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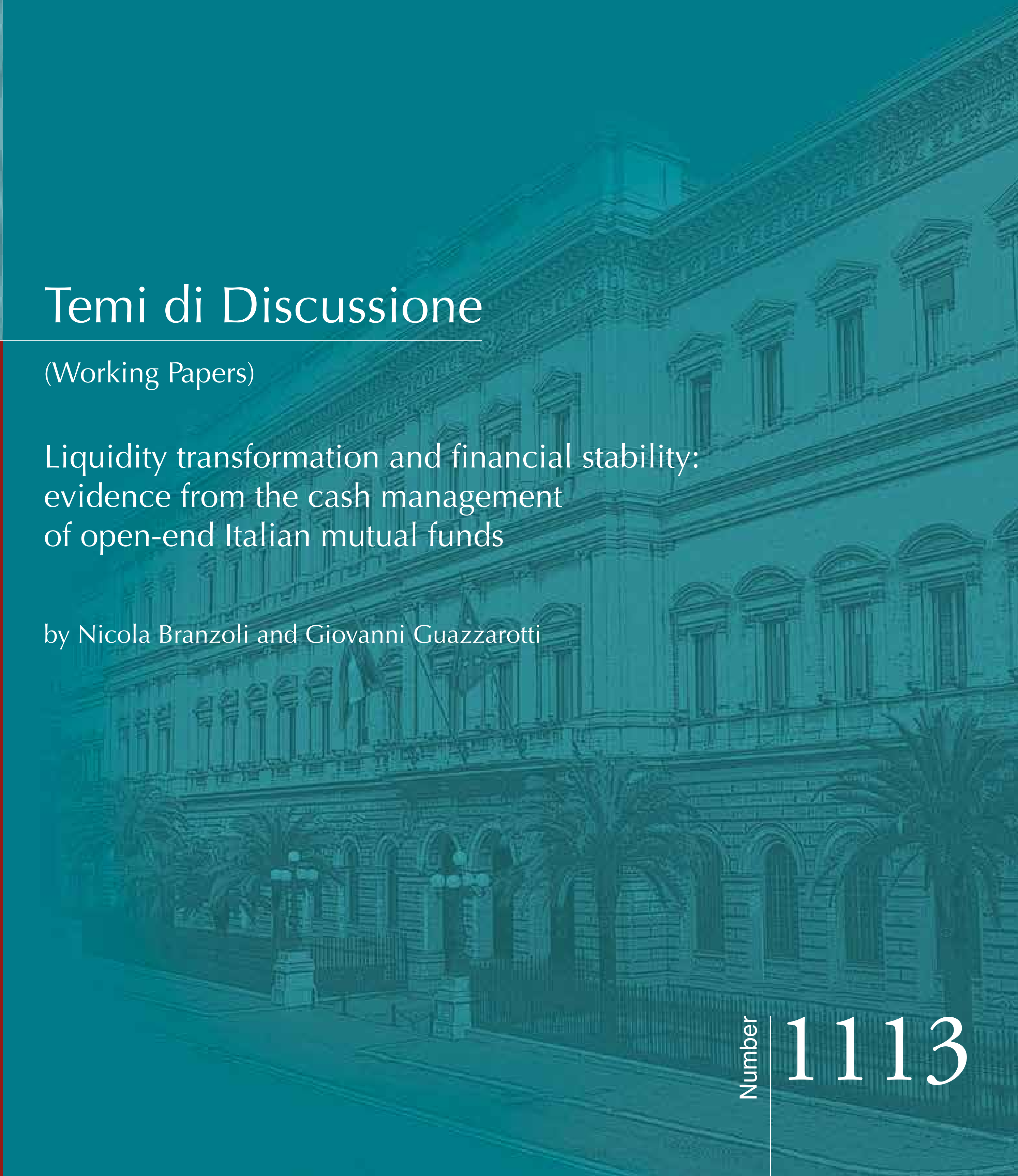

Liquidity transformation and financial stability: evidence from the cash management of open-end Italian mutual funds

by Nicola Branzoli and Giovanni Guazzarotti

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LIQUIDITY TRANSFORMATION AND FINANCIAL STABILITY: EVIDENCE FROM THE CASH MANAGEMENT OF OPEN-END ITALIAN MUTUAL FUNDS

by Nicola Branzoli* and Giovanni Guazzarotti*

Abstract

A key structural vulnerability of open-end mutual funds is the potential liquidity mismatch between assets and liabilities. In this paper we study the management of liquidity transformation by open-end mutual funds through cash holdings and its potential implications for financial stability. Using supervisory data on Italian equity funds, we show that the amount of cash holdings reduces the probability that funds experiencing significant outflows make forced sales of assets that can potentially dislocate market valuations from fundamentals. Moreover, our results indicate that funds engaging in forced sales hold statistically more cash at the end of a month of financial distress than funds in financial distress that do not engage in forced sales. This evidence is consistent with recent empirical findings showing that funds facing significant redemptions may exacerbate periods of market stress by hoarding cash.

JEL Classification: G12, G23.
Keywords: liquidity transformation, open-end mutual funds, financial stability.

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1 Introduction

Global assets under management (AUM) of open-end mutual funds have almost doubled over the past decade, reaching roughly 20 per cent of global financial system assets in 2015 (Financial Stability Board (2017)). Partly favored by the gradual deleveraging of banks and low market returns, in recent years funds have also increased their holdings of less liquid assets.[1]

These developments have increased financial stability concerns related to the activities of open-end mutual funds among regulators. Among the most recent interventions, in October 2016 the Security and Exchange Commission (SEC) adopted new rules to promote effective liquidity risk management across the open-end fund industry (Security and Exchange Commission (2016)) and in January 2017 the Financial Stability Board (FSB) has published its final policy recommendations to address the structural vulnerabilities from asset management activities (Financial Stability Board (2017)).[2]

One of the key structural vulnerabilities of open-ended mutual funds is the liquidity mismatch between daily redemption of fund shares and the liquidity of fund investments. Liquidity transformation can undermine financial stability if significant redemptions by end-investors force fund managers to sell assets in their portfolios, creating price pressures that dislocate market valuations from fundamentals. Such temporary misspricing could have an effect on the balance sheets and financing conditions of other financial intermediaries (for example by reducing collateral values), among other destabilizing effects (see International Monetary Fund (2015)). They could be amplified by the presence of documented phenomena related to the open-end mutual fund industry: investor runs (Chen *et al.* (2010)), herd behavior (Wermers (1999)), and contagion across markets through funds portfolios (Jotikasthira *et al.* (2012)).

This paper studies whether cash holdings by mutual funds can mitigate financial stability risks by re-

[1]For example, over the last 5 years the share of US and foreign corporate bonds held in the US owned by the mutual fund segment has increased from 10 to 20 per cent. See Adrian *et al.* (2015).

[2]Additional evidence on financial stability concerns related to the open-end mutual fund sector include: the federal register notice issued the Financial Stability Oversight Council (FSOC) in December 2014 seeking public comment on whether asset management activities pose potential risks to the US financial system (Financial Stability Oversight Council (2014)); the suggestion to strenghten the macro-prudential oversight of the industry in the Global financial Stability Report of the International Monetary Fund (IMF) in April 2015 (International Monetary Fund (2015)); the inclusion of the open-end mutual fund segment in the European Systemic Risk Board (ESRB) paper on policy strategies to address risks from the non-banking sector in July 2016 (European Systemic Risk Board (2016)).

ducing forced sales of assets by funds under financial distress.[3] This question has sparked considerable debate among academics (Chernenko and Sunderam (2016), Shek *et al.* (2015)) and market participants (BlackRock (2016)). On the one hand, liquidity used to meet redemptions can cushion the effect of investors' outflows on costly forced sales. On the other hand, if funds use liquidity to accomodate redemptions, they could eventually run out of liquid assets and start selling stocks. In this case, found managers would run the risk of incentivizing the first mover advantage and exacerbating run risk by end investors by treating investors who first sell their shares of the fund differently from investors who sell later. For this reason, it is often argued that asset managers tend to cut a vertical slice of their portfolio to meet redemptions (BlackRock (2016)).

To the best of our knowledge, our paper is the first to address the relationship between liquidity and forced sales from an empirical perspective. The main challenge in this analysis is disentangling sales that are forced by investors outflows from sales driven by portfolio rebalancing decided by asset managers. Without a strategy to identify sales forced by financial distress (forced sales) from sales driven by new information on assets' fundamentals (portfolio rebalancing), any attempt to study the relationship between cash management and the potential risks posed by the liquidity transformation of open-end mutual funds can provide misleading results.

To overcome this issue we bring together two strands of the mutual fund literature. The first has analyzed the relationship between investors' redemptions and cash holdings (Yan (2006), Shek *et al.* (2015), Chernenko and Sunderam (2016)), showing that funds hold substantial amounts of cash used to accommodate investors flows. The second (Coval and Stafford (2007), Khan *et al.* (2012), Manconi *et al.* (2012)), which focuses on the price impact of funds' trading activity, developed a methodology to identify forced sales as transactions that occurs whenever a fund under severe investors outflows sells assets that are not sold by funds not subject to investor outflows. We provide evidence that sales identified using this approach have a temporary price effect typical of forced sales, confirming previous results in the literature, and then link these forced sales to funds' cash holdings. In this way we are able to measure to what extent, and under which conditions, cash holdings can mitigate the risks for

[3]There are multiple tools that asset managers and regulators may use to mitigate the risks posed by liquidity transformation in open-ended mutual funds. These span from a general obligation to act in the best interest of unit holders (fiduciary duty) to more specific liquidity risk management tools, including limits to investments in illiquid assets, redemption policies, requirements to hold a minimum amount of cash in the portfolio.

financial stability posed by liquidity transformation of open-end mutual funds.

We perform our analysis using supervisory data on Italian equity funds. This allows us to have more detailed information than other studies on funds' characteristics and portfolios. Although the focus on Italian funds restricts the sample analyzed, we argue that our results may be generalized to funds operating from other countries, given that the Italian regulatory framework of open-end funds is in line with the international standards set by the FSB's recommendations[4] and that the investment and liquidity management behavior of Italian funds are similar to those of US and international funds.

Our results show that cash management is an effective tool for asset managers to avoid forced sales during months of financial distress. In fact, lagged cash holdings reduce the probability that a fund under severe outflows makes a forced sale and, when the fund does make a forced sale, the amount of cash holdings reduces the intensity of forced sales.[5]

The importance of cash holdings in mitigating forced sales appears to be quantitatively significant. Our most conservative estimate indicates that a fund in the bottom quartile of the distribution of liquidity entering financial distress is 20 percentage points more likely to make a forced sale than a fund entering financial distress in the top quartile of the distribution.[6]

A second important set of results relates to the cash management of funds engaging in forced sales. Controlling for past cash holding, we show that funds engaging in forced sales increase the amount of cash at the end of the month of financial distress more than funds that do not engage in forced sales while under financial distress. This suggests that funds forced to sell assets change the asset allocation of their portfolio holding more liquid portfolios. This evidence about cash hoarding can be related, for example, to funds trying to mitigate the risk of future redemptions that might realize because forced sales can be a drag on future returns.[7] Our results show that funds actively manage cash to mitigate liquidity risk, confirming the relevance of liquidity tranformation by open-end mutual

[4]In particular, investment funds are required to conduct periodical stress tests to assess their liquidity risk and adopt suitable investment strategies to mitigate it. Moreover, there is a limit on the amount of the portfolio that can be invested in securities not traded on a regulated market, which are typically less liquid than listed securities and so more susceptible to fire sales.

[5]The intensity of the forced sale is measured by the amount of stocks sold in percentage of the fund portfolio. See Section 4 for more details.

[6]This computation takes into account the non-linearity of our empirical model. Section 5 describes in more details how this effect is computed.

[7]Reducing funds' performance, forced sales are likely to trigger more redemptions in the future.

funds, and support the idea that cash holdings might be an effective policy tool to mitigate this type of risk.

These results hold to a number of robustness checks. We show that if we modify the definition of fund financial distress by increasing the threshold of outflows used to consider whether a fund is forced to sell part of its assets, we obtain larger parameter estimates about the relationship between forced sales and cash holdings. This result is consistent with the interpretation that liquidity becomes more important as financial distress exacerbates. We also perform a placebo experiment that considers as forced sales all sales by funds with significant inflows rather than significant outflows, finding no significant relationship between liquidity and forced sales. Finally, considering alternative empirical models, specifications and measures of liquidity do not change the results.

The rest of the paper is organized as follows. Section 2 provides a survey of the related literature. Section 3 describes the data and presents some descriptive statistics on investor flows and trading behavior of Italian equity mutual funds. Section 4 describes our identification strategy for forced sales and the empirical specification. Sections 5 and 6 present results and robustness checks respectively. Section 7 concludes.

2 Related Literature

This paper is related to two strands of the mutual fund literature. The first focuses on the determinants of cash holdings. Yan (2006) finds that US funds investing in equities of small-caps, which tend to be less liquid than large caps, and funds with more volatile fund flows, hold more cash. Moreover, he shows that cash holdings tend to be persistent and positively related to lagged aggregate fund flows.[8] Simutin (2014) investigates the implications of cash holdings on mutual fund performance using data on US funds from 1992 to 2009. His results indicate that funds with high abnormal cash outperform funds with low abnormal cash by over 2% per year. Chernenko and Sunderam (2016) show that about a quarter of inflows and outflows of US equity and long-term corporate bond funds are accommodated through changes in cash rather than through securities trading. They also find that the use of cash by

[8]Similar conclusions are also suggested by earlier studies on dynamic portfolio choice (e.g. Constantinides (1986)), which show that in the presence of transaction costs it is not optimal for a fund to rebalance its portfolio continuously.

funds is positively related to both the illiquidity of their assets and to the liquidity of markets they trade in. These results document the relationship between cash holdings and fund flows, but they do not analyze why they are related nor the benefits of holding cash. Our contribution is to show that cash holdings allow asset managers to avoid costly forced sales, pointing to one of the reasons why carrying cash can increase the value of fund portfolio.[9]

A second branch of the literature to which we contribute is that on the price impact of mutual funds' forced sales (Coval and Stafford (2007), Khan *et al.* (2012), Manconi *et al.* (2012)). These papers, which study the US and emerging markets, show that large and unexpected redemptions can force funds to sell illiquid assets, depressing asset prices and propagating destabilizing shocks across markets. We contribute to this literature by analyzing the importance of fund liquidity as one of the determinants of sales forced by significant investor outflows.

We are the first paper to merge these two strands of the literature to study the systemic role of cash management by open-end mutual funds. The paper mostly related to our study is Morris *et al.* (2017), which examines the relation between cash management and the sale of non-cash assets. Using data on 36 emerging markets global bond funds from January 2013 to June 2014, they find that asset managers engage in cash hoarding as a response to large redemptions more often than they use their cash holdings as a buffer to mitigate sales of asset. They also show that less liquid funds display a greater tendency toward cash hoarding. These results highlight an important systemic implication of cash management: cash hoarding by fund managers may actually amplify the effects of investor redemptions on market prices. Similarly to Morris *et al.* (2017), our paper focuses on the relation between cash holdings and investments, but unlike them we focus on forced sales rather pooling all trades as potential threats to financial stability. We extend their analysis by distinguishing between disinvestments that are forced by significant outflows from those that are driven by new negative information on asset fundamentals (portfolio rebalancing).

[9] A complementary explanation not investigated in this paper is that liquidity allows funds to maintain investment flexibility during periods in which the arrival of new information provide investment opportunities.

3 Data

We use data on funds' characteristics and their portfolios from the Supervisory Reports of the Bank of Italy. Using proprietary data allows us to have richer and more detailed information on funds' portfolio characteristics than other studies. In this way, we do not need to estimate funds' flows from changes in total assets, as in Chevalier and Ellison (1997), Sirri and Tufano (1998) and Coval and Stafford (2007), which may introduce measurement errors; moreover, we observe the portfolio at the individual stock level (instead of a more aggregate level such as in the EPFR database used by Jotikasthira *et al.* (2012)), which allows us to have a finer look at the changes in the portfolio of assets related to funds' flows, which is central for this study.[10] This richness of data comes at the cost of restricting the analysis to funds based in Italy. We show that the funds in our data display a cash-management and portfolio behavior similar to the funds covered in the most used datasets, arguing therefore that our results could be generalized beyond our sample.

For all funds based in Italy[11] we observe fund flows, balance-sheet data and other funds' characteristics at monthly frequency. We focus on equity funds investing predominantly in the US, Europe, Pacific and emerging markets (covering 85% of the total amount of equity funds).[12] To exclude funds that are still in the incubator stage, we drop those with less than a year of information. We also exclude funds with less than 10 million euro of assets during their entire life.[13] Our analysis spans the period from from July 2003 to June 2016. We merge our data with individual stock information from Datastream. Our final sample covers 390 funds for 157 months, for roughly 28,500 observations at the fund-month level. Table 1 reports summary statistics on the portfolio, inflows and returns.

[10]We also observe information that are generally not available in commercial data, such as the proportion of funds' shares held by institutional investors, i.e. insurance companies and pension funds.

[11]We do not have information on roundtrip funds (the so-called "estero vestiti"), which are funds sponsored by Italian groups but based in other European countries, which account for roughly 2/3 of the funds offered in Italy.

[12]More precisely, the investment styles analyzed are: US stocks, Euro Area stocks, European stocks, International Equity, Italian stocks, Pacific stocks and Emerging markets stocks.

[13]Chernenko and Sunderam (2016) restrict the analysis to funds with more than 100 million dollar of assets.

Fund's portfolio characteristics

	Mean	St. deviation	Percentiles of the distribution			Count
			25^{th} perc.	Median	75^{th} perc.	
Total Net Assets (TNA)	201.9	269.2	34.9	107.5	260.4	28,297
Return (%)	0.39	3.86	-1.56	0.70	2.63	28,039
Flows (% of TNA)	-0.75	3.49	-2.04	-0.79	0.30	27,244
$\sigma_{t-1,t-4}$(flows)	4.19	3.70	1.66	3.10	5.50	25,261
Cash (% of TNA)	4.27	7.85	0.83	2.74	6.09	28,297
%Δ of Cash	0.45	2.43	-0.39	0.00	0.59	27,328
Normalized HHI-index	0.02	0.08	0.00	0.01	0.01	28,297
Stocks (% of TNA)	82.63	16.92	80.29	87.24	92.05	28,297
N. of stocks	143	151	61	95	171	28,297
% of shares held by:						
Retail investors	0.77	0.31	0.66	0.92	0.98	12,243
Banks	0.03	0.11	0.00	0.00	0.01	12,243
Insurance and Pension	0.08	0.20	0.00	0.00	0.02	12,243
Foreign investors	0.02	0.05	0.00	0.00	0.01	12,243
Others	0.09	0.18	0.00	0.01	0.08	12,243

Table 1 *– Notes: summary statistics on funds' portfolios, flows and returns. Monthly data between July 2003 and June 2016. "Total Net Assets" are in million of euro; "$\sigma_{t-1,t-4}$(Flows)" is the standard deviation of inflows in the 3 months prior to an observation; "Cash(% of TNA)" includes money and shares of money market funds; ΔCash(% of TNA) is computed as the change in cash plus net acquisitions of shares in money market funds. The HHI is the normalized Herfindahl-Hirschman Index, which ranges between zero (all assets have the same share in the portfolio) and goes to one as the portfolio becomes concentrated in one asset. The sample covers 390 funds for 157 months between July 2003 to June 2016, for a total number of 28,488 observations.*

Funds in our data are smaller than those in similar studies (see, for example, Chernenko and Sunderam (2016)), however their portfolios are similar to the portfolios of their peers analyzed in other studies. For example, the funds in our sample hold, on average, 4.3 percent of their portfolio in cash (median 2.7 percent). For U.S. equity funds, Yan (2006) reports an average level of cash holdings over assets of 5.3 percent (median 3.7 percent), Simutin (2014) reports an average of 4 percent (median 2.8 percent) and Hanouna *et al.* (2015) reports an average of 2.6 and 3.1 for Foreign Equity and U.S. Equity funds respectively. The total number of stocks in the portfolio of the funds in our sample is similar to the one reported, for example, by Coval and Stafford (2007), and the distribution of the normalized Herfindahl-Hirschman Index is close to the distribution reported by Chernenko and Sunderam (2016).

Regarding the behavior of end-investors, the median fund flow is -0.8 per cent, slightly higher than the value reported for US equity funds by Coval and Stafford (2007) (-0.6%). The standard deviation of inflows in the 3 months prior to an observation varies considerably across observations, showing that liquidity risk varies across funds.

The high monthly variation of cash in the portfolio suggests that funds actively manage their cash holdings. For half of the observations, funds either decrease their cash holdings by more than 40 percent (i.e., more than the first quartile) or increase their cash holdings by more than 59 percent (i.e., more than the third quartile).

The bottom panel of Table 1 reports summary statistics on the amount of funds' shares held by different types of investors (these data are available only after January 2008). In most cases, funds' investors are mainly retail investors, however the 20 percentage points of standard deviation in shares held by insurance companies and pension funds indicates that there is considerable heterogeneity in the role of these institutional investors.

Table 2 provides descriptive statistics on fund behavior in response to financial pressure. We sort all fund-months observations into deciles of the distribution of flows, calculated as a percentage of total assets one month before, and then compute various statistics of their portfolio.

Fund flows and portfolio characteristics							
Decile	Inflows (%)	Prior fund return	N.holdings	Fraction of positions:			
				Mantained	Expanded	Reduced	Eliminated
1 (Inflow)	6.10	1.20	131	0.46	0.23	0.12	0.20
2	1.36	1.33	140	0.66	0.15	0.11	0.10
3	0.31	0.72	137	0.68	0.12	0.12	0.09
4	-0.21	0.47	150	0.68	0.12	0.12	0.09
5	-0.61	0.45	154	0.66	0.12	0.14	0.22
6	-1.01	0.22	155	0.66	0.11	0.15	0.09
7	-1.46	0.27	154	0.63	0.12	0.16	0.19
8	-2.09	-0.02	145	0.61	0.11	0.18	0.15
9	-3.23	-0.18	138	0.60	0.10	0.20	0.15
10 (Outflow)	-7.42	-0.69	119	0.48	0.09	0.30	0.23

Table 2 *– Notes: Mutual fund trading behavior in response actual inflows/outflows. Monthly data between July 2003 and June 2016. Total number of observations: 28,488.*

Funds experience a large range of monthly net flows. The top decile is characterized positive inflows of around 6 per cent of their total assets in a single month, funds in the bottom decile lose more than 7% of their assets. As is well documented in the literature on mutual funds (Chevalier and Ellison (1997), Sirri and Tufano (1998)), inflows chase returns: fund returns in the month before are monotonically related to inflows. Also consistent with the available empirical evidence (Coval and Stafford (2007)), funds with larger inflows and outflows tend to have a portfolio that is less diversified, in terms of number of holdings, than funds in the middle of the distribution of flows.[14]

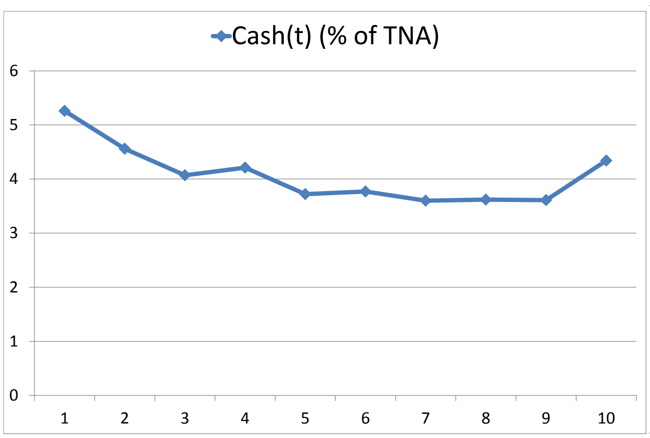
For the sake of comparison with the US market, which is used in most studies, Table 9 in Appendix A reports the same statistics for the US market reported by Coval and Stafford (2007). The evidence described above is substantially similar to the one in the US.[15] The distribution of fund flows seems to be more concentrated in our data and cash holdings are relatively higher, but the two sample seems, overall, comparable.

[14]Funds experiencing large outflows may have a less diversified portfolio because they need to entirely sell some their assets to meet redemptions, while it is less intuitive why funds experiencing large inflows have a less diversified portfolio. We are not aware of any study that investigates this empirical regularity.

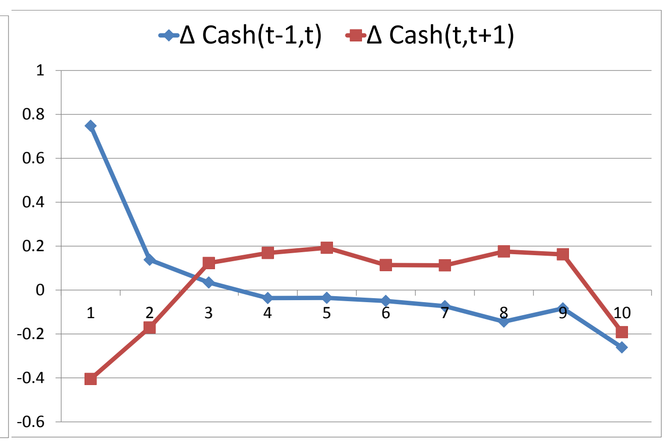
[15]Note that Table 2 reports monthly returns while 9 reports annual returns, so returns are not directly comparable between the two tables.

Columns 5 to 8 of Table 2 report the most important evidence on fund behavior in response to flows: the fraction of assets in their portfolio whose holdings are maintained constant (column 5), expanded (columns 6), sold in part or completely (columns 7 and 8 respectively). More than 60 per cent of the stocks in the funds' portfolio are maintained constant from month to month, except for funds in the two most extreme deciles. Funds in the top decile of inflows are more likely to expand positions while funds experiencing large outflows are more likely to sell off the assets in their portfolio, either completely or in part, to meet their obligations. This monotonic relationship between outflows and selling behavior characterizes not only funds under significant financial pressure, but all funds. In fact, the fraction of assets sold increases with outflows.

Graphs 1a-1b plot, for the ten groups based of flows used in Table 1, the amount of cash in the portfolio (Figure 1a) and the change of cash in the month before and after the one in which the flow is observed (Figure 1b).



(a) Cash holdings.



(b) Change in cash holdings.

Figure 1 *– These figures plot the amount of liquidity (cash and money market funds) scaled by funds' total assets (left graph) and the change in liquidity (right graph) as a function of funds' flows (sorted into percentile of the distribution of flows scaled by total assets, see Table 2).*

Figure 1a shows that funds at the top and at the bottom of the distribution of flows hold more cash, as documented also in other analyses (Warther (1995), Coval and Stafford (2007)). This evidence suggests that cash is used by funds as a liquidity buffer. Funds receiving large inflows are likely to increase their cash because they decide to hold part of their new capital liquid waiting for new investment opportunities. Funds that experience large outflows are likely to keep more cash to meet future redemptions.[16] Figure 1b is consistent with this explanation. Funds that experience large inflows increase their cash in the same month, but significantly reduce their cash holdings in the month following the large inflow. Instead, funds at the bottom of the distribution of flows decrease their cash holdings both in the month with significant outflows and in the month after, because they use cash to meet redemptions. In fact, fund flows tend to be persistent and funds in the bottom of the flow distribution tend to experice outflows also in subsequent months.

4 Empirical methodology

4.1 Identifying sales forced by financial distress

A key challenge in identifying flow-motivated sales by mutual funds is the need to distinguish between sales determined by funds' financial distress from sales driven by a fall in the asset fundamental value (information-driven).

We use the methodology proposed by Khan *et al.* (2012) to distinguish forced sales from information-driven sales.[17] The approach is based on comparing stocks sold by funds with large outflows with stocks traded by all other funds. Significant sales of stocks by funds in normal conditions are, by definition, not driven by financial distress and are therefore presumed to be determined by the arrival of new information on the fundamental value. Therefore assets sold by mutual funds with large outflows but not significantly sold by funds in normal conditions are not driven by new information, and can therefore be associated to the financial distress of the fund. In the implementation of this methodology, we will need to control for the possibility that a given stock sold by a fund under financial distress may not be sold by other funds just because it is not in their portfolio.

Several papers have shown that this approach identifies sales that exert significant temporary price

[16] We have also computed Table 1 and Figure 1 sorting funds according to their expected flows, rather than their actual flows, calculated using a Fama and MacBeth (1973)-style regression (see Sirri and Tufano (1998) and Coval and Stafford (2007)) and the evidence of funds' behaviour is the same. This suggests that the evidence described is, for the most part, predictable.

[17] For a similar approach, see Coval and Stafford (2007), Chen *et al.* (2008) and Jotikasthira *et al.* (2012) among others.

pressures on stocks (Coval and Stafford (2007)), that such price pressures propagate shocks across markets through funds' portfolios (Jotikasthira *et al.* (2012)) and that other market participants actively trade to profit from these temporary price pressures (Chen *et al.* (2008), Khan *et al.* (2012)). At the end of this Section we show that sales identified using this approach have a temporary price impact in the Italian stock market typical of forced sales, confirming previous results in the literature.

Two definitions are key to implement this approach: when funds enter financial distress, and when sales by funds in normal conditions are information-driven. In the rest of this section we discuss these two issues.

We start by the definition of funds' financial distress. We scale flows by funds' total assets and compute, for each month in our sample, the median flow of funds with outflows (negative net flows). We classify a fund as distressed whenever its net flows fall below the median outflow.

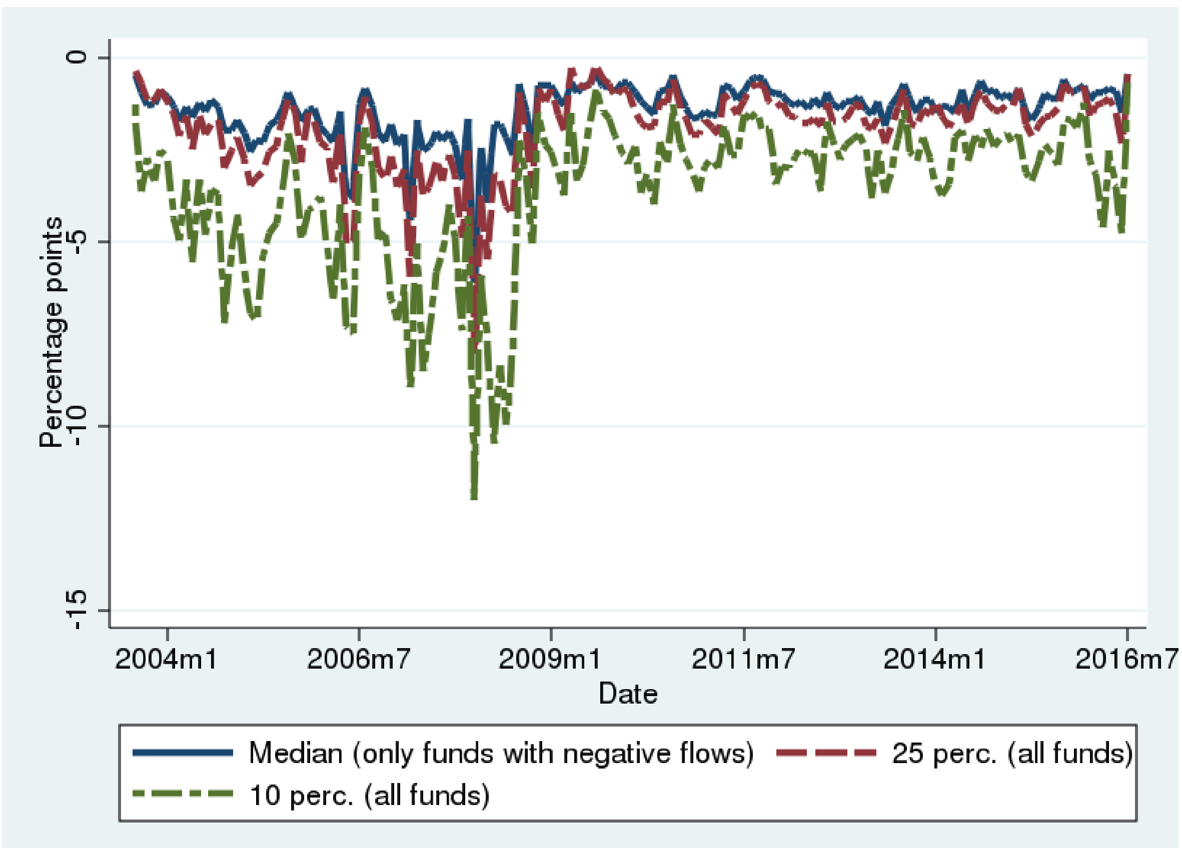


Figure 2 *– This figure plots the time-series of a subset of the percentiles of the distribution of funds' flows. For each month t, we compute the median of the distribution of funds' outflows scaled by funds' total assets. For comparison, we plot also the 10th and the 25th percentiles of the distribution of flows of all funds.*

Figure 2 plots the median outflow with, for comparison, the 10^{th} percentile of the distribution of flows, which is the threshold used by by Coval and Stafford (2007) and Khan *et al.* (2012), and the 25^{th} percentile of the distribution of flows. The median outflow closely tracks the 25th percentiles of the distribution of flows of all funds so, according to our definition, in each month roughly a quarter of the funds experience financial distress. This threshold is less extreme than the one commonly used in the literature. If we consider that between mid-2007 and mid-2008 (when the funds in our sample where experiencing significant aggregate outflows of capital) the flows from all funds were around -2.5 per cent, then an outflow of 1.44 per cent (the average value of the median outflow) seems a plausible but not extreme level of financial distress, while an outflow 3.6 per cent (the mean of the 10^{th} percentile) represents a severe level of financial stress. In the main analysis we will use the median outflow as the threshold value defining financial distress to maintain a significant amount of observations, but we also provide robustness checks using the 10^{th} percentile of the distribution of flows of all funds.

The definition of information-motivated sales follows Khan *et al.* (2012). For stock i in month t, we calculate unforced trading pressure:

$$UPressure_{i,t} = \frac{\sum_j Net\ sales_{i,j,t} | \text{fund } j \text{ is not financially distressed}}{\sum_j holdings_{i,j,t-1} | \text{fund } j \text{ is not financially distressed}} \tag{4.1}$$

where $(Net\ sales_{i,j,t} | \text{fund } j \text{ is not financially distressed})$ is the sum of net sales of stock i by fund j during t, conditional on the fund not being under financial distress. This variable, which we observe directly in the Supervisory Reports, represents net trading activity in a stock by mutual funds not in financial distress and has been commonly used in the literature to identify mutual fund demand imbalances (Lakonishok *et al.* (1992), Wermers (1999)). In each month, we sort all stocks into deciles of the distribution of Upressure and consider information-driven sales the stocks that, in a given month, are sold more than the median value of Upressure when it is negative. The choice of the median share sold of stocks with negative Upressure is arbitrary and mirrors the choice made above for financial distress (Khan *et al.* (2012) use the 10^{th} percentile of all stocks), therefore in Section 6 we will investigate several robustness checks with respect to this choice.

Figure 3 plots our preferred threshold together with the 10^{th} percentile of the distribution of Upressure for all stocks in the sample.

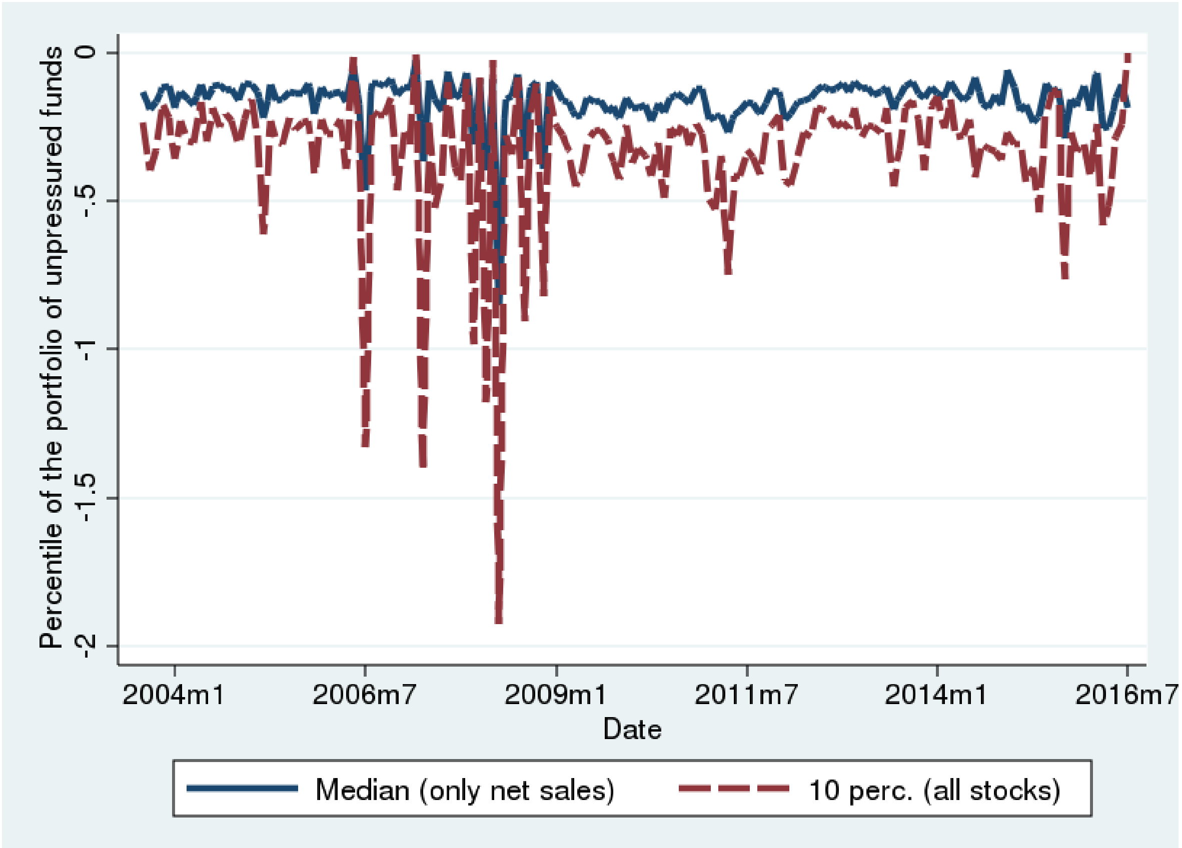


***Figure 3** – This figure plots the time-series of the percentiles of the distribution of UPressure (see Eq.4.1). For each month, we compute the median of the distribution of stocks with negative Upressure and the 10^{th} percentile of the distribution of all stocks.*

A large literature on the price impact of mutual funds (cfr. Section 2) shows that forced sales can dislocate stock prices from their fundamentals, imparing the correct functioning of financial markets. This price effect is larger when forced sales are executed by many funds at the same time, or by large funds, or in periods when market liquidity is low. We have investigated the potential price effects of our forced sales in the Italian stock market.[18] Figure 4 plots the Cumulative Median Abnormal Return (CMAR) of Italian stocks subject to forced sales around the month of fund financial distress (labeled in the figure as month t) and the difference between the CMAR of stocks subject to forced sales and the CMAR of all other Italian stocks held by mutual funds. The figure shows a clear under-performance of stocks in the month of the forced sale. The price effect is temporary, indicating that it is unlikely related to a change in the fundamentals.

[18] We choose these stocks because Italian funds play a more relevant role in the turnover of this market rather than other markets.

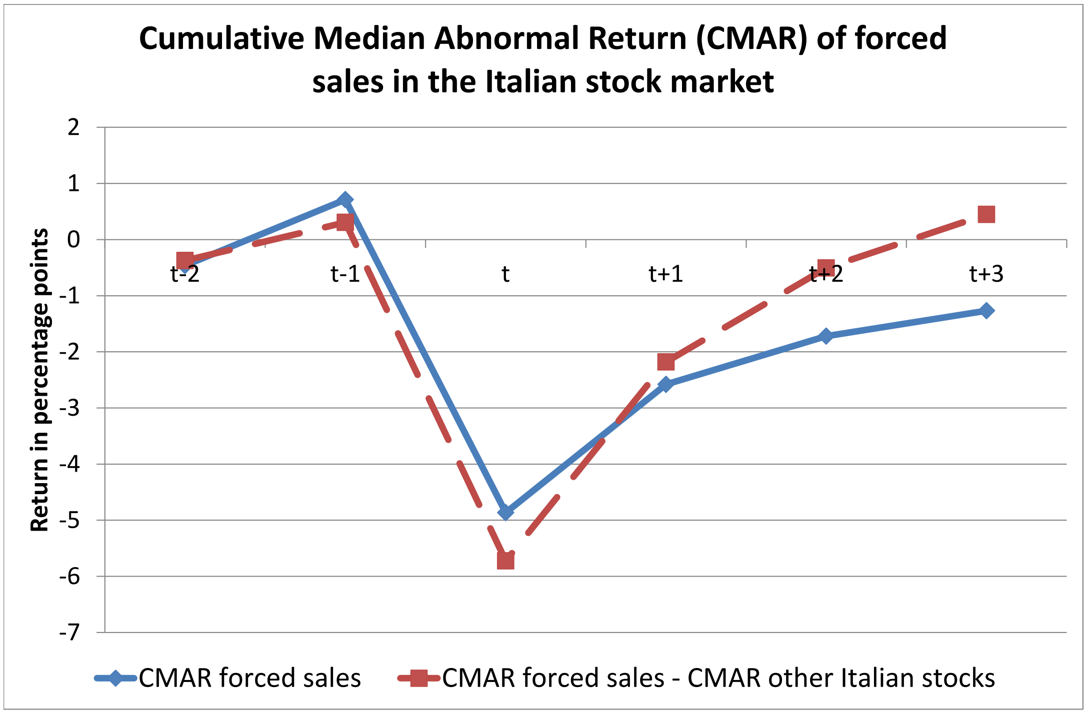


Figure 4 *– Cumulative median abnormal returns (CMAR) around mutual funds' forced sales in the Italian stock market (solid blue line); difference between the CMAR of forced sales and the CMAR of all other Italian stocks held by mutual funds (dashed red line). We first calculated for each month and stock the abnormal return relative to the Italian stock market index. Then we kept all stocks that are not in the top two quartiles of the distribution of net buy and in the bottom two quartiles of the distribution of net sales by funds not in financial distress (this excludes information-driven trades). Finally we required that all stocks are not subject to forced sales in the two months prior and the three months following a forced sale, to eliminate confounding effects. The CMAR of forced trades is computed weighting each stocks by the amount sold by funds under financial distress in the month of the forced sale.*

Using the definition of financial distress (Fig 2) and the definition of information-driven sales by unpressured funds (Eq. 4.1) we construct: a) a dummy identifying funds making forced sales;[19] b) a measure of the intensity of the forced sale, equal to the percentage of the portfolio of assets sold during the forced sale. These two variables are the main dependent variables analyzed in this paper.

[19]This dummy is therefore equal to one if the fund was in financial distress and sold an asset not significantly sold by funds not under financial distress.

4.2 Empirical specification

We estimate two sets of specifications. The first analyzes the relationship between past cash holdings and forced sales through a series of linear and non-linear models that take the following form:

$$Forced\ Sales_{j,t} = \alpha + \beta Liquidity_{j,t-1} + \gamma X_{j,t-1} + \eta MKT_t + \epsilon_{i,t} \tag{4.2}$$

The matrix $X_{j,t-1}$ contains fund specific lagged control variables given by:

$$X_{j,t-1} = [log(AUM_{j,t-1}) \quad Ntit_{j,t-1} \quad HHI_{j,t-1} \quad flow_{t-1}...flow_{t-3} \quad \sigma(flow_{j,t-1 \to t-4})]$$

The dependent variable $Forced\ Sales_{j,t}$ is, depending on the specification, a dummy variable equal to one if fund j in month t has made at least one forced sale, or the amount of the forced sales by fund j in month t normalized by fund portfolio at the end of the month before the forced sale. In the first case the dependent variable captures the probability that a fund in financial distress engages in a flow-motivated sale, in the second case the dependent variable captures the intensity of forced sales. The sample analyzed in all regressions is the unbalanced panel of funds in financial distress in each month. We always consider robust standard errors. When the dependent variable is a dummy, we estimate both a linear probability model and a conditional logit model; when the dependent variable measures the intensity of forced sales, we estimate both a linear model and a tobit model.[20]

The variable $Liquidity_{j,t-1}$ is the explanatory variable we are interested in. It is given by the cash and money market funds (cash-like assets) reported by fund j at the end of the month before financial distress (month $t-1$) divided by fund's total assets. The sign and significance of β capture the relationship between lagged liquidity and forced sales and indicate whether past cash buffers reduce the probability and the intensity of forced sales after significant investor outflows. A negative coefficient would suggest that liquidity is a valuable tool to lower the likelihood and the intensity of forced sales that may put downward pressures on market valuations.

We have included additional explanatory variables that are standard in the literature. The natural

[20] To avoid the "incidental parameters problem" in the non-linear models with fixed effects we estimate a conditional logistic regression for the dummy variables, which avoids the estimation of the fixed effects by calculating the likelihood for each fund. The Tobit model is instead unaffected by this bias (see Green (2004)).

logarithm of fund's total assets captures fund's size ($log(AUM_{j,t-1})$), the number of stocks in the portfolio and the normalized Herfindahl-Hirschman Index ($Ntit_{j,t-1}$ and $HHI_{j,t-1}$ respectively) capture differences in portfolio diversification across funds and months. We also include lagged flows ($flow_{t-1}...flow_{t-3}$) and the standard deviation of monthly flows in the 3 months prior to financial distress ($\sigma(flow_{t-1,t-4})$).[21] MKT_t is a matrix capturing market conditions during months of forced sales. This matrix includes the VIX index, standard deviations of stock market indices of the geographic areas of investment of the funds in our sample (Europe, Italy, Pacific, Emerging markets) and, when used, the time fixed effects explained in more details below. All specifications include fixed effects of fund's asset manager and target market (Europe, Italy, Pacific, Emerging markets).[22]

The second set of specifications investigates the relationship between forced sales and cash hoarding by funds under financial distress. Because liquidity is a stock variable recording the amount of liquid assets in funds' portfolios at the end of the month, and forced sales happen during the month, we estimate a series of linear and tobit models using, as dependent variable, the end-of-month level of liquidity and the change in the liquidity before and after financial distress. The main explanatory variables are the measures of forced sales. More precisely, we estimate:

$$y_{j,t}^{Liquidity} = \tilde{\alpha} + \tilde{\beta} Forced\ Sales_{j,t} + \tilde{\gamma} X_{j,t-1} + \tilde{\eta} MKT_t + \tilde{\epsilon}_{i,t} \tag{4.3}$$

Eq.(4.3) contains the same additional explanatory variables as Eq.(4.2)[23] but focuses on the relationship between forced sales (as the dummy variable or the intensity measure) and the liquidity at the end of the month of financial distress. Depending on the specification, $y_{j,t}^{Liquidity}$ is the share of liquidity at the end of the month of financial distress (i.e. $Liquidity_{j,t}$) or the change in liquidity between the end of the month prior to financial distress and the end of the month of financial distress (i.e. $Liquidity_{j,t} - Liquidity_{j,t-1}$)).[24] A positive coefficient would indicate that, *ceteris paribus*, funds

[21]While trying several specifications for Eq.4.2, we have included also past returns, without observing significant changes in the results. Given that there is no theoretical argument for why past returns should affect forced sales once we control for past flows, we have decided to use as our preferred specification the one without past returns. All specifications also include flows at time t to control for the intensity of financial distress during the period.

[22]The VIX index and the standard deviation are used as an alternative to the time fixed effects.

[23]The only difference is that we include lagged levels of liquidity in the matrix $X_{j,t-1}$.

[24]In this case we do not include lagged liquidity in the matrix $X_{j,t-1}$ (see footnote 23). We have also tried as dependent variable the change in liquid assets betrween $t-1$ and t divided by the total portfolio at $t-1$ ad the results are generally similar to those provided below.

making forced sales, or that make more forced sales, tend to have more cash at the end of the month of financial distress than funds that do not make forced sales.

We support a causal interpretation of our results using two arguments. First, our monthly data allow us to control for many fund characteristics on a monthly basis. Moreover, using Supervisory Report we do not need to estimate controls such as flows, the amount sold of a given stocks, and so on because all these data are directly reported by funds to the Bank of Italy. The second argument is based on the inclusion of time fixed effects. For all models, our estimates include both funds' fixed effects and month fixed effects, which would control for any time-invariant unobserved fund characteristics and any unobserved time-specific event that is common to all funds. However, this approach may still be biased because some unobserved time-varying variable may affect only some funds (for example, the market conditions may change in specific jurisdictions related to funds' investments, or the risk appetite of funds investing in specific markets may change over time).[25] Therefore we estimate also a specification with fund fixed effects interacted with year fixed effects. This specification controls for any unobserved fund characteristics that change from one year to another. In conclusion, although our results lack a quasi-experiment, the robustness of our results across all specifications provides evidence about the importance of liquidity management for flow-motivated sales.

5 Results

Table 3 presents the estimates about the relationship between the probability of a forced sale and the lagged liquidity of funds in financial distress. The top panel contains the results from the linear probability model, the bottom panel shows the estimates of the logit model. In both panels, the first column does not contain fund nor time fixed effects; in the second column we add fund fixed effect and in the third we include also month fixed effects. In the last column we consider fund-year fixed effects. The results on additional control variables included in the specifications are reported in Tables 10 and 11 in Appendix A.

[25] We thank one referee for suggesting this point.

Dep. Variable: Indicator of forced sales				
Linear probability model				
	OLS	Panel estimator		
Fixed Effects:	-	Fund F.E.	Fund and month F.E.	Year-fund F.E.
	(1)	(2)	(3)	(4)
Liquidity$_{j,t-1}$	-0.155***	-0.123***	-0.117***	-0.076***
	(0.027)	(0.031)	(0.032)	(0.025)
N.Obs.	9,174	9,174	9,174	8,873
R^2	0.111	0.102	0.130	0.127
Non-linear probability model				
	Logit	Conditional logit		
Fixed effects:	-	Fund	Fund and month	Time-varying fund
	(1)	(2)	(3)	(4)
Liquidity$_{(t-1)}$	-0.047***	-0.039***	-0.040***	-0.166***
	(0.011)	(0.015)	(0.018)	(0.074)
N.Obs.	9,174	3,330	3,225	237

Table 3 *– Notes: this table shows the estimates about the relationship between the probability of a forced sale and lagged liquidity of funds in financial distress. The dependent variable is a dummy equal to one if the fund has sold at least one stock that is not among information-driven sales of funds in normal financial conditions. The top panel shows the estimates of the linear probability model, the bottom panel shows the estimates of the non-linear (logit) model. Column (1) contains simple ordinary least squares and logit results; in column (2) we add fund fixed effects; in column (3) we add month fixed effects; in columnn (4) we consider fund-year fixed effects. Robust standard errors in parenthesis. Monthly data between July 2003 and June 2018.*

Lagged liquidity enters with negative sign and is highly significant in all specifications. The magnitude of the coefficient is similar across specifications, except for the last column. When fund-year fixed effects are considered, the point estimates drops to 7 percentage points in the linear probability model, while it increases to 0.16 in the conditional logit model. In the latter case, however, we have too few observations to consider it as a relible estimate.[26] Therefore, we take the specification in column (4) of the linear probability model and the specification in column (3) of the logit model as our main reference. The estimate of the linear probability model implies that the expected change in the probability of a forced sale drops by 11 percentage points for each percentage point increase in the liquidity ratio. The β of the conditional logit model implies that the expected change in the log odds of a forced sale is -0.04 for each percentage point increase in the amount of liquidity in the portfolio. One way to appreciate the magnitude of the effect is to multiply these estimates by the inter-quantile range of the distribution of funds' cash holdings (around 5 percentage points, cfr. Table 1). A fund in the bottom quartile of the distribution of liquidity entering financial distress is therefore almost 20 per cent (from the conditional logit model)[27] to 50 per cent (from linear probability model) more likely to make a forced sale than a fund entering financial distress from the top quartile of the distribution. Both models therefore indicate that the amount of cash holdings is a quantitatively important factor in the probability that funds under significant outflows make forced sales. This evidence is consistent with the idea that cash holdings are a valuable tool to lower the likelihood of forced sales. Moreover, as forced sales may exert downward price pressures on stocks (see Section 4), these results show that funds' liquidity have implications for financial stability.

Table 4 presents the estimates about the relationship between the intensity of forced sales and the past cash holdings of funds in financial distress.[28]

[26] In the conditional logit model, the inclusion of fund-year fixed effects force us to drop many observations. Specifically, we loose all observations belonging to fund-year groups in which funds under financial distress always, or never, make forced sales.

[27] For the sake of clarity: $e^{-0.04*5} \approx 0.81$.

[28] Results on the additional variables are reported in Tables 12 and 13 in Appendix A.

Dep. Variable: Forced sales in percentage of fund portfolio				
Linear model				
	OLS	Panel estimator		
Fixed effects:	-	Fund F.E.	Fund and month F.E.	Fund-year F.E.
	(1)	(2)	(3)	(4)
Liquidity$_{j,t-1}$	-0.116***	-0.102***	-0.101***	-0.058***
	(0.031)	(0.037)	(0.036)	(0.017)
N.Obs.	9,174	9,174	9,174	8,873
R^2	0.460	0.457	0.472	0.316
Non-linear model				
		Tobit		
Fixed effects:	-	Fund F.E.	Fund and month F.E.	Fund-year F.E.
	(1)	(2)	(3)	(4)
Liquidity$_{j,t-1}$	-0.076***	-0.070***	-0.064***	-0.285***
	(0.012)	(0.015)	(0.017)	(1.894)
N.Obs.	9,174	9,174	8,873	8,873

Table 4 *– Notes: this table shows the estimates about the relationship between the intensity of forced sales and the liquidity of funds in financial distress. The dependent variable is the amount of forced sales divided by the total fund portfolio at the end of the month prior to financial distress. The top panel shows the estimates of the linear model, the bottom panel shows the estimates of the non-linear (tobit) model. Column (1) contains simple ordinary least squares and probit results; in column (2) we add fund fixed effects; in column (3) we add month fixed effects; in columnn (4) we consider fund-year fixed effects. Robust standard errors in parenthesis. Monthly data between July 2003 and June 2018.*

The estimated coefficients, having the same sign and significance as those shown in Table 3, corroborate our previous results. Lagged liquidity helps funds in financial distress to reduce the intensity of forced sales. The estimate of β indicates that going from the first to the fourth quartile of the distribution of funds' liquidity (equivalent to an increase of 5 percentage points in the amount of liquidity in the portfolio) reduces the intensity of the forced sale by between 0.2 and 0.3 percentage points of the portfolio or one tenth of the median intensity of forced sales.

We now turn to the second set of results, which investigate the relationship between forced sales and the level of liquidity chosen by the fund at the end of the month of financial distress. The structure of Table 5 is similar to that of the previous tables and has two panels. The top panel contains the results using as dependent variable the change in the end-of-month liquidity between $t-1$ and t, the bottom panel contains the results using as dependent variable the end-of-month liquidity in period t. The two dependent variables should give similar results, therefore we show them for robustness purposes.[29] The control variables used in Table 5 are the same used in the previous regressions[30] to which we add both measures of forced sales (dummy and intensity). We show the latter, which is the only significant one.[31]

[29]This is true given that we control for past liquidity in the regression using as dependent variable the level of liquidity.

[30]Except for the fact that we do not include $Liquidity_{t-1}$ for the regression in the top panel.

[31]Tables 14 and 15 in the Append show the results using only one variable at a time.

Dep. Variable: Δ Liquidity $_{end\,of\,month\,t-1 \rightarrow end\,of\,month\,t}$				
		Linear probability model		
	OLS		Panel estimator	
Fixed effects:	-	Fund F.E.	Fund and month F.E.	Fund-year F.E.
	(1)	(2)	(3)	(4)
Forced sales (% of portfolio$_{j,t}$)	0.120***	0.135***	0.137***	0.140***
	(0.0170)	(0.0192)	(0.0189)	(0.00676)
N.Obs.	8,873	8,873	8,873	8,873
R^2	0.316	0.337	0.354	0.325

Dep. Variable: Liquidity $_{end\,of\,month\,t}$				
		Linear probability model		
	OLS		Panel estimator	
Fixed effects:	-	Fund F.E.	Fund and month F.E.	Fund-year F.E.
	(1)	(2)	(3)	(4)
Forced sales (% of portfolio$_{j,t}$)	0.134***	0.147***	0.149***	0.152***
	(0.0172)	(0.0195)	(0.0193)	(0.00698)
N.Obs.	8,873	8,873	8,873	8,873
R^2	0.639	0.460	0.473	0.650

Table 5 *– Notes: this table shows the of the relationship between forced sales and level of liquidity chosen by the fund at the end of financial distress. In the top panel, the dependent variable is the change in the end-of-month liquidity between $t-1$ and t; in the bottom panel the dependent variable is the end-of-month liquidity in period t. Column (1) contains simple ordinary least squares and logit results; in column (2) we add fund fixed effects; in column (3) we add month fixed effects; in columnn (4) we consider fund-year fixed effects. Robust standard errors in parenthesis. The list of additional controls, which is the same as the one in the previous tables and described in Section 4, includes also the dummy of forced sales. Additional results are available upon request. Monthly data between July 2003 and June 2018.*

The results in Table 5 indicate a positive and significant coefficient of the intensity of forced sales.

This estimate suggests that, controlling for fund observed and unobserved time-varying characteristics including past liquidity, funds making more forced sales tend to increase their cash more than funds making less forced sales (top panel). Note that this result is an outcome of funds' decisions. Funds may decide to not modify the asset allocations of their portfolio, in order not to reduce future runs of their investors. In this case we should not observe any significant relationship. Or it may decide to use predominantly cash to pay outflows; in this case we should observe a decrease in liquidity.

Cash holdings at the end of the month of financial distress and trading decisions of the fund are contemporaneous decisions, therefore the significance of the coefficient should be interpreted as a correlation which bear insights on the joint decisions of liquidity and trading strategy of asset managers of funds in financial distress. Its positive sign suggests that part of the liquidity generated by forced sales is kept in the form of cash. This result is consistent with the recent literature focusing on cash hoarding by funds (Shek *et al.* (2015)) and point to the risk that, by hoarding cash in periods of financial distress, funds my exacerbate market illiquidity.

To conclude, our results describe a relationship between cash holdings and forced sales by funds in financial distress. Past liquidity reduces funds' need to use forced sales of assets in their portfolio to meet redemptions and the intensity of the forced sales. Moreover, we find evidence that significant redemptions prompt funds to hoard cash, which is consistent with our results showing that liquidity is an effective tool to mitigate the effect of redemptions on forced portfolio rebelancing. Funds making forced sales and selling more of their portfolio during forced sales tend to have more cash at the end of the month, holding part of the liquidity generated by forced sales in the form of cash. These results are consistent with the recent literature documenting cash hoarding by open-ended funds during periods of significant investor outflows.

6 Robustness analysis

In this section we provide evidence on the robustness of our results through three additional sets of regressions.

First, we use a larger threshold, in absolute value, to define funds' financial distress. In particular, funds are defined in financial distress if their flows are below 10th percentile of the distribution of fund flows in a given month. This threshold is the most commonly used in the literature (Coval and Stafford (2007), Khan *et al.* (2012)). Table 6 presents the results.

Dep. Variable: Indicator of forced sales				
Linear probability model				
	OLS	Panel estimator		
Fixed effects:	-	Fund F.E.	Fund and month F.E.	Fund-year F.E.
	(1)	(2)	(3)	(4)
$\text{Liquidity}_{j,t-1}$	-0.219***	-0.162***	-0.158***	-0.110**
	(0.0432)	(0.0579)	(0.0599)	(0.0449)
N.Obs.	2,609	2,609	2,609	2,439
R^2	0.141	0.052	0.131	0.225

Table 6 *– Notes: this table shows the estimates about the relationship between the probability of a forced sale and lagged liquidity of funds in financial distress. Funds are defined in financial distress if their flows are below 10^{th} percentile of the distribution of fund flows in a given month. See Table 3 for details. The results on additional control variables are available upon request*

The number of observations drops significantly but the parameter estimates remain significant and qualitatively the same. More importantly, for these funds, which are the subsample characterized by larger outflows, β's are larger in absolute terms. In other words, liquidity is quantitatively more important for funds experiencing larger outflows: their lagged level of liquidity has a larger impact on the probability of a forced sale and these funds hoard more of the liquidity generated by forced sales in the form of cash.[32]

Second, we perform a placebo experiment that considers as forced sales all sales by funds in the top half of the distribution of funds with inflows. Since these funds are increasing the amount of assets under management and are not in financial distress, their liquidity should not have any relationship

[32]Table 16 in the Appendix provides evidence on the cash hoarding of funds defined in financial distress if their flows are below 10^{th} percentile of the distribution of fund flows in a given month.

with whether they sell assets not traded by other funds. [33] The results, reported in Table 7, show that for these funds there is no significant relationship between the level of liquidity and the measures of forced sales.[34]

Placebo results
Dep. Variable: Indicator of forced sales

Linear probability model

	OLS	Panel estimator		
Fixed effects:	-	Fund F.E.	Fund and month F.E.	Fund-year F.E.
	(1)	(2)	(3)	(4)
$\text{Liquidity}_{j,t-1}$	-0.158***	-0.0198	-0.00594	0.0168
	(0.0564)	(0.0687)	(0.0709)	(0.0671)
N.Obs.	3,593	3,593	3,593	3,509
R^2	0.096	0.070	0.115	0.337

Table 7 *– Notes: this table shows the estimates about the relationship between the probability of a forced sale and lagged liquidity of funds in financial distress. As a placebo experiment, funds are defined in financial distress if their flows are above the median of the distribution of fund inflows in a given month. See Table 3 for details. The results on additional control variables are available upon request.*

Finally, we consider another alternative approach to define funds in financial distress, namely a constant threshold to tag a fund in financial distress (-2 per cent) and a constant threshold to define information-driven sales by funds not in financial distress (-0.15 per cent of the aggregate portfolio of funds not in financial distress).[35] Table 8 shows also that using constant thresholds to define funds in financial distress and information driven-sales do not change the results.

[33] More precisely, we fictitiously tag in financial distress funds with inflows larger than the median inflow in a given month. Then we construct a measure of information-driven sales by all other funds using Eq. 4.1 and we construct the dummy variable of forced sales by these "placebo" funds in financial distress using the methodology described in Section 4.

[34] Table 17 in the Appendix provides additional evidence from the placebo experiment.

[35] Both values are chosen because they are the median values of their time-varying counterparts (see Figures 2 and 3).

Dep. Variable: Indicator of forced sales				
Linear probability model				
	OLS	Panel estimator		
Fixed effects:	-	Fund F.E.	Fund and month F.E.	Fund-year F.E.
	(1)	(2)	(3)	(4)
$\text{Liquidity}_{j,t-1}$	-0.116***	-0.0915***	-0.0882**	-0.0397***
	(0.0286)	(0.0354)	(0.0358)	(0.0029)
N.Obs.	7,045	7,045	7,045	6,821
R^2	0.100	0.042	0.083	0.139

Table 8 *– Notes: this table shows the estimates about the relationship between the probability of a forced sale and lagged liquidity of funds in financial distress. The definition of financial distress is flows below 2 per cent of the assets and information driven sales are defined as those stocks sold by more than 0.15 per cent of the amount owned by funds not in financial distress. See Table 3 for details. The results on additional control variables are available upon request.*

7 Conclusions

This paper studies to what extent cash holdings by open-end mutual funds can mitigate financial stability risks posed by the potential liquidity mismatch between funds' assets and liabilities. The main challenge in our analysis is to disentangle funds's sales of assets that are forced by investor outflows, and therefore related to fund liquidity transformation, from sales driven by portfolio rebalancing chosen by its asset manager. Our analysis is the first to overcome this issue adapting the methodology used by Coval and Stafford (2007), Khan *et al.* (2012), Manconi *et al.* (2012) among others, which suggests to identify forced sale as sales that occurs whenever a fund under severe investors outflows sells assets that are not sold by funds not subject to investor outflows. We provide evidence that sales identified using this approach have a temporary price effect typical of forced sales, confirming the results in the literature, and link these flow-induced sales to funds' cash holdings. In this way we are able to measure to what extent, and under which conditions, cash holdings can mitigate the risks of forced sales that can potentially dislocate market valuations from fundamentals.

Using detailed supervisory data on Italian equity funds, we find that lagged cash holdings reduce the probability that a fund under severe outflows make a forced sale of the assets in its portfolio, and, when the fund does make a forced sale, reduces the intensity of forced sales. Moreover, we find that funds engaging in forced sales hold statistically more cash at the end of the month of the forced sale than funds in financial distress that do not engage in forced sales.

This evidence suggests that cash holdings might be an effective policy tool for regulators to mitigate the risks posed by liquidity transformation in open-ended mutual funds. Mutual funds both use cash to respond to unexpected outflows in order to reduce forced sales and tend to hoard cash when they expect that forced sales induced by financial distress may deteriorate fund performance and therefore trigger more redemptions in the future. In all the empirical models used the magnitude of the mitigating effect appear to be significant.

Our paper contributes to the existent literature on open-ended mutual funds by proposing an empirical strategy to directly assess the relationship between cash management and forced sales which could potentially turn into fire sales. This is particularly relevant from a macro-prudential policy perspective, as liquidity transformation is a key structural vulnerability of open-ended mutual funds and fire sales by asset-managers are among the main channels through which open-ended mutual funds may become systemically risky. More generally, our approach may be used to evaluate the determinants of funds' pro-cyclical trading, and therefore the effectiveness of related macro-prudential policy measures.

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A Additional data

Fund flows and portfolio characteristics							
Decile	Inflows (%)	Prior fund return	Number of holdings			Ita. holdings (% of the port.)	Cash (%)
			All	Italian	(%)		
1 (Inflow)	23.7	18.7	124.3	-	-	-	2.3
2	8.1	14.9	143.8	-	-	-	2.0
3	3.6	12.9	167.1	-	-	-	1.9
4	1.0	9.9	160.0	-	-	-	1.8
5	-0.6	8.1	143.6	-	-	-	1.8
6	-2.0	6.0	134.3	-	-	-	1.8
7	-3.4	3.3	130.8	-	-	-	1.7
8	-4.9	1.4	130.4	-	-	-	1.6
9	-7.0	0.7	134.1	-	-	-	1.7
10 (Outflow)	-12.5	2.8	117.1	-	-	-	1.8

Table 9 *– Notes: Mutual fund portfolio characteristics associated with actual flows in the US. Quarterly data between 1980 and 2004, excpet for prior month returs, which are in the year before. Number of observations: 142,720. Source Coval and Stafford (2007).*

Linear probability model Dep. Variable: Indicator of forced sales				
VARIABLES	(1)	(2)	(3)	(4)
VIX U.S.$_{(t)}$	-0.0002	-	-	-0.0008
	(0.0002)	(-)	(-)	(0.0006)
Log(Total Assets)$_{(t-1)}$	0.016***	0.026***	0.018***	0.005
	(0.001)	(0.004)	(0.005)	(0.005)
Flows$_{(t)}$	-0.0007***	-0.0007***	-0.0006***	-0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
$\sigma_{t-1,t-4}$(flows)	0.00002	-0.00001	-0.00002	-1.1e^{-6}
	(0.00004)	(0.00004)	(0.00004)	(0.00003)
N. of stocks$_{(t-1)}$	0.00003**	0.00003*	0.00002	0.00001
	(0.00001)	(0.00002)	(0.00002)	(0.00001)
HHI$_{(t-1)}$	-0.718***	-0.581***	-0.580***	-0.145***
	(0.026)	(0.035)	(0.035)	(0.038)
Flows$_{(t-1)}$	-0.00001	-0.00001	-0.00002	-0.00003
	(0.0001)	(0.0001)	(0.00002)	(0.00009)
N.Obs.	9,174	9,174	9,174	8,873

Table 10 *– Notes: additional parameter estimates. See Table 3 for details.*

Logit model Dep. Variable: Indicator of forced sales				
VARIABLES	(1)	(2)	(3)	(4)
VIX U.S.$_{(t)}$	-0.004	-	-	-0.028
	(0.012)	(-)	(-)	(0.060)
Log(Total Assets)$_{(t-1)}$	0.458***	0.464*	0.403***	6.928*
	(0.001)	(0.251)	(0.118)	(3.724)
Flows$_{(t)}$	-0.159***	-0.197***	-0.241***	-0.267***
	(0.029)	(0.042)	(0.051)	(0.096)
$\sigma_{t-1,t-4}$(flows)	-0.002***	-0.001	-0.002	-0.024
	(0.00004)	(0.004)	(0.005)	(0.039)
N. of stocks$_{(t-1)}$	0.003**	0.003	0.0003**	-0.007
	(0.0007)	(0.002)	(0.001)	(0.015)
HHI$_{(t-1)}$	-4.816***	-3.919***	-1.960**	-8.406*
	(0.698)	(0.900)	(0.884)	(4.717)
Flows$_{(t-1)}$	0.012	-0.001	-0.003	-0.129*
	(0.011)	(0.001)	(0.006)	(0.052)
N.Obs.	9,174	3,330	3,225	237

Table 11 *– Notes: additional parameter estimates. See Table 3 for details.*

Linear model Dep. Variable: Forced sales in percentage of fund portfolio				
VARIABLES	(1)	(2)	(3)	(4)
VIX U.S.$_{(t)}$	-0.089**	-	-	-0.057
	(0.037)	(0.038)	(-)	(-)
Log(Total Assets)$_{(t-1)}$	-0.212**	-0.457	-0.405	-0.254
	(0.001)	(0.385)	(0.443)	(0.211)
Flows$_{(t)}$	-0.595***	-0.577***	-0.566***	-0.328***
	(0.068)	(0.074)	(0.077)	(0.012)
$\sigma_{t-1,t-4}$(flows)	0.003	0.001	0.001	0.0008
	(0.004)	(0.003)	(0.003)	(0.0027)
N. of stocks$_{(t-1)}$	-0.003***	-0.004**	-0.004**	-0.004***
	(0.00004)	(0.002)	(0.002)	(0.0008)
HHI$_{(t-1)}$	-9.298***	-10.809***	-10.647***	-7.906***
	(0.628)	(1.595)	(1.569)	(1.979)
Flows$_{(t-1)}$	-0.006	-0.003	-0.006	-0.002
	(0.008)	(0.007)	(0.007)	(0.005)
N.Obs.	9,174	9,174	9,174	8,873

Table 12 *– Notes: additional parameter estimates. See Table 4 for details.*

Tobit model Dep. Variable: Forced sales in percentage of fund portfolio				
VARIABLES	(1)	(2)	(3)	(4)
VIX U.S.$_{(t)}$	-0.094***	-	-	-0.015
	(0.021)	(-)	(-)	(0.033)
Log(Total Assets)$_{(t-1)}$	-0.162**	-0.181*	0.229*	0.107***
	(0.065)	(0.123)	(0.122)	(0.943)
Flows$_{(t)}$	-0.598***	-0.590***	-0.343***	-0.240***
	(0.007)	(0.006)	(0.051)	(0.011)
$\sigma_{t-1,t-4}$(flows)	0.001	-0.0003	0.001	-0.012***
	(0.002)	(0.0018)	(0.002)	(0.003)
N. of stocks$_{(t-1)}$	-0.003***	-0.004***	-0.004***	-0.033***
	(0.0005)	(0.0008)	(0.0007)	(0.003)
HHI$_{(t-1)}$	-17.288***	-16.573***	-9.523***	-6.444**
	(1.607)	(1.665)	(0.884)	(2.526)
Flows$_{(t-1)}$	-0.006	-0.004	-0.003	-0.022***
	(0.005)	(0.004)	(0.004)	(0.006)
N.Obs.	9,174	9,174	8,873	8,873

Table 13 *– Notes: additional parameter estimates. See Table 3 for details.*

Dep. Variable: Δ Liquidity $_{end\,of\,month\,t-1 \rightarrow end\,of\,month\,t}$				
	Linear probability model			
	OLS	Panel estimator		
Fixed effects:	-	Fund	Fund and month	Time-varying fund
	(1)	(2)	(3)	(4)
Forced sale dummy$_{(t)}$	0.0107***	0.0131***	0.0126***	0.0122***
	(0.00333)	(0.00329)	(0.00337)	(0.00347)
N.Obs.	8,823	8,823	8,823	8,823
R^2	0.286	0.304	0.322	0.290
Forced sales (% of portfolio)$_{(t)}$	0.120***	0.137***	0.137***	0.141***
	(0.0168)	(0.0189)	(0.0186)	(0.00671)
N.Obs.	8,823	8,823	8,823	8,823
R^2	0.315	0.337	0.354	0.290

Table 14 *– Notes: this table shows the of the relationship between forced sales and the change in the end-of-month liquidity between $t-1$ and t. In the top panel, the main explanatory variable is the dummy of furced sales, in the bottom panel it is the intensity of forced sales. See Table 5 for more details.*

Dep. Variable: Liquidity $_{end\,of\,month\,t}$				
		Linear probability model		
	OLS	Panel estimator		
Fixed effects:	-	Fund	Fund and month	Time-varying fund
	(1)	(2)	(3)	(4)
Forced sale dummy$_{(t)}$	0.0121***	0.0148***	0.0145***	0.0139***
	(0.00331)	(0.00361)	(0.00370)	(0.00360)
N.Obs.	8,873	8,873	8,873	8,873
R^2	0.622	0.430	0.444	0.631
Forced sales (% of portfolio)$_{(t)}$	0.134***	0.149***	0.150***	0.153***
	(0.0169)	(0.0192)	(0.0190)	(0.00692)
N.Obs.	8,873	8,873	8,873	8,873
R^2	0.640	0.460	0.473	0.651

Table 15 *– Notes: this table shows the of the relationship between forced sales and the end-of-month liquidity at time t, i.e. at the end of the month of financial distress. In the top panel, the main explanatory variable is the dummy of furced sales, in the bottom panel it is the intensity of forced sales. See Table 5 for more details.*

Dep. Variable: Δ Liquidity $_{end\,of\,month\,t-1 \rightarrow end\,of\,month\,t}$				
	Linear probability model			
	OLS	Panel estimator		
Fixed effects:	-	Fund F.E.	Fund and month F.E.	Fund-year F.E.
	(1)	(2)	(3)	(4)
Forced sales (% of portfolio$_{j,t}$)	0.198***	0.219***	0.224***	0.218***
	(0.0357)	(0.0422)	(0.0388)	(0.0155)
N.Obs.	2,439	2,439	2,439	2,439
R^2	0.146	0.154	0.223	0.301

Dep. Variable: Liquidity $_{end\,of\,month\,t}$				
	Linear probability model			
	OLS	Panel estimator		
Fixed effects:	-	Fund F.E.	Fund and month F.E.	Fund-year F.E.
	(1)	(2)	(3)	(4)
Forced sales (% of portfolio$_{j,t}$)	0.160***	0.174***	0.174***	0.157***
	(0.0299)	(0.0325)	(0.0314)	(0.0157)
N.Obs.	2,439	2,439	2,439	2,439
R^2	0.568	0.334	0.388	0.584

***Table 16** – Notes: this table shows the of the relationship between forced sales and level of liquidity chosen by the fund at the end of financial distress. Funds are defined in financial distress if their flows are below 10th percentile of the distribution of fund flows in a given month. In the top panel, the dependent variable is the change in the end-of-month liquidity between $t-1$ and t; in the bottom panel the dependent variable is the end-of-month liquidity in period t. Column (1) contains simple ordinary least squares and logit results; in column (2) we add fund fixed effects; in column (3) we add month fixed effects; in columnn (4) we consider fund-year fixed effects. Robust standard errors in parenthesis. The list of additional controls, which is the same as the one in the previous tables and described in Section 4, includes also the dummy of forced sales. Additional results are available upon request. Monthly data between July 2003 and June 2018.*

Placebo results **Dep. Variable: Δ Liquidity** $_{end\,of\,month\,t-1 \rightarrow end\,of\,month\,t}$				
	Linear probability model			
	OLS		Panel estimator	
Fixed effects:	-	Fund F.E.	Fund and month F.E.	Fund-year F.E.
	(1)	(2)	(3)	(4)
Forced sales (% of portfolio$_{j,t}$)	0.0384	0.0387	0.0476*	0.0391
	(0.0244)	(0.0271)	(0.0285)	(0.0275)
N.Obs.	3,509	3,509	3,509	3,509
R^2	0.044	0.036	0.095	0.148

Dep. Variable: Liquidity $_{end\,of\,month\,t}$				
	Linear probability model			
	OLS		Panel estimator	
Fixed effects:	-	Fund F.E.	Fund and month F.E.	Fund-year F.E.
	(1)	(2)	(3)	(4)
Forced sales (% of portfolio$_{j,t}$)	0.0413*	0.0524	0.0618	0.0504
	(0.0219)	(0.0358)	(0.0372)	(0.0301)
N.Obs.	3,509	3,509	3,509	3,509
R^2	0.628	0.347	0.388	0.538

Table 17 *– Notes: this table shows the of the relationship between forced sales and level of liquidity chosen by the fund at the end of financial distress. As a placebo experiment, funds are defined in financial distress if their flows are above the median of the distribution of fund inflows in a given month. In the top panel, the dependent variable is the change in the end-of-month liquidity between $t-1$ and t; in the bottom panel the dependent variable is the end-of-month liquidity in period t. Column (1) contains simple ordinary least squares and logit results; in column (2) we add fund fixed effects; in column (3) we add month fixed effects; in columnn (4) we consider fund-year fixed effects. Robust standard errors in parenthesis. The list of additional controls, which is the same as the one in the previous tables and described in Section 4, includes also the dummy of forced sales. Additional results are available upon request. Monthly data between July 2003 and June 2018.*

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