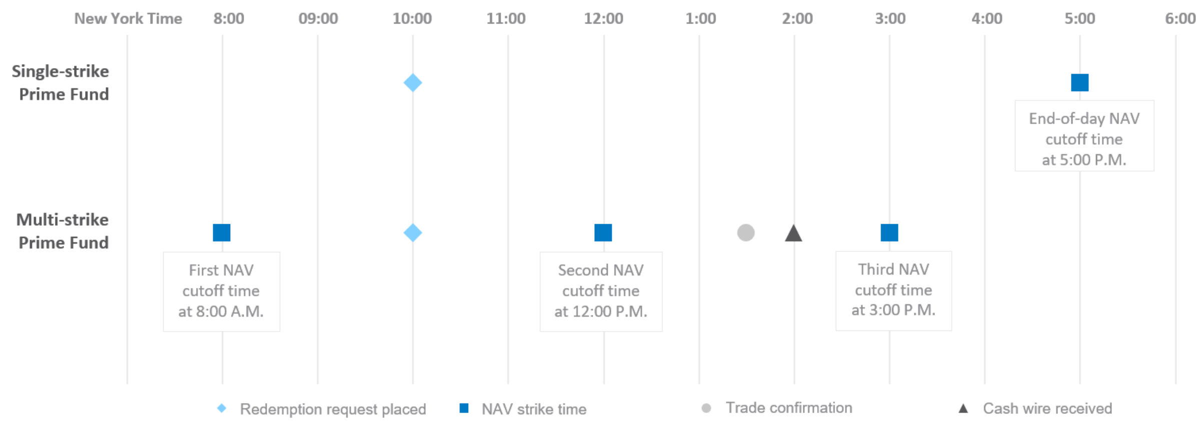


Figure 4. An Example of Intraday NAV Trading under the Multi-strike Pricing System. This figure reports an illustrative example of the timeline of NAV trading for a typical multi-strike fund offering three intraday trading windows at 8:00 A.M., 12:00 P.M. and 3:00 P.M., on each trading day the fund accepts purchases and redemptions. For instance, an institutional investor lodging a redemption request after the cutoff time of 8:00 A.M. but before the next cutoff time of 12:00 P.M. would receive the NAV price computed at 12:00 P.M., and enjoy same-day (T+0) redemption settlement as transfer agents and other financial intermediaries would typically require about 2 hours to process the investor redemption order. A multi-strike system would also allow institutional investors to obtain real time indicators of which strike times—and associated four-digit NAV prices—have passed before they can lodge trading orders. By contrast, a single-strike prime institutional fund with only one end-of-day NAV striking window at 5:00 P.M. is most likely to offer next-day (T+1) redemption settlements as NAV prices obtained from transfer agents or other financial intermediaries would arrive after the 6:00 P.M. deadline for initiating third-party transfers set by the Federal Reserve Cash Wire.

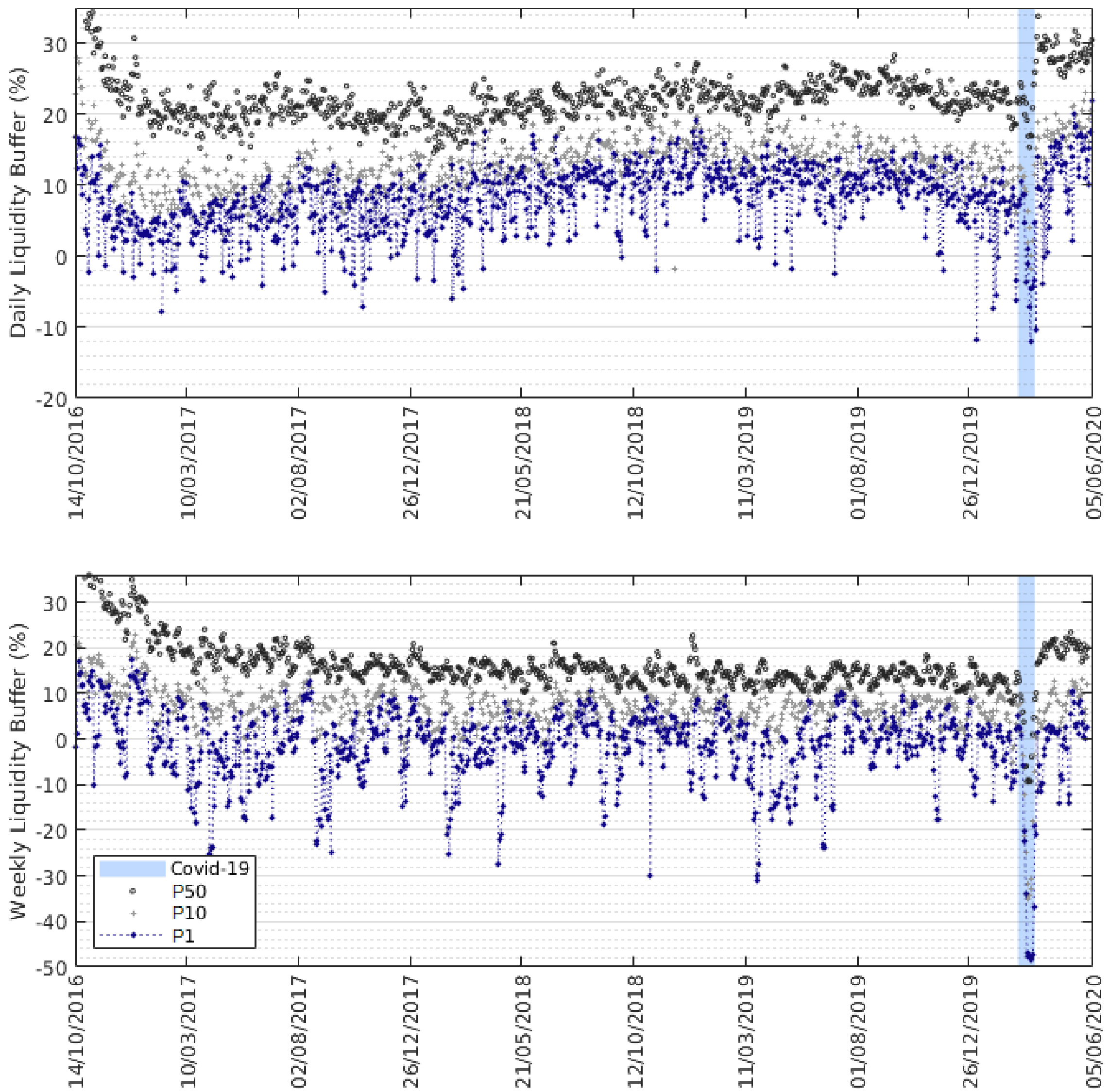


Figure 5. Redemption Shocks and Actual Liquidity Buffers of Prime Institutional Funds. The figure illustrates the daily time series of the actual percentage liquidity buffers of prime institutional money market funds. The top subplot illustrates the 50-th (*P50*), 10-th (*P10*), and 1-st (*P1*) percentiles of the distribution of the percentage daily liquidity buffers (LBD) which are computed as the sum of the percentage of daily liquid assets (DLA) and the fund's next-day percentage net cash flows, net of the minimum liquidity threshold of 10%. The bottom subplot reports the 50-th, 10-th, and 1-st percentiles of the distribution of the percentage weekly liquidity buffers (LBW) which are computed as the sum of the daily percentage of weekly liquid assets (WLA) and the next-day percentage net cash flows of the fund, net of the minimum liquidity threshold of 30%. The shaded area in both subplots identifies the period of high uncertainty surrounding the COVID-19 pandemic from 2 March to 23 March 2020, when the FED established the Money Market Mutual Fund Liquidity Facility. Our sample period extends from 14 October 2016 to 5 June 2020.

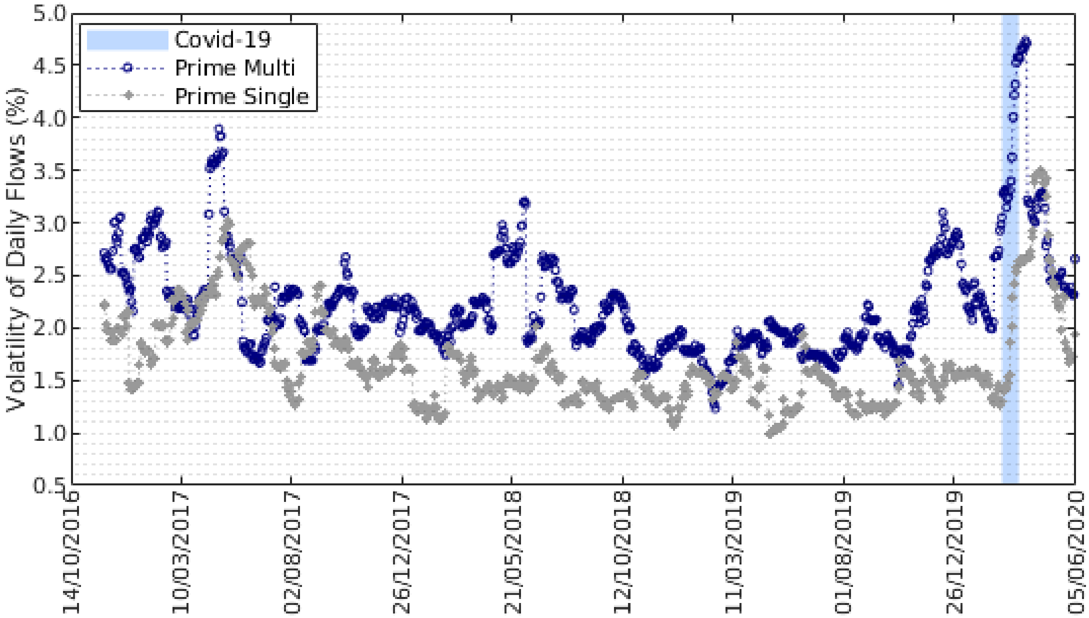


Figure 6. Volatility of Daily Net Cash Flows of Prime Institutional Funds. The figure illustrates the average 30-day volatility of daily net cash flows experienced by prime institutional money market funds over the daily sample period from 14 October 2016 to 5 June 2020. We compute the 30-day volatility of daily net cash flows separately for single-strike prime institutional money market funds (*Prime Single*) and multiple-strike prime institutional money market funds (*Prime Multi*). The shaded area in both subplots identifies the high uncertainty period surrounding the COVID-19 pandemic from 2 March to 23 March 2020, when the FED established the Money Market Mutual Fund Liquidity Facility.

Table 1
Summary Statistics

This table presents the summary statistics of our sample of U.S. prime institutional money market mutual funds during the period from 14 October 2016 to 5 June 2020. The following fund and fund sponsor characteristics are summarized in Panel A: total assets under the management of the fund (*FNDTNA*), in $ billion; the number of years since fund's inception (*FNDAGE*); total assets under the management of the fund sponsor (*FAMTNA*), in $ billion; fund sponsor's assets under management excluding institutional prime funds divided by the sponsor's total assets under management (*NOPRMBUS*); the annual percentage total expense ratio (*OPEX*); the percentage daily gross-of-fee annualized income yield (*GYIELD*); the percentage of fund's net cash flows (*NFLOWS*); and the number of times the fund strikes its four-digit mark-to-market NAV during the day (*NSTRIKES*). In Panel B, we report fund's portfolio holdings of the following assets expressed as a percentage of its total assets under management: U.S. Treasury obligations (*USTR*); U.S. government agency obligations (*AGENCY*); tri-party short-term (overnight) repurchase agreements collateralized by U.S. treasury and government agency obligations (*REPO*); asset-backed commercial paper (*ABCP*); financial and non-financial commercial paper (*CP*); total bank obligations (*BNKOB*); safe assets (*SAFE*) aggregated across *USTR*, *REPO*, and *AGENCY*; and risky and less-liquid assets (*RISKY*) aggregated across *BNKOB*, *CP*, and *ABCP*. In Panel C, we present the summary statistics of the following fund-level characteristics: percentage of daily liquid assets (*DLA*); percentage of weekly liquid assets (*WLA*); aggregate weighted average maturity of fund's portfolio (*WAM*); aggregate weighted average life of fund's portfolio (*WAL*); fund's daily liquidity buffer (*LBD*) which is computed as the sum of daily percentage liquid assets (*DLA*) and next-day percentage net cash flows of the fund, net of the minimum threshold of 10% of *DLA*; and fund's weekly liquidity buffer (*LBW*) which is computed as the sum of weekly percentage liquid assets (*WLA*) and next-day percentage net cash flows of the fund, net of the minimum threshold of 30% of *WLA*.

		Percentiles				
	Mean	5-th	25-th	50-th	75-th	95-th
Panel A—Fund and Fund Sponsor Characteristics:						
FNDTNA (in $b)	7.27	0.02	0.43	2.24	7.24	39.07
FNDAGE	17.62	1.09	9.67	14.37	26.98	39.28
FAMTNA (in $b)	569.2	12.5	146.5	246.3	636.2	2323.5
NOPRMBUS	96.65	90.66	95.21	98.11	99.20	99.86
OPEX	0.15	0.08	0.12	0.15	0.18	0.20
GYIELD	1.75	0.66	1.22	1.84	2.32	2.66
NFLOWS	0.00	-0.04	-0.01	0.00	0.01	0.04
NSTRIKES	2.15	1.00	1.00	3.00	3.00	3.00
Panel B—Percentage Portfolio Holdings:						
SAFE	22.93	4.68	13.55	22.27	30.44	41.62
RISKY	58.47	36.17	53.77	60.19	65.77	74.00
USTR	9.66	0.32	2.64	7.03	13.01	26.40
AGENCY	10.33	0.45	3.62	8.17	15.33	25.08
REPO	14.49	0.28	5.77	13.05	20.26	32.39
ABCP	14.80	1.60	6.84	13.25	21.95	32.80
CP	23.28	8.40	17.09	21.99	28.79	41.82
BNKOB	22.83	6.48	16.61	22.69	29.12	37.42
Panel C—Liquidity Holdings and Maturity Risk:						
WAM	28.07	12.00	20.00	28.00	36.00	48.00
WAL	59.52	14.00	49.00	62.00	74.00	87.00
DLA	37.61	21.91	30.47	36.74	43.01	54.02
WLA	54.60	41.61	47.66	53.22	58.76	74.16
LBD	24.39	9.94	16.92	22.42	28.42	45.30
LBW	18.53	2.46	10.78	15.68	22.38	43.93

Table 2

Summary Statistics: Single- and Multi-Strike Prime Institutional Funds

This table presents the descriptive statistics of several fund and fund sponsor characteristics of prime institutional money market funds, for the period from 14 October 2016 to 5 June 2020. The daily descriptive statistics are reported separately for single-strike funds (*Single-strike*) and multi-strike funds (*Multi-strike*). The following daily fund and affiliated fund sponsor characteristics are summarized in Panel A: total assets under the management of the fund (*FNDTNA*), in $ billion; the number of years since fund's inception (*FNDAGE*); total assets under the management of the fund sponsor (*FAMTNA*), in $ billion; the percentage daily gross-of-fee annualized income yield (*GYIELD*); percentage daily after-fee annualized income yield (*NYIELD*); percentage of net cash flows (*NFLOWS*); 30-day volatility of the percentage of net cash flows (*FLOWVOL*); the annualized expense ratio charged to institutional investors (*OPEX*); a dummy variable for whether the fund is affiliated to a bank (*BNKFND*); and the minimum investment (in $ million) for institutional investors to open an account with the fund (*MININV*). In Panel B, we examine differences in the percentage holdings of the following money market securities separately for single-strike and multi-strike funds: U.S. treasury obligations (*USTR*); U.S. government agency obligations backed by the U.S. Government (*AGENCY*); collateralized tri-party short-term (overnight) repurchase agreements (*REPO*); foreign bank obligations (*FBNKOB*); domestic bank obligations (*DBNKOB*); asset-backed commercial paper (*ABCP*); and financial and non-financial commercial paper (*CP*). In the last column of Panel A and Panel B, we report the $t-$statistics (in parentheses) of the difference in fund and fund sponsor characteristics between multi-strike funds and single-strike funds (*Multi – Single*).

	Panel A—Daily Statistics of Fund and Fund Sponsor Characteristics			
	Single-strike	*Multi-strike*	*Multi – Single*	t-stat
FNDTNA (in $b)	7.71	7.68	-0.03	(-0.15)
FNDAGE	15.36	19.04	3.68	(10.48)
FAMTNA (in $b)	631.41	565.70	-65.71	(-6.17)
NOPRMBUS	97.75	96.69	-1.06	(-0.49)
GYIELD	1.76	1.73	-0.03	(-2.68)
NYIELD	1.60	1.57	-0.03	(-2.48)
OPEX	0.16	0.15	-0.02	(-4.31)
BNKFND	30.04	51.51	21.47	(33.12)
NFLOWS	0.13	0.12	-0.01	(-0.40)
FLOWVOL	1.68	2.34	0.65	(33.51)
MININV (in $m)	14.97	84.38	69.41	(27.42)
	Panel B—Monthly Portfolio Holdings of Money Market Securities			
	Single-strike	*Multi-strike*	*Multi – Single*	t-stat
USTR	7.72	10.82	3.09	(17.77)
AGENCY	9.71	11.30	1.59	(12.32)
REPO	12.98	15.85	2.86	(16.33)
DBNKOB	6.22	6.49	0.27	(1.73)
FBNKOB	18.09	12.33	-5.75	(-49.39)
ABCP	17.24	15.44	-1.81	(-4.06)
CP	24.32	22.05	-2.28	(-9.34)

Table 3
Liquidity Risk and Maturity Risk Conditional on the Number of Intraday NAV Strikes

This table presents the liquidity buffer and maturity risk of PIFs conditional on their intraday NAV striking system over the sample period from 14 October 2016 to 5 June 2020. In Panel A and Panel B, we first separate PIFs into single-strike funds (*Single-strike*) and multi-strike funds (*Multi-strike*). Multi-strike funds allow institutional investors to redeem their shares at specified intervals—two (*Multi: 2 Strikes*) or three (*Multi: 3 Strikes*) times during the day. In Panel A, we average the following daily liquidity measures: the percentage of daily liquid assets (*DLA*); the percentage of weekly liquid assets (*WLA*); the percentage daily liquidity buffer (*LBD*) which is computed as the sum of the *DLA* and the next-day percentage net cash flows of the fund, net of the minimum threshold of 10% of *DLA*; and the percentage weekly liquidity buffer (*LBW*) computed as the sum of the *WLA* and the next-day percentage net cash flows of the fund, net of the minimum threshold of 30% of *WLA*. In Panel B we report the summary statistics of the following maturity risk proxies conditional on the number of intraday strikes offered by a fund: portfolio-level aggregate weighted average maturity (*WAM*); portfolio-level aggregate weighted average life (*WAL*); asset-level weighted average maturity of risky holdings (*WAM_RISKY*); and asset-level weighted average maturity of safe assets (*WAM_SAFE*). In Panel A and Panel B, we also report the differences in the relevant measures between the multi-strike funds and single-strike funds. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A—Liquidity Holdings by Number of Intraday NAV Strikes				
	Observations	DLA	WLA	LBD	LBW
Single-strike	7,667	30.81	53.90	22.46	19.59
Multi-strike	10,219	38.98	56.41	26.17	24.01
Difference: *Multi – Single*		8.17***	2.51***	3.70***	4.42***
Multi: 2 Strikes	1,280	35.02	53.45	21.09	20.20
Difference: *2 Strikes – Single*		4.20***	-0.45	-1.37	0.61*
Multi: 3 Strikes	8,939	40.02	56.73	26.46	24.30
Difference: *3 Strikes – Single*		9.20***	2.82***	4.00***	4.71***

	Panel B—Maturity Risk by Number of Intraday NAV Strikes				
	Observations	WAM	WAL	WAM_RISKY	WAM_SAFE
Single-strike	7,643	31.22	56.97	39.93	7.51
Multi-strike	10,192	23.89	53.27	34.34	6.45
Difference: *Multi – Single*		-3.69***	-3.80***	-5.58***	-1.05***
Multi: 2 Strikes	1,275	27.58	53.55	39.63	19.88
Difference: *2 Strikes – Single*		-3.64***	-3.42***	-0.30	12.37***
Multi: 3 Strikes	8,917	22.88	53.22	33.58	4.63
Difference: *3 Strikes – Single*		-8.33***	-3.75***	-6.35***	-2.88***

Table 4
Intraday NAV Strikes and Liquidity Buffers

This table presents the estimated regression coefficients of fund's percentage of daily liquid assets on several fund and fund sponsor characteristics over the period from 14 October 2016 to 5 June 2020. The dependent variable in Panel A is the percentage of daily liquid assets, *DLA*, as reported by the fund. The dependent variable in Panel B is the daily liquidity buffer, *LBD*. In both panels the main independent variable of interest is the number of times the fund strikes its four-digit intraday NAV, *NSTRIKES*. We also interact *NSTRIKES* with the following proxies of investors' liquidity preferences across funds: (a) the dummy variable *H_INVSOPH* which is equal to 1 if institutional investors pay an operating expense ratio below the median value of 15 basis points (i.e., high degree of sophistication); and (b) the degree of predictability of institutional investors' liquidity demand, *LIQDEM*, which is computed as the past 30-day volatility of fund's percentage daily net cash flows. To augment our measure of investor sophistication, we interact *H_INVSOPH* with the variable *H_STAKES*, which is equal to 1 if investors' minimum investment in the fund is greater than $10 million (50-th percentile). In column (v) of Panel A (Panel B) we include lagged values of the dependent variable, *LAGGED_DLA* (*LAGGED_LBD*). Other lagged control variables—omitted for brevity—include fund and fund sponsor characteristics, and the levels and first-order interactions of *H_INVSOPH*, *H_STAKES*, and *LIQDEM*. In all models we include sponsor and time fixed effects with standard errors (in parentheses) clustered by both fund and time. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A—Daily Liquidity Assets (*DLA*)				
	(i)	(ii)	(iii)	(iv)	(v)
NSTRIKES	2.001***	2.267**	2.649**	2.224**	2.700**
	(0.697)	(0.859)	(0.961)	(0.975)	(1.126)
× *H_INVSOPH*		1.482***	0.561	1.940***	1.369***
		(0.496)	(0.346)	(0.547)	(0.369)
× *H_INVSOPH* × *H_STAKES*			1.493***	0.141	0.537
			(0.374)	(0.555)	(0.339)
× *H_STAKES*			-1.193	-1.218	-2.030*
			(0.866)	(0.880)	(1.153)
× *H_INVSOPH* × *LIQDEM*				18.628**	14.942**
				(6.787)	(5.283)
× *LIQDEM*				-31.062***	-21.719***
				(6.627)	(5.377)
× *H_INVSOPH* × *H_STAKES* × *LIQDEM*				29.462***	20.229***
				(6.416)	(5.867)
LAGGED_DLA					0.585***
					(0.034)
Observations	17,601	16,854	16,854	16,001	15,922

	Panel B—Daily Liquidity Buffer (*LBD*)				
	(i)	(ii)	(iii)	(iv)	(v)
NSTRIKES	2.018**	2.173**	2.454**	2.071**	2.587**
	(0.804)	(0.838)	(0.974)	(0.979)	(1.179)
× *H_INVSOPH*		1.533***	0.548	1.999***	1.640***
		(0.509)	(0.358)	(0.551)	(0.413)
× *H_INVSOPH* × *H_STAKES*			1.550***	0.053	0.295
			(0.370)	(0.564)	(0.350)
× *H_STAKES*			-0.928	-0.960	-1.771
			(0.864)	(0.882)	(1.179)
× *H_INVSOPH* × *LIQDEM*				16.770**	15.312**
				(6.532)	(6.462)
× *LIQDEM*				-32.059***	-27.455***
				(6.655)	(6.699)
× *H_INVSOPH* × *H_STAKES* × *LIQDEM*				33.857***	27.082***
				(6.950)	(6.972)
LAGGED_LBD					0.440***
					(0.042)
Observations	17,571	16,569	16,569	15,987	15,908

Table 5

Instrumental Variable Models of Intraday NAV Striking System

We estimate 2-stage instrumental variable models of the relation between fund liquidity measures and the number of intraday NAV strikes during the period October 14, 2016 to June 5, 2020. Panel A reports the estimated coefficients of the first-stage regression. In all models, the number of intraday NAV strikes, *NSTRIKES*, is instrumented for by the percentage share of government institutional MMFs offered by the fund sponsor (in proportion to its total institutional MMF business) averaged during the pre-sample year of 2012 ($GOVSHARE_{2012}$) and 2013 ($GOVSHARE_{2013}$). Panel B reports the results of the second-stage regression where the dependent variable in columns (i) and (iii) is the actual percentage of daily liquid assets, *DLA*, as reported by the fund. The dependent variable in columns (ii) and (iv) of Panel B is our proxy of the daily liquidity buffer, *LBD*. In both Panel A and Panel B, we control for alternative options available to the fund sponsor to increase within-sponsor asset retention during the transition period from November 2015 to October 2016 by including: (i) the logarithm of one plus the number of PIFs converted to government institutional funds during the transition period, *PIF_TO_GOV*; and (ii) the logarithm of one plus the number of new government institutional MMFs launched by the fund sponsor during the transition period, *NEW_GOV*. In both Panels, we also include the dummy variable *H_INVSOPH* which is equal to 1 if institutional investors pay an operating expense ratio below the median value of 15 basis points; and the past 30-day volatility of fund's percentage daily net cash flows, *LIQDEM*. Other lagged control variables—omitted for brevity—in both Panels include: the logarithm of the assets under the management of the fund (*LFNDTNA*); the logarithm of the assets under the management of the fund sponsor (*LFAMTNA*); the logarithm of the number of days since fund inception (*LFNDAGE*); the proportion of a fund sponsor's assets under management that are not related to PIFs, i.e., the sponsor's non-PIF assets (*NOPRMBUS*); total operating expenses charged by the fund (*OPEX*); the percentage of net cash flows (*NFLOWS*); and fund's daily gross annualized income yield (*GYIELD*). In all models we include time fixed effects with standard errors (in parentheses) clustered by fund and time. The bottom row of Panel B displays the *p*-value for Hansen's J-test of the null hypothesis that the instrumental variable employed is orthogonal to the errors. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A—First Stage Regressions	
	(i)	(ii)
GOVSHARE	-0.523***	-0.438***
	(0.023)	(0.019)
NEW_GOV	-0.043***	-0.046***
	(0.004)	(0.003)
PIF_TO_GOV	-0.389***	-0.375***
	(0.005)	(0.004)
H_INVSOPH	0.212***	0.223***
	(0.007)	(0.007)
LIQDEM	0.001***	0.001***
	(0.000)	(0.000)
Instrument	$GOVSHARE_{2012}$	$GOVSHARE_{2013}$

	Panel B—Second Stage Regressions			
	DLA	*LBD*	*DLA*	*LBD*
	(i)	(ii)	(iii)	(iv)
NSTRIKES	3.672***	3.736***	3.327***	3.462***
	(0.746)	(0.811)	(0.823)	(0.898)
Instrument	$GOVSHARE_{2012}$	$GOVSHARE_{2012}$	$GOVSHARE_{2013}$	$GOVSHARE_{2013}$
Hansen's J (p-value)	0.65	0.61	0.58	0.49
Observations	16,857	16,857	16,840	16,840

Table 6
Covid-19 Shock: Net Cash Outflows and Illiquid Portfolio Holdings

This table presents estimated coefficients from a regression of a fund's daily net cash flows (*NFLOWS*) on several fund and fund sponsor characteristics during the period March 2-31, 2020. The primary independent variable is the number of times the fund strikes its four-digit NAV during the day, *NSTRIKES*. In Panel A, the dummy variable $I_{\text{9-18 March}}$ identifies the crisis period from March 9 to March 18, 2020 prior to the Federal Reserve's announcement of the Money Market Mutual Fund Liquidity Facility (MMFLF); the dummy variable $I_{\text{9-20 March}}$ identifies the period March 9-20, 2020 prior to the MMFLF's launch on 23 March 2020; and the dummy variable $I_{\rightarrow 31\text{ March}}$ identifies the period March 23-31, 2020 in column (ii), and the period 19-31 March, 2020 in all other columns. In columns (iii) and (iv) we include the lagged percentage weekly liquid assets as of day t–2, *WLA*. The variable *LIQDEM_FEB* in column (iv) represents the volatility of net cash flows computed over the past 30 days ending on 28 February 2020. Panel B reports coefficients from a regression of *NFLOWS* during the crisis peak (March 9-18, 2020) on the lagged percentage of less-liquid holdings as reported by the fund for the period ending January 2020. Proxies of a fund's illiquid holdings, *ILLIQUID_HLD*, include: unsecured financial commercial paper (*FINCP*) in column (i); foreign bank obligations (*FBNKOB*) in column (ii); asset-backed commercial paper (*ABCP*) in column (iii); and risky assets aggregated across bank obligations, commercial paper and *ABCP* (*RISKY*), in column (iv). Other control variables, omitted for brevity, are identical to those in Table 5. All models include sponsor and time fixed effects with standard errors (in parentheses) clustered by fund and time. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A—Percentage Net Cash Flows (NFLOWS)			
	(i)	(ii)	(iii)	(iv)
NSTRIKES	0.122	0.122	0.082	-0.067
	(0.182)	(0.182)	(0.185)	(0.318)
NSTRIKES × $I_{\text{9-18 March}}$	-0.998***		-0.731**	-0.751**
	(0.307)		(0.322)	(0.373)
NSTRIKES × $I_{\text{9-20 March}}$		-0.647***		
		(0.325)		
NSTRIKES × $I_{\rightarrow 31\text{ March}}$	0.585***	0.534***	0.599***	0.593***
	(0.147)	(0.176)	(0.158)	(0.158)
WLA			-0.012	0.006
			(0.009)	(0.040)
WLA × $I_{\text{9-18 March}}$			0.185***	0.164***
			(0.044)	(0.053)
WLA × *NSTRIKES*			-0.004	-0.013
			(0.005)	(0.019)
LIQDEM_FEB				-0.777
				(0.854)
LIQDEM_FEB × $I_{\text{9-18 March}}$				-0.170
				(0.237)
LIQDEM_FEB × *NSTRIKES*				0.322
				(0.509)
Observations	529	529	496	496

	Panel B—Net Flow Response to Illiquid Holdings			
	(i)	(ii)	(iii)	(iv)
	FINCP	*FBNKOB*	*ABCP*	*RISKY*
ILLIQUID_HLD	-0.479***	-1.363***	0.134	-0.966**
	(0.102)	(0.386)	(0.084)	(0.449)
ILLIQUID_HLD × *NSTRIKES*	-0.174***	-0.819***	-0.100***	-0.110***
	(0.023)	(0.204)	(0.020)	(0.024)
GYIELD × *NSTRIKES*	0.016	-0.024	0.007	0.015
	(0.030)	(0.025)	(0.032)	(0.031)
Observations	134	134	128	134

Table 7
Percentage Holdings of Risky Assets and Safe Assets and the COVID-19 Redemption Shock

This table presents the estimated coefficients of weekly regressions of weekly percentage portfolio holdings of single- and multi-strike prime institutional money market funds on several fund and fund sponsor characteristics, over the period October 14, 2016 to June 5, 2020. The dependent variable in Panel A includes: holdings of risky assets (*RISKY*) comprising bank obligations, commercial paper, and asset-backed commercial paper, in column (i); holdings risk (*HR*) which is computed as the difference in fund allocation weights between foreign bank obligations and U.S. Treasury and government agency securities and collateralized repo contracts, in column (ii); holdings of financial and non-financial commercial paper (*CP*) in column (iii); asset-backed commercial paper (*ABCP*) in column (iv); and foreign bank obligations (*FBNKOB*) in column (v). In Panel B, the dependent variable includes a fund's weekly percentage portfolio holdings of one of the following assets: safe assets (*SAFE*) comprising U.S. Treasury and government agency securities and collateralized repurchase agreements, in column (i); U.S. Treasury securities (*USTR*) in column (ii); repurchase agreements collateralized by U.S. Treasury and government agency securities (*REPO*) in column (iii); U.S. government agency securities (*AGENCY*) in column (iv); and floating-rate notes (*OTHER*) in column (v). The main independent variable of interest is the number of times the fund strikes its four-digit mark-to-market NAV during the day, *NSTRIKES*. We evaluate the funds' weekly portfolio rebalancing responses in the wake of exogenous redemption shocks by interacting the variable *NSTRIKES* with the dummy variable *COVID19* which is equal to 1 during the three-week period from March 11 to March 31, 2020 (weekly holdings are available on the Wednesday of each week). Other lagged control variables are those discussed previously in Table 5, and are omitted for brevity. In all models, we include sponsor and time fixed effects with standard errors (in parentheses) clustered by fund and time. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A—Percentage Holdings of Risky Assets				
	(i)	(ii)	(iii)	(iv)	(v)
	RISKY	HR	CP	ABCP	FBNKOB
NSTRIKES	-1.097***	-0.958*	-0.290	-0.756***	-0.382***
	(0.362)	(0.557)	(0.197)	(0.132)	(0.110)
× *COVID19*	-0.950	-1.754**	-1.165***	-0.196	-0.345
	(0.600)	(0.755)	(0.381)	(0.300)	(0.283)
Controls	Y	Y	Y	Y	Y
Sponsor-Time FE	Y	Y	Y	Y	Y
Observations	4,208	4,208	4,208	4,208	4,208

	Panel B—Percentage Holdings of Safe Assets				
	(i)	(ii)	(iii)	(iv)	(v)
	SAFE	USTR	REPO	AGENCY	OTHER
NSTRIKES	0.139	0.127***	0.147	-0.412***	0.037
	(0.224)	(0.020)	(0.213)	(0.035)	(0.089)
× *COVID19*	0.804***	0.097	1.198***	-0.297***	-0.111
	(0.241)	(0.108)	(0.346)	(0.052)	(0.227)
Controls	Y	Y	Y	Y	Y
Sponsor-Time FE	Y	Y	Y	Y	Y
Observations	4,208	4,208	4,208	4,208	4,208

Table 8
U.S. Debt Ceiling Shock and Portfolio Rebalancing Decisions of Single-strike and Multi-strike Funds

This table presents the estimated coefficients of regressions of maturity risk and percentage holdings of U.S. Treasury securities in PIF portfolios around the exogenous event represented by the suspension of the U.S. debt ceiling on February 9, 2018. On this date, the U.S. Congress voted to authorize the suspension of the U.S. debt ceiling before the U.S. Treasury Department exhausted its borrowing authority and faced the risk of technical default on its outstanding debt obligations. The regressions in the table are estimated monthly because the time to maturity of U.S. Treasury securities is only available in the reported monthly portfolio holdings. In columns (i) and (ii), the dependent variable is the fund's percentage holdings of U.S. Treasury securities, *USTR*. In columns (iii) and (iv), the dependent variable is the weighted average maturity (WAM) of U.S. Treasury securities held by a fund in its portfolio, *WAM_USTR*. The main independent variable of interest is the number of times the fund strikes its four-digit mark-to-market NAV during the day, *NSTRIKES*. To measure the response of PIFs to the increasing risk of a technical default of the U.S. Treasury, we include the interaction terms *NSTRIKES* $\times$ *EVENT*, where the vector variable *EVENT=(S–3M,S–2M,...,S+3M)* comprises dummy variables for each of the six months from November 2017 to April 2018 surrounding the debt ceiling suspension date (S) of February 9, 2018. For example, the dummy variable *S–3M* equals 1 for the month of November 2017, and 0 otherwise. We also include the dummy variable *H_INVSOPH* which is equal to 1 if institutional investors pay an operating expense ratio below the median value of 15 basis points; and the past 30-day volatility of fund's percentage daily net cash flows, *LIQDEM*. Other lagged control variables—omitted for brevity—include: the logarithm of fund assets (*LFNDTNA*); the logarithm of fund sponsor assets (*LFAMTNA*); the logarithm of the number of days since fund inception (*LFNDAGE*); fund's gross annualized income yield (*GYIELD*); fund sponsor's assets under management excluding institutional prime funds divided by the fund sponsor's total assets under management (*NOPRMBUS*); total operating expenses charged by the fund (*OPEX*); and the percentage of net cash flows (*NFLOWS*). In all models we include sponsor and time fixed effects with standard errors (in parentheses) clustered by fund and time. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	USTR		WAM_USTR	
	(i)	(ii)	(iii)	(iv)
NSTRIKES	2.721***	2.902***	-0.732	-1.607**
	(0.161)	(0.165)	(0.714)	(0.784)
NSTRIKES × *S–3M*	-0.568	-0.374	-5.846	-5.935
	(0.503)	(0.498)	(5.786)	(5.410)
NSTRIKES × *S–2M*	-0.578	-0.397	-8.660	-9.770
	(0.482)	(0.491)	(9.535)	(10.136)
NSTRIKES × *S–1M*	-2.080***	-2.138***	-11.901***	-12.279***
	(0.420)	(0.347)	(3.034)	(3.395)
NSTRIKES × *S+1M*	1.372***	1.479**	14.315***	13.869***
	(0.402)	(0.663)	(3.581)	(3.218)
NSTRIKES × *S+2M*	0.517	0.502	1.452***	1.537***
	(0.470)	(0.473)	(0.344)	(0.498)
NSTRIKES × *S+3M*	0.173	0.189	0.452	0.555
	(0.459)	(0.460)	(0.536)	(0.528)
LIQDEM		-0.456		2.125
		(0.271)		(2.549)
H_INVSOPH		3.674**		-15.007**
		(1.543)		(7.028)
Controls	Y	Y	Y	Y
Sponsor-Time FE	Y	Y	Y	Y
Observations	1,089	1,089	1,089	1,089

Table 9
Exposure of Single-strike and Multi-strike Funds to Simulated Daily Percentage Liquidity Shortfalls

This table presents the summary statistics of daily percentage liquidity shortfalls and the estimated coefficients of the daily regressions of a fund's liquidity shortfall on selected fund and fund sponsor characteristics, over the period from 14 October 2016 to 5 June 2020. Panel A reports the descriptive statistics of the percentage daily liquidity shortfall, *LBD_NEGATIVE*, which is defined as the negative realizations of the daily liquidity buffer, *LBD*. We report these statistics separately for single-strike funds and multi-strike funds. The last column of Panel A reports the difference in the average daily liquidity shortfall between these two categories of funds. We consider different negative realizations of *LBD* resulting from: (a) actual next-day net cash flows (*NFLOWS (Actual)*) and (b) simulated next-day net cash flows corresponding to different percentiles of the historical distribution of *NFLOWS*. For instance, *NFLOWS (left tail 1%)* represents the simulated percentage daily liquidity shortfall which is computed as the sum of the percentage daily liquid assets (*DLA*) and the 1-st percentile of the historical distribution of fund's percentage net cash flows, net of the minimum threshold of 10% of *DLA*. In Panel B the dependent variable in all regressions is *DSHORT*. This variable is computed as the sum of the percentage of assets in the form of daily liquid assets held by fund (*DLA*) and the simulated next-day net cash flows corresponding to different left-tail percentiles of the historical distribution of *NFLOWS*, net of the minimum liquidity threshold of 10%. We consider different simulated realizations of *DSHORT* based on the first percentile (*NFLOWS (left tail: 1%)*), 5-th percentile (*NFLOWS (left tail: 5%)*), and 10-th percentile (*NFLOWS (left tail: 10%)*) of the historical distribution of the percentage net cash flows of a fund. The main independent variables of interest are the number of times the fund strikes its four-digit mark-to-market NAV during the day (*NSTRIKES*), and its interaction with the annualized Fed target rate, *FEDRATE*. Other lagged control variables for fund and fund sponsor characteristics are those discussed previously in Table 5, and are omitted for brevity. In all models of Panel B we include sponsor and time fixed effects with standard errors (in parentheses) clustered by both fund and time. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Descriptive statistics of actual and simulated *LBD_NEGATIVE*

	Single-strike funds			Multi-strike funds			Multi −
	Obs.	Average	Worst	Obs.	Average	Worst	Single
NFLOWS (Actual)	16	-3.03	-8.69	66	-5.34	-12.53	-2.31**
NFLOWS (10%)	8	-3.50	-13.63	5	-7.42	-13.45	-3.93
NFLOWS (5%)	21	-2.23	-14.97	20	-2.75	-16.40	-0.51
NFLOWS (1%)	307	-2.45	-21.66	817	-7.89	-28.78	-5.44***
NFLOWS (Worst)	1,709	-11.02	-50.67	2,557	-17.97	-53.98	-6.95***

Panel B - Simulated Daily Liquidity Shortfall (*DSHORT*)

	NFLOWS (left tail: 1%)		*NFLOWS* (left tail: 5%)		*NFLOWS* (left tail: 10%)	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
NSTRIKES	-0.475***	-2.326***	-0.441***	-2.267***	-0.086	-1.872***
	(0.121)	(0.192)	(0.121)	(0.192)	(0.122)	(0.192)
× *FEDRATE*		0.978***		0.966***		0.944***
		(0.090)		(0.090)		(0.090)
Controls	Y	Y	Y	Y	Y	Y
Sponsor-Time FE	Y	Y	Y	Y	Y	Y
Observations	16,626	16,626	16,626	16,626	16,626	16,626

Table 10
Performance of Prime Institutional Funds
Conditional on the Number of Intraday NAV Strikes

This table presents the estimated coefficients from daily regressions of the performance of prime institutional money market funds on selected fund and fund sponsor characteristics, over the period from 14 October 2016 to 5 June 2020. The dependent variable in column (i) is the total return of a fund, *TOTRET*, which is computed as the sum of the daily annualized gross income yield (*GYIELD*) and the daily capital gain (loss) on the four-digit mark-to-market NAV. In column (ii) the dependent variable is the daily annualized gross income yield (*GYIELD*). In column (iii), the dependent variable is the daily annualized after-fee income yield (*NYIELD*). In column (iv), the dependent variable is the daily capital gain (loss) on the four-digit mark-to-market NAV, obtained by iMoneyNet directly from the fund's website ($YIELD1_{NAV}$). In column (v), the dependent variable is the daily capital gain (loss) on the four-digit shadow NAV, as reported by the fund to the SEC in form N-MFP ($YIELD2_{NAV}$). In column (vi), the dependent variable is the absolute value of the daily change in a fund's four-digit mark-to-market NAV, $|\Delta NAV|$. The main independent variable of interest is the number of times the fund strikes its four-digit mark-to-market NAV throughout the day, *NSTRIKES*. Other lagged control variables are those discussed previously in Table 5, and are omitted for brevity. In all models, we include sponsor and time fixed effects with standard errors (in parentheses) clustered by both fund and time. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	TOTRET	*GYIELD*	*NYIELD*	$YIELD1_{NAV}$	$YIELD2_{NAV}$	$\|\Delta NAV\|$
NSTRIKES	-0.798**	-0.136**	-0.135**	-0.409***	-0.341**	0.382**
	(0.381)	(0.053)	(0.053)	(0.093)	(0.143)	(0.135)
Controls	Y	Y	Y	Y	Y	Y
Sponsor-Time FE	Y	Y	Y	Y	Y	Y
Observations	16,420	16,420	16,420	16,420	11,349	16,420

Internet Appendix—Prime Time for Prime Funds: Floating NAV, Intraday Redemptions and Liquidity Risk During Crises

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This Internet Appendix presents additional empirical results, mostly robustness results, complementing the results presented in the paper. Most of the findings presented here are summarized in the paper.

Robustness Tests:

- Table IA.1: Intraday NAV Strikes and Liquidity Buffers: Manager-level Fixed Effects;
- Table IA.2: Intraday NAV Strikes and Weekly Liquidity Buffers;
- Table IA.3: Instrumental Variable Models of Intraday NAV Striking System: Weekly Liquid Assets;
- Table IA.4: Exposure of Single-strike and Multi-strike Funds to Simulated Weekly Percentage Liquidity Shortfalls;
- Table IA.5: Covid-19 Shock: Net Cash Outflows and Illiquid Portfolio Holdings: Normalized Ranks of Gross-of-fee Annualized Income Yield.

Table IA.1

Intraday NAV Strikes and Liquidity Buffers: Manager-level Fixed Effects

This table presents the summary statistics of fund managers' characteristics and the estimated coefficients from daily regressions of fund's daily liquid assets on several fund and fund sponsor characteristics over the period from 14 October 2016 to 5 June 2020. Panel A reports the descriptive statistics of the following characteristics: the size of the fund management team (*TEAMSIZE*); the dummy variable *POSTGRAD* which is equal to 1 if (one of) the fund manager(s) has a postgraduate qualification; the dummy variable *IVYLEAGUE* which is equal to 1 if (one of) the fund manager(s) attended an Ivy League School; the dummy variable *CFA* which is equal to 1 if (one of) the fund manager(s) has a Chartered Financial Analyst (CFA) designation; the tenure (in years) of the leading manager (*TENURE_MGR*); and the average tenure (in years) of the fund management team (*TENURE_TEAM*). The dependent variable in columns (i) and (ii) of Panel B is the percentage of daily liquid assets, *DLA*, as reported by the fund. The dependent variable in columns (iii) and (iv) of Panel B is the daily liquidity buffer, *LBD*. The main independent variable of interest is the number of times the fund strikes its four-digit intraday NAV, *NSTRIKES*. We also interact *NSTRIKES* with the following proxies of investors' liquidity preferences across funds: (a) the dummy variable *H_INVSOPH* which is equal to 1 if institutional investors pay an operating expense ratio below the median value of 15 basis points (i.e., high degree of sophistication); and (b) the degree of predictability of institutional investors' liquidity demand, *LIQDEM*, which is computed as the past 30-day volatility of fund's percentage daily net cash flows. To augment our measure of investor sophistication, we interact *H_INVSOPH* with the variable *H_STAKES*, which is equal to 1 if investors' minimum investment in the fund is greater than \$10 million (50-th percentile). Other lagged control variables—omitted for brevity— include fund and fund sponsor characteristics, and the levels and first-order interactions of *H_INVSOPH*, *H_STAKES*, and *LIQDEM*. In all models we include sponsor, time and manager-level fixed effects with standard errors (in parentheses) clustered by both fund and time. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A—Statistics of Fund Manager Characteristics				
	Obs.	Mean	P25	P50	P75
TEAMSIZE	23,256	2.230	2	2	3
POSTGRAD	23,402	0.528	0	1	1
IVYLEAGUE	23,402	0.0390	0	0	0
CFA	23,526	0.574	0	1	1
TENURE_MGR	20,772	20.823	13	23	26
TENURE_TEAM	20,772	16.428	10	13	20

	Panel B—Manager-level Fixed Effects			
	DLA	DLA	LBD	LBD
	(i)	(ii)	(iii)	(iv)
NSTRIKES	2.228**	2.140**	2.180**	2.240**
	(0.956)	(1.003)	(0.959)	(1.019)
× *H_INVSOPH*		1.994***		2.027***
		(0.553)		(0.545)
× *H_INVSOPH* × *H_STAKES*		-0.036		-0.110
		(0.491)		(0.490)
× *H_STAKES*		-1.773**		-1.498**
		(0.628)		(0.643)
× *H_INVSOPH* × *LIQDEM*		19.327**		16.979**
		(7.117)		(6.641)
× *LIQDEM*		-31.814***		-32.337***
		(6.778)		(6.542)
× *H_INVSOPH* × *H_STAKES* × *LIQDEM*		28.828***		33.199***
		(6.502)		(7.035)
Controls	Y	Y	Y	Y
Sponsor-Time-Manager FE	Y	Y	Y	Y
Observations	16,854	16,001	16,569	15,740

Table IA.2
Intraday NAV Strikes and Weekly Liquidity Buffers

This table presents the estimated coefficients from daily regressions of fund's weekly liquid assets on fund and fund sponsor characteristics over the period from 14 October 2016 to 5 June 2020. The dependent variable in Panel A is the daily percentage of weekly liquid assets, *WLA*, as reported by the fund. The dependent variable in Panel B is the weekly liquidity buffer, *LBW*. In both panels the main independent variable of interest is the number of times the fund strikes its four-digit intraday NAV, *NSTRIKES*. We also interact *NSTRIKES* with the following proxies of investors' liquidity preferences across funds: (a) the dummy variable *H_INVSOPH* which is equal to 1 if institutional investors pay an operating expense ratio below the median value of 15 basis points (i.e., high degree of sophistication); and (b) the degree of predictability of institutional investors' liquidity demand, *LIQDEM*, which is computed as the past 30-day volatility of fund's percentage daily net cash flows. To augment our measure of investor sophistication, we interact *H_INVSOPH* with the variable *H_STAKES*, which is equal to 1 if investors' minimum investment in the fund is greater than $10 million (50-th percentile). In column (v) of Panel A (Panel B) we include lagged values of the dependent variable, *LAGGED_WLA* (*LAGGED_LBW*). Other lagged control variables—omitted for brevity— include fund and fund sponsor characteristics, and the levels and first-order interactions of *H_INVSOPH*, *H_STAKES*, and *LIQDEM*. In all models we include sponsor and time fixed effects with standard errors (in parentheses) clustered by both fund and time. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A—Weekly Liquidity Assets (*WLA*)				
	(i)	(ii)	(iii)	(iv)	(v)
NSTRIKES	2.544***	2.251***	2.573***	2.646***	3.262**
	(0.649)	(0.702)	(0.758)	(0.793)	(1.530)
× *H_INVSOPH*		1.797**	0.796	2.680***	3.119***
		(0.657)	(0.559)	(0.918)	(1.513)
× *H_INVSOPH* × *H_STAKES*			1.386***	0.458	1.597
			(0.706)	(1.026)	(1.499)
× *H_STAKES*			0.344	0.267	-2.697*
			(0.952)	(0.973)	(1.554)
× *H_INVSOPH* × *LIQDEM*				24.517***	12.081
				(8.285)	(8.983)
× *LIQDEM*				-42.133***	-55.037*
				(10.889)	(32.004)
× *H_INVSOPH* × *H_STAKES* × *LIQDEM*				40.770***	61.096*
				(10.460)	(31.199)
LAGGED_WLA					1.755***
					(0.065)
Observations	17,601	16,854	16,854	16,001	15,922

	Panel B—Weekly Liquidity Buffer (*LBW*)				
	(i)	(ii)	(iii)	(iv)	(v)
NSTRIKES	2.971**	3.001**	3.199***	3.326***	3.028**
	(1.094)	(1.086)	(1.075)	(1.109)	(1.413)
× *H_INVSOPH*		1.459***	0.512	1.884***	1.340***
		(0.490)	(0.371)	(0.549)	(0.368)
× *H_INVSOPH* × *H_STAKES*			1.464***	1.443***	0.484
			(0.359)	(0.385)	(0.366)
× *H_STAKES*			-0.733	-0.745	-1.626
			(1.047)	(1.077)	(1.310)
× *H_INVSOPH* × *LIQDEM*				14.748**	11.921**
				(6.161)	(5.436)
× *LIQDEM*				-30.221***	-21.583***
				(6.511)	(5.716)
× *H_INVSOPH* × *H_STAKES* × *LIQDEM*				31.413***	22.438***
				(7.269)	(6.360)
LAGGED_LBW					0.827***
					(0.058)
Observations	17,571	16,569	16,569	15,987	15,908

Table IA.3
Instrumental Variable Models of Intraday NAV Striking System: Weekly Liquid Assets

We estimate 2-stage instrumental variable models of the relation between fund liquidity measures and the number of intraday NAV strikes during the period October 14, 2016 to June 5, 2020. The results of the first-stage regressions are presented in Table 5 in the paper. In all models, the number of intraday NAV strikes, *NSTRIKES*, is instrumented for by the percentage share of government institutional MMFs offered by the fund sponsor (in proportion to its total institutional MMF business) averaged during the pre-sample year of 2012 ($GOVSHARE_{2012}$) and 2013 ($GOVSHARE_{2013}$). The table reports the results of the second-stage regression where the dependent variable in columns (i) and (iii) is the actual percentage of weekly liquid assets, *WLA*, as reported by the fund. The dependent variable in columns (ii) and (iv) of Panel B is our proxy of the weekly liquidity buffer, *LBW*. Other lagged control variables—omitted for brevity—include: the logarithm of the assets under the management of the fund (*LFNDTNA*); the logarithm of the assets under the management of the fund sponsor (*LFAMTNA*); the logarithm of the number of days since fund inception (*LFNDAGE*); the proportion of a fund sponsor's assets under management that are not related to PIFs, i.e., the sponsor's non-PIF assets (*NOPRMBUS*); total operating expenses charged by the fund (*OPEX*); the percentage of net cash flows (*NFLOWS*); fund's daily gross annualized income yield (*GYIELD*); the logarithm of one plus the number of PIFs converted to government institutional funds during the transition period, *PIF_TO_GOV*; the logarithm of one plus the number of new government institutional MMFs launched by the fund sponsor during the transition period, *NEW_GOV*; the dummy variable *H_INVSOPH* which is equal to 1 if institutional investors pay an operating expense ratio below the median value of 15 basis points (i.e., high degree of sophistication); and the past 30-day volatility of fund's percentage daily net cash flows, *LIQDEM*. In all models we include time fixed effects with standard errors (in parentheses) clustered by fund and time. The bottom row of the table displays the *p*-value for Hansen's J-test of the null hypothesis that the instrumental variable employed is orthogonal to the errors. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	WLA	*LBW*	*WLA*	*LBW*
	(i)	(ii)	(iii)	(iv)
NSTRIKES	4.400***	5.657***	5.318***	6.911***
	(0.519)	(0.924)	(0.573)	(1.028)
Instrument	$GOVSHARE_{2012}$	$GOVSHARE_{2012}$	$GOVSHARE_{2013}$	$GOVSHARE_{2013}$
Hansen's J (p-value)	0.42	0.51	0.48	0.45
Observations	16,857	16,857	16,857	16,857

Table IA.4
Exposure of Single-strike and Multi-strike Funds to Simulated Weekly Percentage Liquidity Shortfalls

This table presents the summary statistics of weekly percentage liquidity shortfalls and the estimated coefficients of the daily regressions of fund's liquidity shortfall on selected fund and fund sponsor characteristics, over the period from 14 October 2016 to 5 June 2020. Panel A reports the descriptive statistics of the percentage weekly liquidity shortfall, *LBW_NEGATIVE*, which is defined as the negative realizations of the weekly liquidity buffer, *LBW*. We report these statistics separately for single-strike funds and multi-strike funds. The last column of Panel A reports the difference in the average weekly liquidity shortfall between these two categories of funds. We consider different negative realizations of *LBW* resulting from: (a) actual next-day net cash flows (*NFLOWS (Actual)*) and (b) simulated next-day net cash flows corresponding to different percentiles of the historical distribution of *NFLOWS*. For instance, *NFLOWS (left tail 1%)* represents the simulated percentage weekly liquidity shortfall which is computed as the sum of the percentage weekly liquid assets (*WLA*) and the 1-st percentile of the historical distribution of fund's percentage net cash flows, net of the minimum threshold of 30% of *WLA*. In Panel B the dependent variable in all regressions is *WSHORT*. This variable is computed as the sum of the percentage of assets in the form of weekly liquid assets held by fund (*WLA*) and the simulated next-day net cash flows corresponding to different left-tail percentiles of the historical distribution of *NFLOWS*, net of the minimum liquidity threshold of 30%. We consider different simulated realizations of *WSHORT* based on the first percentile (*NFLOWS (left tail: 1%)*), 5-th percentile (*NFLOWS (left tail: 5%)*), and 10-th percentile (*NFLOWS (left tail: 10%)*) of the historical distribution of the percentage net cash flows of a fund. The main independent variables of interest are the number of times the fund strikes its four-digit mark-to-market NAV during the day (*NSTRIKES*), and its interaction with the annualized Fed target rate, *FEDRATE*. Other lagged control variables for fund and fund sponsor characteristics are those discussed previously in Table 5, and are omitted for brevity. In all models of Panel B we include sponsor and time fixed effects with standard errors (in parentheses) clustered by both fund and time. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Descriptive statistics of actual and simulated *LBW_NEGATIVE*

	Single-strike funds			Multi-strike funds			Multi −
	Obs.	Average	Worst	Obs.	Average	Worst	Single
NFLOWS (Actual)	108	-6.13	-36.08	678	-7.75	-48.24	-1.62***
NFLOWS (10%)	6	-0.72	-1.35	4	-11.97	-33.45	-11.25
NFLOWS (5%)	29	-0.94	-2.69	79	-2.01	-36.40	-1.07
NFLOWS (1%)	780	-1.68	-6.33	1,747	-7.83	-44.89	-6.14**
NFLOWS (Worst)	3,520	-6.81	-28.68	4,730	-18.03	-55.87	-11.22***

Panel B - Simulated Weekly Liquidity Shortfall (*WSHORT*)

	NFLOWS (left tail: 1%)		*NFLOWS (left tail: 5%)*		*NFLOWS (left tail: 10%)*	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
NSTRIKES	-1.442***	-0.743***	-1.419***	-0.698***	-1.071**	-0.312*
	(0.494)	(0.192)	(0.436)	(0.192)	(0.427)	(0.191)
× *FEDRATE*		0.366***		0.378***		0.398***
		(0.076)		(0.076)		(0.076)
Controls	Y	Y	Y	Y	Y	Y
Sponsor-Time FE	Y	Y	Y	Y	Y	Y
Observations	16,626	16,626	16,626	16,626	16,626	16,626

Table IA.5

Covid-19 Shock: Net Cash Outflows and Illiquid Portfolio Holdings: Normalized Ranks of Gross-of-fee Annualized Income Yield

This table presents the estimated coefficients from a regression of a fund's daily net cash flows (*NFLOWS*) on several fund and fund sponsor characteristics. The primary independent variable is the number of times the fund strikes its four-digit NAV during the day, *NSTRIKES*. We regress *NFLOWS* during the peak of the crisis from March 9 to March 18, 2020 on the two-month lagged percentage of less-liquid holdings as reported by the fund for the period ending January 2020. Proxies of a fund's illiquid holdings, *ILLIQUID_HLD*, include: unsecured financial commercial paper (*FINCP*) in column (i); foreign bank obligations (*FBNKOB*) in column (ii); asset-backed commercial paper (*ABCP*) in column (iii); and risky assets aggregated across bank obligations, commercial paper and *ABCP* (*RISKY*), in column (iv). Following La Spada (2018), we include the variable *PERFRANK* which is computed as the rank of fund i's percentage daily gross-of-fee annualized income yield in day t. This rank is expressed in percentiles normalized over the interval [0, 1], with 0 indicating the worst performance and 1 indicating the best performance. Other lagged control variables are those discussed previously in Table 5, and are omitted for brevity. All models include sponsor and time fixed effects with standard errors (in parentheses) clustered by both fund and time. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(i)	(ii)	(iii)	(iv)
	FINCP	*FBNKOB*	*ABCP*	*RISKY*
ILLIQUID_HLD	-0.478***	-1.360***	0.122	-0.964**
	(0.110)	(0.387)	(0.085)	(0.447)
ILLIQUID_HLD × *NSTRIKES*	-0.195***	-0.902***	-0.103***	-0.108***
	(0.020)	(0.205)	(0.019)	(0.021)
PERFRANK × *NSTRIKES*	0.002	-0.018	0.003	0.005
	(0.018)	(0.019)	(0.016)	(0.019)
PERFRANK	0.069*	0.117***	0.071**	0.066*
	(0.035)	(0.040)	(0.033)	(0.036)
NSTRIKES	-8.349	-1.117	0.312	-4.144
	(8.386)	(2.695)	(1.194)	(11.681)
Controls	Y	Y	Y	Y
Sponsor-Time FE	Y	Y	Y	Y
Observations	134	134	128	134