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Money Market Funds (MMFs) and the Covid-19 pandemic: Has the MMLF benefited money markets?

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ARTICLE INFO

JEL Codes:
Q54
G11
G21
G23

Keywords:
US MMFs
Covid-19
MMLF facility
CoVaR systemic risk

ABSTRACT

This paper explores the impact of Covid-19, and that of the MMLF program on US MMFs systemic risk through the CoVaR methodology. Using 149 listed prime MMFs, between January 2019 and April 2020, the results document that while Covid-19 increased their systemic risk, the MMLF facility scheme mitigated it.

1. Introduction

As uncertainty surrounding the Covid-19 pandemic increases, prime money market funds (MMFs) face large redemption pressures, while outflows are mirrored by large inflows into government MMFs. To prevent outflows from prime MMFs from turning into an industry-wide run, i.e. to ‘break the buck’, the Fed announced the establishment of the Money Market Mutual Fund Liquidity Facility (MMLF) on March 18, which was officially launched on March 23. The facility can benefit the MMFs market in two ways. First, it helps MMFs to meet redemptions under stressful liquidity conditions in the secondary market. Second, it reduces MMFs investors’ incentive to withdraw preemptively, leading to reduced overall outflows.

The goal of this paper is twofold. First, to explore whether MMFs are safer amidst the Covid-19 crisis, and second whether the MMLF program mitigated systematic risk. MMFs target to offer stable yields over the time of investment by holding a diversified portfolio of top-quality securities with an average maturity of 60 days or less. Therefore, losses in cash portfolios can be avoided by investing only in U.S. Treasury and other government-backed securities, i.e. government money market funds, albeit investors usually accept low yields, because those on T-bills are well below 1%. By contrast, the yields on prime MMFs (i.e., top-quality commercial debt of large companies) are currently about 30% higher than yields on government MMFs.

The risks in prime MMFs are greater than those in government MMFs. The most significant risk is that securities in the portfolio may default or, more likely, drop sharply in price due to concerns about the creditworthiness of the issuer, although Securities and Exchange Commission (SEC) rules prohibit these funds from investing more than a specified percentage in the securities of any issuer. To address this risk, the Covid-19 legislation reinstated the U.S. Treasury’s authority to offer government insurance against shareholder losses in a US-based MMF. The other significant risk is that MMFs may not have enough liquid assets to meet a barrage of redemption requests. As stated above, to address such liquidity concerns, the Fed in March 2020 established the Money Market Mutual Fund
Liquidity Facility, which provides low-cost loans to banks for buying high-quality, but illiquid, securities from MMFs.

Despite the significant bulk of research on MMFs on international basis, certain distinguishing parts of their activities, especially during crisis periods, are still unexplored, and an empirical assessment of their contribution to systemic risk is yet needed. According to Poszar (2008), Poszar et al. (2012), and Adrian and Ashcraft (2016), MMFs have been often criticized for spreading systemic risk, while Kodres (2015) emphasizes that during the 2008 financial crisis, substantial runs occurred on MMFs that had provided funding to commercial and universal banks.

The analysis adopts the Conditional Value-at-Risk (CoVaR) measure, recommended by Adrian and Brunnermaier (2016). The method quantifies the contribution of MMFs to systemic risk. In other words, CoVaR indicates the Value-at-Risk (VaR) of financial institution i, conditional on financial institution j being in distress. They argue that their method provides a more complete measure of risk since it captures alternative sources of risk which affect institution i even though they are not generated by it.

In the empirical analysis, the CoVaR method allows us to generate time-varying estimates of the systemic risk contribution of MMFs prior and during the Covid-19 event. The theoretical justification of the goal follows Hsu and Moroz (2010) who argue that during tranquil times, MMFs do not have any problems connected with the presence of a maturity mismatch between assets and liabilities. In contrast, MMFs may experience issues linked with liquidity mismatch in periods of crisis, because they could not have an immediate cash availability to tune the request of investors’ shares redemption with the sale of assets on the market. The tested hypothesis examined here is: During a crisis, the higher is the liquidity mismatch of MMFs, the lower is the contribution to systemic risk.

2. Methodology

The measure of risk used by financial institutions is the value-at-risk (VaR), which focuses on the risk of an individual institution. The q%-VaR is the maximum dollar loss within the q%-confidence interval. The q-VaR for an institution i is defined as:

\[ \text{Prob}\left( X^i \leq \text{VaR}_q^i \right) = q\% \]  

where \( X^i \) is the variable of institution i for which the \( \text{VaR}_q^i \) is when \( X^i \) is the growth rate of market-valued total financial assets. The indicator of systemic risk, CoVaR, is defined as the VaR of the financial system as a whole, conditional on some event \( C(X_i) \) of institution i. That is, CoVaR is defined by the q-th quantile of the conditional probability distribution:

\[ \text{Prob}\left( X^{\text{system}}|C(X^i) \leq \left( \text{CoVaR}_{q}^{\text{system}(C(X^i))} \right) = q\% \]  

where \( X^i \) is the market-valued asset return of institution i, and \( X^{\text{system}} \) is the return of the portfolio, computed as the average of the \( X^i \)s weighted by the lagged market value assets of the institutions in the portfolio. Adrian and Brunnermeier (2016) employ quantile regressions to estimate CoVaR. We can estimate the predicted value of a quantile regression where the financial sector losses \( X_q^{\text{system};X_i} \) are determined given the losses of an institution i for the q%-quantile:

\[ X_q^{\text{system};X_i} = \alpha_q + \beta_q X^i \]  

where \( X_q^{\text{system};X_i} \) denotes the predicted value for a particular q%-quantile of the system, conditional on a return realization \( X^i \) of institution i. From the definition of VaR, in Eq. (1), we get:

\[ \text{VaR}_q^{\text{system}(X^i)} = X_q^{\text{system};X_i} \]  

The predicted value from the quantile regression of the system losses on institution i losses provides the value at risk of the financial system conditional on \( X^i \), because the \( \text{VaR}_q^{\text{system}(X^i)} \) is the conditional quantile. Using the particular predicted value of \( X^i = \text{VaR}_q^i \) yields the CoVaR measure. More formally, within the quantile regression framework, the CoVaR measure is:

\[ \text{CoVaR}_q^i = \text{VaR}_q^{\text{system}(X^i = \text{VaR}_q^i)} = \alpha_q + \beta_q \text{VaR}_q^i \]  

In what follows, q is always set to be 5%, so that CoVaR identifies the system losses predicted on the 5% loss of institution i. This measure is defined as time-varying; to estimate the time-varying VaR, as in Eq. (3), and CoVaR, as in Eq. (5), the analysis includes a set of variables to capture the time variation in conditional moments of asset returns. With references to these specific market factors, the analysis follows the implementation adopted by Lopez-Espinosa et al. (2012) and considers the following variables:

1 SP500 index-Vol: the weekly price of the S&P500 index as a volatility index
2 Liquidity Spread: the liquidity spread defined as the difference between the three months US repo rate and the 3-month US T-bill
3 T-bill change: the change in US 3-month T-bill
4 Curve slope: the change in the slope of the yield curve, represented by US 10-year minus 3-month yield on government bonds
5 Credit spread: the change in credit spread, proxied by the difference between BBB corporate bonds and the 10-year US government bonds
6 Equity Return: the weekly equity returns from the S&P500.
Once estimated the CoVaR, the analysis will explore the role of Covid-19 through the identification of certain controls.

3. Data

The analysis uses 149 US prime funds, continuously listed between January 2019 and April 2020, thus covering the Covid-19 crisis. Weekly data are on financial market losses $X_i^t$ as well. Indicating with $ME_i^t$ the market value of MMFs, and with $LEV_i^t$ the ratio between total assets and common equity, yields:

$$X_i = \left[ ME_i^t \times LEV_i^t - ME_{i-1}^t \times LEV_{i-1} \right] / \left[ ME_{i-1}^t \times LEV_{i-1} \right]$$

(1)

where the sum of all $X_i$ of the sample gives $X_{\text{system}}$, the growth rate of the market value of total assets of financial sector under analysis.

Like Chernenko and Sunderam (2014), the analysis excludes feeder funds and variable annuities. The values of VaR are obtained through quantile regressions (95%) of daily lagged returns of market variables and computing the expected value of the regression. The CoVaR is the expected value of the quantile regression (95%) of capital losses on the financial losses of individual institution.

4. Empirical analysis

The analysis estimates a panel model with fixed effects:

$$CoVaR_i = \beta_0 + \beta_1 X_{\text{system}}(\alpha - 1) + \beta_2 \text{Levi}_{i}(\alpha - 1) + \beta_3 \text{MMe}_{i}(\alpha - 1) + \beta_4 \text{ERV}_{i}(\alpha - 1)
+ \beta_5 \text{MBV}_{i}(\alpha - 1) + \beta_6 \text{Size}_{i}(\alpha - 1) + \beta_7 \text{Covid19}_{i} + \beta_8 \text{DMMLF}_{i} + a_i + \epsilon_{it}$$

(2)

Table 1 reports the results of Eq. (2). They report two modeling specification, one as in Eq. (2), and the second when the DMMLF dummy is explicitly introduced. In terms of column (1), they highlight that the Covid19 dummy exerts a positive and statistically significant impact of the Covid-19 event on systemic risk, implying that US money market funds have contributed to increase systemic

| Variable          | Mean   | SD     | Min   | Max   |
|-------------------|--------|--------|-------|-------|
| Leverage          | 0.018  | 0.0104 | 0.009 | 0.036 |
| Liquidity mismatch| 2.74   | 8.31   | 0.15  | 138.52|
| ERV               | 0.0062 | 0.0026 | 0.0000 | 0.033 |
| Beta              | 0.89   | 0.31   | 0.10  | 1.87  |
| MtB               | 4.96   | 10.14  | 0.71  | 89.10 |
| Size ($bil)       | 67.92  | 12.83  | 46.40 | 84.31 |
| SP500-Vol         | 0.41   | 0.14   | 0.13  | 0.83  |
| Liquidity spread  | 6.52   | 4.96   | 5.47  | 8.26  |
| T-bill change     | -0.14  | 0.29   | -1.14 | 0.05  |
| Curve slope       | 0.49   | 0.64   | -0.19 | 1.07  |
| Credit spread     | 1.19   | 0.61   | 0.03  | 2.42  |
| Equity returns    | 0.00017| 0.0079 | -0.06 | 0.04  |
| Xi(i)             | 0.00264| 0.31   | -19.80| 53.25 |
| VaR               | -0.019 | 0.145  | -17.62| 10.80 |
| CoVaR             | -0.0235| 0.0154 | -0.29 | 0.49  |
| ΔCoVaR            | -0.0204| 0.014  | -0.25 | 0.42  |

Note: SD = standard deviation.
risk during the Covid-19 pandemic period. This result seems to represent a contribution to the relevant literature. Moreover, liquidity mismatch has a positive impact on systemic risk, while money market funds’ beta and market to book value are likely to enhance systemic risk. The same is also true for the case of equity return volatility. Such findings indicate that for US MMFs, their characteristics are likely to increase systemic risk due to pandemic turmoil, thus rejecting the hypothesis presented earlier. The other variables included turned out to be statistically insignificant. In contrast, when the MMLF program is explicitly considered (column 2), the new findings illustrate that the relevant dummy is negative, implying lower systemic risk, while all the other potential system risk drivers run weaker to nil.

### 5. Conclusion

This paper explored the impact of the Covid-19 pandemic on the systemic risk of US listed MMFs, spanning the period January 2019-April 2020. The findings highlighted that the Covid-19 pandemic positively affected systemic risk, while the MMLF program reduced it by weakening outflows from prime MMFs, easing the strains in money markets due to the pandemic. Therefore, the provision of credit to the real economy has substantially benefit.

### Author statement

The only contributor of this paper is Nicholas Apergis.

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