Similar Investors *

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Abstract

We test the prediction that investors divest from an asset in anticipation of large liquidation costs when their portfolio similarity with other asset holders is high. We provide evidence supporting this hypothesis using detailed data on money market funds that invest in the debt securities of financial institutions. We develop an instrument that exploits variation in portfolio similarity driven by idiosyncratic redemptions from other funds to confirm our results. The effect of portfolio similarity on divestment is stronger for ex-post illiquid securities, for more illiquid and diversified funds, and for actively managed institutional funds.

Keywords: institutional investors, liquidity risk, portfolio similarity, wholesale funding.

JEL Classification: G1, G21

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1 Introduction

Financial intermediaries with similar assets in their portfolios are exposed to correlated losses, which can lead to simultaneous demands for funding liquidity or capital. Assets held by "similar investors" are difficult to liquidate precisely when these investors simultaneously experience losses and require liquidity. The liquidation value of such assets is low because the highest potential buyer is a similar investor who faces the same constraints as the seller (Shleifer and Vishny, 1992). In addition, the investment decisions of similar investors might reflect an ex-ante "fear of fire sales" (Diamond and Rajan, 2011), which could lead to sudden liquidity dry-ups. In this paper, we examine the portfolio allocation decisions of financial intermediaries with varying levels of portfolio similarity. Specifically, we investigate whether investors internalize the risk of incurring large liquidation costs when liquidating assets simultaneously due to correlated liquidity needs. To explore this question, we use a detailed dataset on money market funds (MMFs) that invest in the debt securities of other financial institutions as our empirical laboratory.

Our main contribution is to show that investors internalize the risk of expected future liquidation costs in their investment decisions. The prediction that investors reduce their exposure to an asset in anticipation of large future liquidation costs is not straightforward. For example, in Diamond and Rajan (2011), limited liability induces banks to hold onto illiquid assets despite exposing them to default risk. Our tests derive from the large literature that models the liquidation value of assets endogenously based on the characteristics or constraints faced by industry specialists (Shleifer and Vishny, 1992, 1997; Allen and Gale, 1994; Gromb and Vayanos, 2002; Diamond and Rajan, 2011). In particular, we show the response of investors to changes in liquidation risk that are not related to fundamental characteristics of the asset (Greenwood and Thesmar, 2011), but rather stem from who holds the asset and their portfolio composition. Our

tests are also closely related to the predictions in the model of Wagner (2011), where investors face a "diversity-diversification trade-off" in investment decisions as they balance liquidation costs against the benefits of diversification. A key feature of this model is that joint liquidation costs arise endogenously, and depend on the portfolio similarity of investors holding the asset.

Empirically testing for endogenous liquidation costs poses significant challenges, as it requires the econometrician to observe both the identity of asset holders and the complete composition of their portfolios. To address these challenges, we rely on detailed data on the securities held by U.S. MMFs and develop a measure of portfolio similarity to specifically test for the presence of a "diversity-diversification trade-off" in investors' portfolio allocation decisions. MMFs provide a suitable laboratory for this empirical analysis because they are susceptible to runs (Kacperczyk and Schnabl, 2013; Chernenko and Sunderam, 2014; Schmidt et al., 2016), are not covered by deposit insurance, and may face difficulties in liquidating assets to meet redemptions (Financial Stability Board, 2021). Additionally, MMFs are constrained by regulations that limit the types of assets they can hold, which increases the similarity of their portfolios (Gandhi and Purnanandam, 2023). Importantly, U.S. MMFs can observe the portfolio holdings of other MMFs, thanks to post-crisis regulations requiring the Securities and Exchange Commission (SEC) to collect and publicly disclose these holdings on a monthly basis. Lastly, MMFs play a crucial role in short-term funding markets by investing in repurchase agreements and unsecured debt securities of other financial institutions. Understanding whether MMFs internalize the risk of joint liquidation costs has broader financial stability implications beyond money markets.[1]

We propose several tests and find that MMFs divest from securities when their portfolio

[1] Several interventions and regulatory reforms targeting money market funds during the financial crisis and the Covid19 pandemic attest to the importance of their role in intermediating short-term funding markets for financial stability (Duygan-Bump et al., 2013; Kacperczyk and Schnabl, 2013; Hanson et al., 2015; Li et al., 2021; Baghai et al., 2022). Bouveret et al. (2022) estimate that U.S. and European USD MMFs hold between 30 and 40 percent of U.S. financial commercial papers and negotiable certificates of deposit.

similarity with other holders of the same security is high. However, multiple factors could challenge the interpretation that endogenous liquidation costs explain why funds choose not to roll over securities held by similar funds. To reduce the scope for alternative explanations, we take the following steps. First, to eliminate the possibility that our results are driven by the quality of the security's underlying collateral, we focus on unsecured debt securities such as certificates of deposit and financial commercial papers. Second, we compare several funds investing in the same security issuer at the same time, thereby addressing the alternative explanation that our findings reflect MMFs' concerns about the issuer's fundamental characteristics. Third, we limit our sample to the period from November 2010 to August 2014, a timeframe during which no major regulatory changes in money markets occurred that could influence our results.

The intuition behind our empirical strategy is as follows. Consider the example of three funds, each holding a certificate of deposit issued by the same bank in their portfolio. We measure the portfolio similarity between each pair of funds by calculating the Euclidean distances of their portfolio weights. Consequently, for each fund, we obtain two distances corresponding to the other two funds that also hold the same certificate of deposit. We then average these two distances for each fund, resulting in a unique average portfolio similarity for each MMF.[2]

Our results indicate that the fund most similar to other holders of a security (i.e., with the smallest average distance) is the most likely to divest from the bank issuing that security. A one standard deviation increase in portfolio similarity is associated with a 0.7 percentage point (p.p.) increase in the probability of divestment and a 0.87 p.p. reduction in the fund's exposure the following month.[3] This latter estimate corresponds to an average monthly divestment of $\$1,749$, compared to an unconditional average divestment of \$563 and an average outstanding amount of $\$201,000$.

[2] In addition, the weights used to average the distances depend on the bank's reliance on the other two funds.

[3] We rescale the average distance into a similarity measure that takes the value of 0% for the least similar fund (a fund investing in completely different assets), and 100% for the most similar fund (a fund investing in the exact same portfolio).

The interpretation that funds divest in anticipation of higher liquidation costs is reinforced by the finding that the marginal effect of portfolio similarity on divestment is more pronounced when the fund reports the security as illiquid one month later. In such cases, a one standard deviation increase in portfolio similarity leads to a 24 p.p. rise in the probability of divestment and a 10.6 p.p. decrease in the fund's exposure. Additionally, the response to portfolio similarity varies according to the fund's exposure to liquidity risk. For instance, the marginal effect of portfolio similarity increases with the fund's weighted average life, which is commonly used as a proxy for exposure to credit and liquidity risk. A shorter average life denotes a shorter average maturity of the securities in the fund's portfolio, typically indicating a greater ability for the fund to liquidate its securities quickly.

Our results also suggest the existence of a trade-off between diversity and diversification. Specifically, we find that the impact of portfolio similarity on divestment decreases with portfolio concentration, as measured by the Hirschman-Herfindahl Index (HHI) based on the fund's portfolio weights. Our estimates indicate that the effect of portfolio similarity on divestment disappears when the fund's portfolio HHI reaches 40%. In other words, when a fund's initial diversification is low, the benefits of diversification outweigh concerns about joint liquidation costs. Conversely, when initial diversification is high, investors gain less from additional diversification and instead begin to focus on their exposure to joint liquidation costs.

The results described above are derived from panel regressions on MMFs' exposure-level data, incorporating high-dimensional fixed effects. Specifically, we control for all heterogeneity in observed and unobserved issuer characteristics by including issuer fixed effects interacted with time fixed effects (issuer×time fixed effects), along with other fixed effects and control variables detailed in Section 3. The identification challenges related to a fund's divestment decision are similar to those in standard studies of credit supply. MMFs effectively provide credit to issuers through certificates of deposit or financial commercial papers. Identifying a fund-

ing supply effect requires the assumption that a fund's net liquidity supply shock, driven by changes in portfolio similarity, is orthogonal to the issuer's funding demand (Khwaja and Mian, 2008). In our earlier example, this assumption would be violated if the bank's funding demand systematically decreased as the portfolio similarity of its MMFs increased.

We consider concerns about the endogeneity problem described above, and about reverse causality, in three ways. First, in all tests where the dependent variable represents a fund's divestment from a security issuer, portfolio similarity is calculated based on the "rest of the portfolio"—excluding the specific issuer in question. This approach reduces the likelihood that changes in a specific issuer's funding demand significantly impact the similarity of the rest of the funds' portfolios. Second, we compare the responses of institutional and retail funds, finding that only institutional funds react to portfolio similarity. Assuming that (i) institutional funds are more actively managed, and (ii) institutional and retail prime MMFs do not invest in completely distinct portfolios, these results suggest a credit supply effect driven by the fund's decision to divest from securities held by similar funds. Third, we develop an instrumental variable that exploits the variation in a fund's portfolio similarity caused by idiosyncratic net redemptions at other funds exposed to the same security issuer. This instrument aids in identifying a funding supply effect, provided that redemptions at other funds exposed to the same issuer are not accompanied by a corresponding reduction in the issuer's funding demand. The first-stage estimation results indicate that a fund's portfolio similarity significantly increases when other funds reallocate their portfolios in response to net redemptions. The second-stage results support the interpretation that a fund reduces its exposure to an issuer due to an exogenous increase in portfolio similarity.

We conduct several additional tests to address concerns about potential confounds at the fund or fund-issuer level that could explain our results. In particular, we show that the effect of portfolio similarity on divestment is not driven by correlated investor redemptions and

subscriptions across funds exposed to the same issuer. Our baseline results hold at the fund complex level and are not driven by bank-affiliated funds. Including fund×time fixed effects or fund×issuer fixed effects does not qualitatively alter our findings. Moreover, we observe that the effect of portfolio similarity disappears when the security is secured by high-quality collateral, such as government agency or treasury repurchase agreements. This aligns with the prediction that joint liquidation costs are less of a concern when the security is backed by high-quality, liquid collateral. Additionally, our empirical strategy assumes that MMFs observe the portfolios of other MMFs at the end of the month and can respond as early as the following month. However, during our sample period, MMF exposures were disclosed by the SEC with a delay of at least two months. To account for this, we reproduce our tests, allowing for longer delays between the measurement of portfolio similarity and the divestment outcome. We find that our baseline results, which assume a one-month delay in the portfolio allocation response, are more conservative than the results that account for a three- or four-month delay—timing that is more consistent with the actual disclosure practices for MMF exposures during our sample period.

Importantly, funds' portfolio allocation decisions based on similarity have implications for an issuer's funding fragility. We show that the average similarity of funds exposed to a financial firm predicts correlated divestments, leading multiple funds to reduce their exposure to the firm at the same time. This finding is consistent with Girardi et al. (2021), who document that portfolio similarity among insurers predicts common sales. We further find that average similarity predicts the percentage change in the principal amount lent by U.S. MMFs to the firm. These findings align with the increased credit risk observed at financial firms with highly concentrated liabilities (Manconi et al., 2016; Doerr, 2024). Even after controlling for other concentration measures in a firm's liabilities, such as the firm's HHI and the number of funds the firm borrows from, the similarity of its funding sources still contributes to concentration risk.

Notably, we do not observe the same results for non-financial firms, suggesting that concentration risk in liabilities is primarily a concern for lenders to financial institutions.

Finally, we show that the consequences of similarity extend beyond investor flows to affect security pricing: during periods of systemic financial stress, issuers borrowing from more similar investors face significantly higher yields. After controlling for a standard measure of price pressure induced by investor flows (Edmans et al., 2012), a one standard deviation increase in portfolio similarity is associated with a 1.4 to 1.6 basis point increase in the cost of funding when systemic risk is high—an effect of non-negligible magnitude relative to average yields in money markets.

Related Literature. Our paper primarily contributes to two strands of literature. First, we add to the literature that identifies common exposures of financial intermediaries as a channel for propagating and amplifying shocks (Krishnamurthy, 2010; Allen et al., 2012; Greenwood et al., 2015). Gandhi and Purnanandam (2023) document increased similarity in the banking sector due to post-crisis regulatory constraints. The concerns about fire sales are, however, not specific to the banking sector and extend to assets held by non-bank financial intermediaries (Coval and Stafford, 2007; Ellul et al., 2011). For example, Falato et al. (2021) present evidence of fire sale spillover effects among fixed-income mutual funds holding the same asset. Girardi et al. (2021) find that insurers with greater portfolio similarity engage in larger common sales following a negative shock to their balance sheets, impacting asset prices. Relatedly, Chaderina et al. (2022) find that bonds which are liquid and commonly held by insurers experience the largest price declines during fire sales, since many insurers choose to sell the same securities. We instead study the divestment decision for a specific asset, showing that a fund is more likely to sell securities co-held by similar peers. In other words, portfolio similarity determines which asset a fund chooses to liquidate, because this asset carries higher endogenous liquidation costs. This channel reflects anticipatory behavior outside periods of stress and links

directly to the diversity–diversification trade-off in Wagner (2011).

Our paper aligns closely with the literature that provides empirical evidence of investors internalizing the negative spillovers of their portfolio allocation decisions. For example, Chernenko and Sunderam (2020) show that equity funds use their cash buffers to avoid fire sales, particularly when multiple funds are managed by the same fund manager or advised by the same investment adviser, interpreting this behavior as funds internalizing the negative price impact on others. Similarly, Favara and Giannetti (2017), Giannetti and Saidi (2019), and Giannetti and Jotikasthira (2024) document that lenders internalize fire sale externalities when they hold a large market share of a borrower's debt. Specifically, Giannetti and Jotikasthira (2024) show that mutual funds are less likely to sell their holdings of a bond when they hold a large share of the bond issue, anticipating the potential negative price impact of their sale. In our paper, the anticipation of large liquidation costs does not result from a fund holding a large market share of an issuer's debt or from relationships with other funds. Instead, it arises from the similarity of its portfolio with other funds holding the same debt security.

This economic mechanism, described in Wagner (2011), is also explored in the larger mortgage market by Bongaerts et al. (2021), who utilize the measure of portfolio similarity developed in this paper. However, mortgage credit data typically do not allow for full control of a borrower's fundamental risk, as households rarely borrow from multiple lenders. Within the MMF laboratory, we can instead disentangle fundamental risk from endogenous liquidity risk (Greenwood and Thesmar, 2011; Manconi et al., 2012) by comparing the differential responses of several holders of the same security at the same time.

Second, we contribute to the literature that studies frictions in the shadow banking system, and to the policy debate surrounding the regulation of shadow banks (Gorton and Metrick, 2010; Hanson et al., 2015; Bouveret et al., 2022). MMFs offer investors alternatives to bank deposits, but they also have incentives to take risks and are vulnerable to runs (Kacperczyk and

Schnabl, 2013). Large international banks heavily rely on their relationships with U.S. MMFs for U.S. dollar funding, meaning disruptions in money markets can create spillovers that extend beyond local shocks and short-term funding markets (Chernenko and Sunderam, 2014; Aldasoro et al., 2022).[4] Our results align with the studies documenting differences between institutional and retail MMFs, with institutional investors being more sophisticated and more responsive to information about a fund's credit and liquidity risk compared to retail investors (Gallagher et al., 2020; Cipriani and La Spada, 2024). This disciplining effect of institutional investors leads to more active management, consistent with our finding of a differential response of institutional funds to portfolio similarity. We also relate to the conclusions of the Financial Stability Board (2021) and Bouveret and Danielli (2021), who highlight MMFs' portfolio similarity in certain securities and their significant presence in money markets as key challenges for liquidity, potentially hampering the simultaneous sale of these securities. We provide empirical evidence that institutional prime MMFs internalize this risk for their holdings of unsecured debt securities and respond by divesting from securities held by MMFs with similar portfolios.

2 Conceptual Framework and Data

In Section 2.1, we expose the theoretical framework that guides our predictions and empirical tests. We then formally define the measure of portfolio similarity in Section 2.2. Finally, we describe the data and sample on money market funds' holdings of securities, and present descriptive statistics in Section 2.3.

[4] Regulatory reforms have sought to mitigate risk-taking and run vulnerabilities in the MMF industry. In particular, several studies examine the impact of the 2014 reform, which introduced redemption gates and liquidity fees to reduce the incentives for prime MMF investors to run (Cipriani and La Spada, 2018; Li et al., 2021; Baghai et al., 2022).

2.1 Conceptual Framework

Classical portfolio theories predict that investors hold identical portfolios to fully exploit the benefits of diversification. However, full portfolio diversification may become suboptimal when frictions affect liquidation costs. Our analysis builds on the literature that models the liquidation value of assets endogenously based on the characteristics or constraints faced by industry specialists, such as financial intermediaries (Shleifer and Vishny, 1992, 1997; Allen and Gale, 1994; Gromb and Vayanos, 2002; Diamond and Rajan, 2011). Similar to Greenwood and Thesmar (2011), we consider cases where assets are subject to non-fundamental shifts in demand, for example, due to concentrated ownership or correlated shocks faced by asset holders. This paper focuses on non-fundamental risk stemming from the ex-ante portfolio composition of investors holding an asset.

Specifically, we investigate the portfolio allocation of financial intermediaries managing assets subject to endogenous liquidation costs. Our empirical results support the existence of a *demand for diversity* among investors, consistent with the predictions of Wagner (2011). In his model, the demand for diversity arises from the risk of systemic joint liquidation costs, which influences investors' ex-ante portfolio choices. Liquidation costs are systemic because they are disproportionately higher when multiple investors liquidate an asset simultaneously, compared to the costs incurred by an individual investor liquidating in isolation. This friction makes full portfolio diversification suboptimal. Under full portfolio diversification, investors would hold identical portfolios, exposing them to common shocks, correlated liquidity demands, and ultimately, joint liquidation costs. To mitigate this risk, investors prefer to hold different portfolios to distinguish themselves from one another. Thus, investors face a trade-off between the benefits of holding *diversified* portfolios and holding *diverse* portfolios.

We test for the presence of a diversity-diversification trade-off using data on money mar-

ket funds (MMFs). Money markets provide an interesting laboratory for this empirical analysis since they are susceptible to runs, are not protected by deposit insurance, and might face difficulties to liquidate assets quickly.[5] Additionally, while the mandate of MMFs is to invest in "money-like assets," they are also constrained by regulation to invest in a limited pool of highly-rated issuers. Importantly, U.S. MMFs can observe the portfolio holdings of other MMFs, thanks to regulatory changes in 2010 requiring the SEC to collect and publicly disclose these holdings on a monthly basis.

2.2 Measuring Portfolio Similarity

We introduce a measure of portfolio similarity that fully exploits the granular information about funds' security holdings. This measure captures the similarity of a fund's portfolio with the portfolios of other funds exposed to the same asset.

The portfolio similarity measure is based on a weighted average of Euclidean distances of fund f's portfolio to the portfolios of other funds investing in security issuer i at time t:

$$Distance_{fit} = \sum_{\varphi \neq f} w_{\varphi it} d_{f\varphi t} = \sum_{\varphi \neq f} w_{\varphi it} \sqrt{\sum_{j=1, j\neq i}^{J} \left(\frac{Amount_{fjt}}{FundSize_{ft}} - \frac{Amount_{\varphi jt}}{FundSize_{\varphi t}} \right)^2}, \quad (1)$$

where J is the total number of securities in a fund's portfolio at time t, $Amount_{fjt}$ is the outstanding amount invested by fund f in issuer j at time t, and the fund sub-portfolio size is $FundSize_{ft} = \sum_{j=1, j\neq i}^{J} Amount_{fjt}$, leaving issuer i out of this sub-portfolio to avoid reverse causality concerns in our empirical strategy.

The measure in equation (1) can be decomposed into two elements: (i) a distance de-

[5] During the European sovereign debt crisis, MMFs reduced their unsecured exposure to euro area issuers following massive withdrawals by investors concerned about elevated risks in the region (Chernenko and Sunderam, 2014).

scribing the similarity in portfolio holdings between fund f and another fund φ, denoted $d_{f\varphi t}$ (pairwise Euclidean distance); and (ii) a weighting function denoted $w_{\varphi it}$ that aggregates the pairwise fund distances into an average distance for fund f. The weight attributed to the pairwise distance between fund f and the *other* fund φ is based on fund φ's share of issuer i's outstanding amount relative to all other funds investing in i.

$$w_{\varphi it} := \frac{Amount_{\varphi it}}{\sum_{\varphi \neq f} Amount_{\varphi it}} \in [0,1],$$

where $\sum_{\varphi \neq f} Amount_{\varphi it}$ is the amount issuer i borrows from other funds (except f) at time t. Intuitively, if fund φ does not hold any security of issuer i (i.e., $Amount_{\varphi it} = 0$), it cannot divest from that issuer and thus its weight will be zero ($w_{\varphi it} = 0$). In contrast, if the securities of issuer i are held exclusively by fund f and fund φ, then $w_{\varphi it} = 1$, i.e., only the portfolio similarity between funds φ and f matters.

To ease interpretation, we rescale the distance in equation (1) as a similarity measure that takes the value of zero if all other funds investing in issuer i have no portfolio overlap with fund f, and 100% if the other funds investing in issuer i have the exact same portfolio holdings as fund f. The similarity of fund f to other funds investing in security issuer i at time t is:

$$Similarity_{fit} = 100 \times \left(1 - \frac{1}{\sqrt{2}} Distance_{fit}\right) \in [0,100], \tag{2}$$

In our empirical tests, we compare the similarity of one fund to the similarity of other funds in a given security issuer i. This comparison restricts our sample to issuers that borrow from at least three funds. In Section C.1 in the Appendix, we provide an illustrative example to build intuition for the similarity measure presented in this section.

2.3 Data and Descriptive Statistics

Our main data source is the regulatory N-MFP forms which cover monthly information about U.S. MMFs' exposures collected by the SEC and are available from iMoneyNet. Following the global financial crisis, the SEC approved changes to Rule 2a-7 of the Investment Company Act of 1940 in 2010 to strengthen the regulatory framework of MMFs. The SEC regulation requires U.S. MMFs to report monthly mark-to-market net asset value (NAV) per share of their portfolios on Form N-MFP, which is then published by the SEC. We collect the principal amounts, maturities, and yields of 14,876 securities held by U.S. MMFs (including certificates of deposit, repurchase agreements, and financial commercial papers) from November 2010 until August 2014. Since regulatory data in N-MFP forms are self-reported, a manual consolidation procedure of the 14,876 securities was necessary. This resulted in a total of 311 individual security issuers, of which 213 are financial institutions (as reported in Panel A of Table SI-1 in the Appendix).

We focus our analysis on *unsecured* securities held by MMFs—namely, certificates of deposit and financial commercial papers—avoid considerations related to the quality of a security's collateral. We note that 85% of the amount U.S. MMFs invest is composed of unsecured investments on average (Panel B of Table SI-1 in the Appendix). Confining our research to unsecured funding centers our analysis on prime MMFs as opposed to government MMFs. We additionally require that issuers borrow from at least two funds in the same month to derive a measure of similarity between the funds exposed to the same issuer at the same time,[6] and report descriptive statistics for this sample of issuers in Panel A of Table 1. The sample comprises 171 issuers. Among those, 115 are financial institutions, 87 are banks, and 26 banks are located in the euro area. The weighted average portfolio similarity of the funds lending to an issuer ($Similarity_{it}$) is 84%, with a standard deviation of 8%. The average principal amount invested

[6] Comparing with the descriptive statistics reported in Panel B of Table SI-1, the restriction to borrow simultaneously from two MMFs selects issuers with more diversified MMF liabilities, and issuers borrowing larger principal amounts with shorter average maturities.

in an issuer ($Amount_{it}$) is \$7.2 million. The percentage change in the principal amount borrowed by an issuer ($\Delta Outstanding_{it}$) is 0.33%, and the fraction of funds divesting from an issuer in a month ($CorrOutflows_{it}$) is 23% on average. The average yield of debt securities is 27 basis points, and the average maturity is 46 days. Issuers tend to diversify their liabilities: they borrow from 40 funds on average, among which 32 lend unsecured, and the average Hirschman-Herfindahl index (HHI) measured on MMF liabilities of issuers is 28%.

[INSERT TABLE 1 HERE]

Figure 1 illustrates the exposure of issuers to similar funds, and the relationship between funds' portfolio similarity and issuers' access to money market unsecured funds. In Panel A, we project the unsecured principal amounts lent by similar MMFs on the vertical axis and by non-similar MMFs on the horizontal axis for each issuer-month observation. We refer to a fund as "similar" for a given issuer in a given month, if its portfolio similarity is larger than the median similarity of all funds lending to the issuer in the same month. The 45 degree line indicates the case of an issuer borrowing simultaneously the exact same amounts from similar and non-similar funds. We observe that the cloud of issuer-month observations largely departs from the 45 degree line in the direction of a larger exposure to similar funds. For example, for the issuers borrowing the largest amounts, their exposure to similar funds is close to \$50 million, while they only borrow \$10 to \$15 million from non-similar funds at the same time. This figure therefore illustrates the reliance of issuers of MMF securities on funds that hold similar portfolios. A reliance on similar funds that is five times larger for the largest issuers.

[INSERT FIGURE 1 HERE]

Panel B of Figure 1 illustrates the relationship between portfolio similarity and fund divestment. The figure shows the relationship between monthly percentage change in the invest-

ments from MMFs (y-axis) and the average fund similarity of an issuer in the previous month (x-axis), for a sample restricted to issuers borrowing unsecured from at least 90 MMFs (corresponding to the 90th percentile of the distribution), and with a HHI below 5% (corresponding to the 10th percentile of the distribution). For these "diversified" issuers, standard measures of concentration might give the illusion of a diversified liability base. However, if the portfolios of the funds lending to the issuer are the same, it is as if the issuer were borrowing from the same fund. Portfolio similarity would undo the benefits of diversification obtained by borrowing from multiple funds. The diversified issuers in our sample are all financial institutions, and a simple regression analysis corresponding to the regression line in the figure indicates that fund flows in an issuer are 2 p.p. lower for a one p.p. increase in the portfolio similarity of its MMFs.

In Panel B of Table 1, we report descriptive statistics at the security level. We restrict the sample to issuers that borrow from at least *three* distinct U.S. MMFs at the same time. This sample corresponds to the requirements of our empirical strategy for our regressions at the fund-issuer-month level, and this selection criterion has almost no effect on reported descriptive statistics.[7] As a result, we report the descriptive statistics for a sample of securities of 144 issuers. The similarity of a fund to the other funds investing in the same issuer is 82% on average, with a standard deviation of 6.2%. The average principal amount is \$201,000, and the average monthly percentage change in the exposure of a fund to an issuer ($\Delta Exposure_{fit}$) is -0.28%. The probability of a fund to divest by not renewing or liquidating some financial commercial papers or certificates of deposit of an issuer ($Divest_{fit}$) is 0.24. The average yield of a security is 29 basis points, and the average maturity is 50 days.

[7] In Table SI-2 (Panel A) in the Appendix, we examine the effect of this selection criterion on descriptive statistics. While the sample increases to 297 issuers, removing the criterion that issuers should borrow simultaneously from three funds barely affects descriptive statistics at the security level. The average principal amount is \$198,000, the percentage change in the unsecured principal amount borrowed by an issuer is -0.28%, the average outflow probability is 0.24, the average yield is 29 basis points, the average maturity is 51 days, and the average similarity is 82%. In addition, Panel B of Table SI-2 reports descriptive statistics for the whole sample of securities, including secured ones.

In Panel C of Table 1, we report descriptive statistics on the characteristics of MMFs. The table shows statistics for institutional and retail funds separately, and for similar and non-similar funds. We find that similarity is slightly higher for the portfolios of institutional funds (79%) than retail funds (76%). Institutional funds also tend to be more diversified than retail ones, but the difference is more pronounced between similar and non-similar funds. Similar funds have the lowest HHI (8%) and lend to more issuers, compared to non-similar funds (HHI of 17%). Institutional funds are larger than retail funds, and the difference in size is also more pronounced between similar and non-similar funds. Therefore, size and diversification of a fund will be important fund-level confounding variables to account for as we highlight the effect of portfolio similarity.[8] In addition, institutional funds outperform retail ones based on the 7-day simple yield, which is a SEC-approved-yield that describes the annualized income that the fund investors earned over the last seven days. Institutional funds also experience more net redemptions than retail funds, but there is no significant difference in the net redemptions of similar and non-similar funds.

In our analysis, we employ three measures of the fund's sensitivity to liquidity risk. Descriptive statistics of these measures are also reported in Panel C of Table 1. The first two measures—the weighted average life (WAL) and the weighted average maturity (WAM) of a fund—capture a dollar-weighted average maturity of the securities of the fund's portfolio. However, while the final maturity is the date at which the security expires for the WAL, the WAM also uses the interest rate resets for floating-rate securities as the final maturity of a security. Therefore, the WAM is generally smaller than the WAL (due to the interest rate resets before a security expires).[9] Importantly, while the WAM is usually interpreted as a measure of sensitivity to in-

[8] In the Appendix, Table SI-4 further investigates what explains the variation in the fund similarity measure. We find a strong inverse relationship between portfolio similarity and the fund's portfolio concentration. Similar funds are diversified and large. Similarity also increases with the average maturity of the securities. Furthermore, there are quadratic effects that explain the variation in fund similarity; in particular, while similarity increases with fund size and diversification, similarity starts decreasing for very large diversified funds.

[9] The SEC limits the WAM and the WAL for money market mutual funds to 60 and 120 days, respectively.

terest rate changes, the WAL is considered to reflect the fund's sensitivity to changes in liquidity and/or credit risk. A third measure of the fund sensitivity to liquidity risk is the euro area exposure of the fund in June 2011, given that funds exposed to the euro area experienced significant net redemptions from their investors in the summer of 2011 (Chernenko and Sunderam, 2014). While the difference between institutional and retail funds is minimal for all three measures, we observe a higher sensitivity of similar funds to liquidity risk. Indeed, the average WAL is longer for similar funds (63 days) than non-similar funds (56 days), and similar funds are on average more exposed to euro area issuers in June 2011 (20%) than non-similar funds (16%).

3 Funds' Portfolio Allocation Response to Portfolio Similarity

We present our empirical strategy to assess the response of funds to portfolio similarity in Section 3.1, and report the baseline results in Section 3.2. We provide empirical evidence in line with our interpretation of funds' divestments related to their exposure to joint liquidation costs in Section 3.3. In Section 3.4, we show the contrasting response of institutional and retail funds to portfolio similarity. We discuss the trade-off between portfolio diversity and portfolio diversification in Section 3.5. We provide robustness tests and additional analyses in Section 3.6.

3.1 Empirical Strategy

We assess the portfolio allocation decisions of funds related to portfolio similarity by estimating the following specification using fund-issuer-month level data:

$$y_{fit} = \alpha_{it} + \alpha_f + \beta Similarity_{fit-1} + \delta Controls + \varepsilon_{fit} \quad (3)$$

where $Similarity_{fit}$ is the similarity of fund f to the other funds investing in issuer i at time t, and y_{fit} is (i) the percentage change in the exposure of fund f to security issuer i at time t ($\Delta Exposure_{fit}$); or (ii) the probability that fund f reduces its exposure to security issuer i at time t ($Divest_{fit}$).[10] We also include issuer×time fixed effects (α_{it}), fund fixed effects (α_f), and control variables for the average characteristics of the securities of issuer i held by fund f at time t (e.g., maturity, yield), and fund characteristics such as the size and portfolio diversification (measured by the HHI) in the previous month.

Testing the prediction that portfolio similarity predicts funds' portfolio allocation decisions requires us to address three main empirical challenges: (i) the dependent variables describe an equilibrium outcome, and investors' funding supply shocks might be correlated with issuers' funding demands, which calls for the identification of funding outflows that are the result of funds' decisions to divest, and not the result of issuers' heterogeneous funding demands; (ii) reverse causality is likely a concern given the construction of the similarity measure based on previous exposures; and (iii) funds make investment decisions on the basis of issuer fundamental risk, such that an additional identification challenge comes from the potential correlation between fundamental risk and security illiquidity.

Our empirical strategy examines changes in the funding supply of several funds investing in the same issuer in a given month, where the funds differ in their degree of similarity to other funds exposed to the same issuer. We absorb all the heterogeneity in fund flows coming from observed and unobserved issuer characteristics by including issuer fixed effects interacted with year-month fixed effects in our regressions. To have heterogeneity in funds' similarity within an issuer at time t, we restrict the sample of issuers to those borrowing unsecured from at least

[10] More precisely, $Divest_{fit}$ is an indicator variable equal to one if a fund f had a non-zero exposure in issuer i at time $t-1$ and reduced the exposure to issuer i at time t, and equal to zero otherwise. $\Delta Exposure_{fit}$ is the percentage change in the security exposure of fund f to issuer i between time $t-1$ and time t given by $\log(Amount_{fit}/Amount_{fit-1}) \times 100$, excluding observations outside the $[-100\%, 100\%]$ range. This is akin to Chernenko and Sunderam (2014), who use the percentage change in the average exposure of fund f to issuer i as a dependent variable.

three money market funds in the same month. We study the potential selection bias implied by this restriction in Section 2.3.

For the first empirical challenge, the assumption for the identification of a funding supply effect relies on the fund's net liquidity supply shock due to portfolio similarity being orthogonal to the issuer's funding demand (Khwaja and Mian, 2008). This assumption would fail, for example, if higher portfolio similarity of a fund in an issuer were systematically followed by the issuer's decreasing funding demand from that fund. We address the concern of a correlation between fund's portfolio similarity and the issuer's funding demand in two ways. First, we compare the responses of institutional and retail funds to portfolio similarity in Section 3.4. The literature on MMFs has documented that institutional funds are more actively managed than retail funds (Gallagher et al., 2020; Cipriani and La Spada, 2024). For money market funds, where the pool of available securities is limited, it is reasonable to assume that institutional and retail funds do not invest in totally distinct portfolios. A stronger response of institutional funds to portfolio similarity would therefore indicate that monitoring similarity is part of active management, and not the result of a correlation between funding supply and demand shocks. Second, we develop an instrumental variable that exploits variation in portfolio similarity of a fund that comes from the idiosyncratic redemptions of the investors of other funds in Section 3.6.1. The instrument should help with the identification of a supply effect as long as the idiosyncratic redemptions of other funds investing in issuer i are not followed by a decreasing funding demand of issuer i.

The reverse causality concern is partly addressed by the exclusion of issuer i from the portfolios of funds investing in issuer i in the definition of portfolio similarity of equation (2). However, the portfolio allocation in other issuers is likely to be correlated with the decision to invest in issuer i. It is possible that the decision of fund f to roll over funding to issuer i affects portfolio similarity at time t and given the persistence in portfolio similarity, it would correlate

with portfolio similarity at time $t-1$. The instrumental variable approach that we adopt in Section 3.6.1 should address this concern as it focuses on variation in portfolio similarity resulting from idiosyncratic redemptions at *other* funds.

Finally, the third empirical challenge comes both from an omitted variable problem and a measurement error problem. To address the omitted variable bias concern, we rely on different sets of fixed effects and control variables. In particular, the inclusion of issuer×time fixed effects absorbs all heterogeneity in issuer characteristics including issuer fundamental risk that could explain our results. We also corroborate our interpretation of $Similarity_{fit}$ as an indicator of a fund's ex-ante exposure to systemic joint liquidation costs using measures of funds' exposure to liquidity risk and an ex-post indicator of illiquid securities in Section 3.3.

This empirical strategy also entails the assumption that the fund can observe other funds' investments one month after reporting. We carefully examine the validity and consequences of this assumption in Section 3.6.2, replicating our tests while allowing for longer time lags between the portfolio similarity measure and the dependent variable.

3.2 Baseline Results

Table 2 presents the results corresponding to the empirical specification of of equation (3), where we compare several funds investing in the same issuer in the same month, controlling for security and fund characteristics.[11]

[11] Out of 668,008 security-level observations, we drop secured debt securities (leaving 493,166 remaining observations), we aggregate observations at the fund-issuer-month level (360,141 observations), and drop observations of issuers that borrow from fewer than three funds (305,129 remaining observations). The analysis of $Divest$ requires funds to have a non-zero exposure to an issuer at time $t-1$. The analysis of $\Delta Exposure$ requires funds to have a non-zero exposure at time t and $t-1$. Out of these 305,129 observations, we have 130,973 non-missing observations for $Divest$ and 108,682 non-missing values for $\Delta Exposure$. Additional observations are dropped in the regressions when observations for the lagged similarity measure or for the control variables are missing.

[INSERT TABLE 2 HERE]

Columns (1) to (4) report the results for the divestment probability ($Divest$) as the dependent variable. In Columns (5) to (8), the dependent variable is the percentage change of a fund's exposure to an issuer ($\Delta Exposure$). Columns (1) and (5) report the results of our baseline specification. Columns (2) and (6) document the effect of fund similarity, while excluding control variables (i.e., fund size and average yield and maturity of securities) from the regression to assess the stability of our parameter estimates (Altonji et al., 2005; Oster, 2019). Columns (3) and (7) include issuer×fund fixed effects to exploit the funding supply variation within the same fund-issuer pair over time, controlling for observable and unobservable time-invariant fund-issuer pair characteristics (such as relationship or geographical distance between a fund and an issuer). Lastly, Columns (4) and (8) exclude from the sample observations for which the average maturity is less than 30 days to mitigate concerns that the effect of fund similarity is only due to concurrently expiring securities.

In Column (1), the coefficient associated with the fund's portfolio similarity of 0.11 implies a 0.7 p.p. increase in the probability that a fund reduces its exposure ($Divest$), corresponding to a one standard deviation increase in portfolio similarity. The estimate remains unchanged without control variables (Column (2)), while the R^2 drops from 21% to 13%, emphasizing the stability of our parameter estimates. Our estimate stays stable after including fund×issuer fixed effects (Column (3)), and increases to 3.2 p.p. on a sample restricted to fund-issuer-month observations for which the average security expires in more than a month (Column (4)).

The coefficient of −0.14 in Column (5) implies a reduction of −0.87 p.p. in the fund's exposure ($\Delta Exposure$) associated with a one standard deviation increase in $Similarity$. The estimate translates into an additional average monthly divestment of $1,749, relative to an unconditional average divestment of $ − 563, and to an average exposure of $201,000. Among

the funds investing in the same issuer, a fund that is one standard deviation more similar reduces its exposure to the issuer by an additional 0.87 p.p. The estimate remains stable in the absence of control variables in Column (6). The effect is −1.4 p.p. in Column (7) after including fund×issuer fixed effects, and of similar magnitude (−0.68 p.p.) when we restrict to observations with an average remaining maturity of more than a month (Column (8)). All the estimates obtained for the effect of fund similarity on $\Delta Exposure$ in Table 2 are significant at the 5% level.

3.3 Portfolio Similarity and Ex-Post Illiquidity

In this section, we connect our interpretation of portfolio similarity as exposure to joint liquidation costs to ex-post illiquidity. While portfolio similarity might reflect a fund's ex-ante concerns about joint liquidation costs associated with a security issuer, higher similarity does not necessarily imply that liquidation costs will be realized ex post. However, as an ex-ante measure of a fund's exposure to joint liquidation costs, we expect portfolio similarity to be a better predictor of fund divestment in an issuer when the security becomes illiquid ex post. This result would suggest that similar funds divest in expectation of the security becoming illiquid.

We exploit additional information available from the regulatory reporting of MMFs in the N-MFP forms, and, in particular, the fact that funds report illiquid securities according to the SEC definition.[12] In Panel A of Table 3, we report the differential effect of portfolio similarity on divestment when a fund f reports at least one security issued by issuer i as illiquid at time t (in Columns (1) and (3)), and at time $t+1$ (in Columns (2) and (4)). Therefore, in Columns (1) and (3), a fund divests from an issuer in month t while the fund reports the issuer's securities as illiquid, based on information about portfolio similarity available at the end of the previous month ($t-1$). In Columns (2) and (4), a fund divests from an issuer in month t in anticipation

[12] A security is considered illiquid if it "cannot be sold or disposed of in the ordinary course of business within seven calendar days at approximately the value ascribed to it by the fund" (Rule 2a-7, see 17 CFR 270.2a-7(a)(18)).

of the issuer's securities becoming illiquid the next month $(t+1)$, and based on information about portfolio similarity from the previous month $(t-1)$. The dependent variable is $Divest$ in Columns (1) and (2), and $\Delta Exposure$ in Columns (3) and (4).

[INSERT TABLE 3 HERE]

The coefficient of 3.74 associated with $Similarity_{fit-1} \times IlliquidSec_{fit}$ reported in Column (1) implies that the probability of divestment increases by 24 p.p. when the fund reports illiquid securities from issuer i at time t, with a one standard deviation increase in portfolio similarity. This contrasts with the 0.7 p.p. effect of a standard deviation increase in portfolio similarity (0.11 coefficient of $Similarity_{fit-1}$ in Column (1)) for funds that do not report any illiquid securities from issuer i. Similarly, the coefficient of -1.58 in Column (3) translates into additional similarity-associated divestments of 10.6 p.p. when a fund reports illiquid securities from issuer i, compared to similarity-associated divestments of 0.8 p.p. in the baseline case. The results suggest that the similarity of portfolio holdings in the previous month $(t-1)$ predicts larger divestments when securities become illiquid the next month (t).[13] We obtain similar results in Columns (2) and (4), where we assess similarity-associated divestments in anticipation of the issuer's securities becoming illiquid the next month $(t+1)$. The results are qualitatively similar, albeit smaller in economic magnitude, suggesting that the funds also reduce their exposure to an issuer in anticipation of future liquidation costs.

In Panel B of Table 3, we study the heterogeneous response of funds to similarity depending on the sensitivity of their portfolios to liquidity risk. We measure the exposure to liquidity risk of a fund using its weighted average life (WAL), its weighted average maturity (WAM), and

[13] Interestingly, the coefficient of -3.12 associated with $IlliquidSec_{fit}$ in Column (1) captures the effect of reporting illiquid securities on the probability of divestment for a non-similar fund. Even if the fund reports a security of issuer i as illiquid at time t, the fund is less likely to divest from the issuer as the perceived risk of joint liquidation costs is lower for a fund holding a diverse portfolio. Note, however, that the number of events where a fund reports securities of an issuer as illiquid is small (346), representing about 0.1% of observations in the sample.

its euro area exposure in June 2011. The results reported in Panel B of Table 3 are consistent with a stronger response to portfolio similarity by funds sensitive to liquidity risk. The coefficient of 0.35 in Column (1) implies that the marginal effect of portfolio similarity on $Divest$ increases by 2.2 p.p. for each additional day of weighted average life of the fund's portfolio (restricted by the SEC to a maximum of 120 days). In Column (2) the coefficient 0.49 implies an increase of the marginal effect of similarity of 3 p.p. for each additional day of weighted average maturity (restricted by the SEC to a maximum of 60 days). In Columns (4) and (5) we show similar heterogeneous effects for the dependent variable $\Delta Exposure$, although the marginal effect of portfolio similarity does not change significantly with the weighted average maturity of the fund. In general, the coefficients associated with $Similarity_{fit-1} \times WAM_{ft-1}$ are less significant than the coefficients associated with $Similarity_{fit-1} \times WAL_{ft-1}$,[14] suggesting that the effect of portfolio similarity depends more on the weighted average life than on the weighted average maturity of the fund's portfolio. In other words, concerns about future joint liquidation costs depend on the fund's ability to liquidate other securities of its portfolio quickly, rather than on the sensitivity of the portfolio securities to interest rate changes.

Finally, in Column (3), we consider the exposure of a fund to euro area issuers as of June 2011 ($EurExp_f$) as an alternative measure of the fund's exposure to liquidity risk. All the euro area issuers in our sample are financial institutions, and severe disruptions in money markets were documented during the European sovereign debt crisis (Chernenko and Sunderam, 2014; Gallagher et al., 2020). U.S. MMFs cut their unsecured exposure to euro area banks drastically in the summer of 2011, following massive withdrawals by their investors concerned about euro area risks, which in turn also impacted short-term funding of non-euro area issuers. The co-

[14] Note that the coefficients associated with $Similarity_{fit-1}$ (first line of Table 3) represent the marginal effect of portfolio similarity for a fund with zero average life in Columns (1) and (4), and for a fund with zero average maturity in Columns (3) and (5). Similarly, the coefficients associated with WAL_{ft-1} and WAM_{ft-1}), respectively, describe the marginal effect of an additional day of weighted average life and maturity of the fund's portfolio on $Divest$ in Columns (1) and (2), and $\Delta Exposure$ in Columns (4) and (5) for a diverse fund (i.e., a fund with zero portfolio similarity with the other funds investing in the issuer).

efficient of 0.57 associated with $Similarity_{fit-1} \times EurExp_f$ implies that the effect of a one standard deviation increase in portfolio similarity on $Divest$ is 1.4 p.p. for euro area-exposed funds, while the effect is −2.3 p.p. for funds that were not exposed to euro area issuers. We find similar results for $\Delta Exposure$ in Column (6), where a one standard deviation increase in similarity is associated with 1.1 p.p. divestment the following month for euro area-exposed funds only, while the effect of portfolio similarity is not significant for non-exposed funds.

Panel A of Figure 2 illustrates the massive reduction of U.S. MMFs' unsecured investments in euro area banks (about $200 billion) between June 2011 and December 2011. The figure presents the unsecured principal amounts invested in euro area (dashed line) versus non-euro area financial institutions (solid line).[15] In Panel B, we keep the dashed line of Panel A, corresponding to unsecured principal amounts at euro area financial institutions, and use this line as an indicator of the severity of the European sovereign debt crisis for our sample period. In addition, the solid line in Panel B represents the differential 7-day simple yield (in basis points) of similar funds relative to non-similar funds. Consistent with a risk-return trade-off, MMFs should offer higher yields when their portfolios are riskier, and, as long as MMFs do not default on their repayments to their investors, a positive differential yield reflects riskier securities held by similar MMFs on average compared to those held by non-similar MMFs. The figure shows that this differential yield increased in the summer of 2011, indicating a higher risk associated with similar funds over this period.

[INSERT FIGURE 2 HERE]

Overall, the results of Table 3 suggest that divestments associated with portfolio similarity are related to (i) securities becoming illiquid ex post, and (ii) the fund's portfolio exposure to liquidity risk. In addition, portfolio similarity explains divestments of euro area-exposed funds,

[15] Figure 4, in the Appendix, shows a breakdown of unsecured funding to euro area financial institutions from similar and non-similar MMFs. The figure reveals that most MMFs exposed to euro area banks were similar funds.

and the risk associated with similar funds increased during the European sovereign debt crisis.

3.4 Portfolio Similarity Response of Institutional versus Retail Funds

This section provides evidence consistent with a negative funding supply effect due to portfolio similarity. In Table 4, we replicate the results of Table 2 on the subsamples of institutional funds (Columns (1) to (4)) and retail funds (Columns (5) to (8)) separately. MMFs report their category on N-MFP forms, indicating whether they classify as institutional or retail funds, depending on the type of investors that constitute the largest fraction of their investor base. Institutional funds are typically more actively managed and held by more sophisticated investors. They are also prone to preemptive runs, where investors may withdraw funds early in anticipation of potential negative events or market downturns (Schmidt et al., 2016; Cipriani and La Spada, 2018). While the effect of portfolio similarity on divestment could be the result of issuers not selling their securities to similar funds, the negative funding demand effect from issuers should not differ depending on whether securities are held by institutional or retail funds. Alternatively, if portfolio similarity only affects the allocation decisions of institutional funds and not of retail funds, it suggests that the similarity-associated outflows are driven by the decisions of institutional funds to divest, rather than a mere lack of new securities being issued by the issuers.

[INSERT TABLE 4 HERE]

Table 4 shows that the marginal effect of portfolio similarity is only statistically significant for institutional funds (Columns (1) to (4)), while it is almost zero for retail funds (Columns (5) to (8)). In addition, compared to Table 2, the economic magnitude of the effect of portfolio similarity almost doubles for institutional funds. In Column (1) of Table 4, the coefficient of 0.21 implies an increase in the divestment probability of 1.3 p.p. for a one standard deviation

higher portfolio similarity. This estimate for institutional funds compares to 0.7 p.p. in Column (1) of Table 2 for the full sample. The −0.23 coefficient in Column (3) implies a divestment of −1.4 p.p. associated with a one-standard deviation increase in similarity compared to −0.87 p.p. estimated for the full sample (in Column (5) of Table 2). Similar differences in economic magnitudes of the effect of similarity are obtained when introducing issuer×fund fixed effects in Column (2) for $Divest$ and Column (4) for $\Delta Exposure$, controlling for specific relationships issuers might have with some MMFs.

Overall, the results of this section suggest that the effect of portfolio similarity on divestment is a supply-side effect, i.e., a decision of the fund to not roll over funding to an issuer exposed to similar funds. In addition, it suggests that the estimates we obtain on the full sample of funds are conservative with respect to the sample of institutional funds that are the economic agents reacting to portfolio similarity and seeking to reduce their exposure to liquidation costs.

3.5 Portfolio Similarity and Portfolio Diversification

In Table 5, we document a differential effect of fund similarity on the decision of the fund to divest depending on the fund's initial portfolio diversification. We augment our baseline specification to include a measure of the fund's overall portfolio concentration (the fund's HHI index, HHI_{ft}), and the fraction of the fund's portfolio invested in issuer i (its portfolio weight, $Weight_{fit}$). We report the coefficients relative to the dependent variable $Divest$ in Panel A, and relative to the dependent variable $\Delta Exposure$ in Panel B. In Columns (1) and (2), we introduce HHI_{ft-1} and $Weight_{fit-1}$ as control variables for the level of diversification of the fund's portfolio to address the concern that the fund's portfolio diversification could confound the effect of the fund's portfolio similarity ($Similarity_{fit-1}$). In Columns (3) and (4), we add an interaction term between similarity and portfolio concentration ($Similarity_{fit-1} \times HHI_{ft-1}$) to

highlight a potential trade-off the fund faces between holding a diverse portfolio and a diversified one. Then, we interact similarity and the fund's portfolio weight in the issuer ($Weight_{fit-1}$) in Columns (5) and (6) to assess to what extent a fund's response to similarity depends on its initial exposure to the issuer.[16]

[INSERT TABLE 5 HERE]

In Columns (1) and (2) of Table 5, we find that funds reduce their exposure to an issuer when portfolio similarity increases, holding constant the level of concentration of the fund's portfolio. Including control variables for the fund's overall portfolio concentration (HHI_{ft-1}), and in particular for the fund's portfolio share in issuer i ($Weight_{fit-1}$), helps us address the concern that the effect of fund similarity is purely driven by fund concentration limits. Indeed, fund's portfolio concentration is regulated, and concentration limits define the maximum exposure of a fund to a single issuer. As a result, funds following similar investment strategies would have to liquidate assets at the same time, not due to their concerns over liquidation costs, but simply because they might reach the concentration limit in an issuer at the same time.

Although the results in Table 5 are consistent with funds limiting their concentrations in single issuers, we find that the effect of fund similarity is not driven by it. If the effect of portfolio similarity was fully subsumed by the effect of concentration limits, the coefficient relative to portfolio similarity in Columns (1) and (2) would not appear statistically significantly different from zero. Instead, both coefficients associated with $Weight_{fit-1}$ and $Similarity_{fit-1}$ are statistically significant at least at the 10% level, suggesting that both channels of joint liquidation costs and concentration limits seem to be at work. Consistent with concentration limits, funds with larger exposures in a single issuer are more likely to reduce their exposure (positive coefficient associated with $Weight_{fit-1}$). Once we control for the fund's concentration

[16] Note that portfolio diversification and portfolio similarity variables are simultaneously measured and lagged by one month to reflect information available to the fund when rolling over funding to an issuer in month t.

in issuer i with $Weight_{fit-1}$, the variable HHI_{ft-1} captures concentration in the rest of the portfolio of the fund (excluding issuer i). A negative coefficient associated with HHI_{ft-1} in Columns (1) and (2) reflects that funds divest more from an issuer when the rest of their portfolio is more diversified. To summarize, divestment in an issuer is more likely when the fund's initial exposure to the issuer is large but the rest of the portfolio of the fund is diversified. Additionally, the marginal effect of fund similarity does not vanish, and is even stronger when we add issuer×fund fixed effects to control for fund-issuer relationships in Column (2). The same conclusions apply for the dependent variable $\Delta Exposure$ in Panel B.

In Columns (3) and (4) of Table 5, we find that the marginal effect of fund similarity on divestment increases with fund diversification, consistent with higher average joint liquidation costs for more diversified portfolios (Wagner, 2011).[17] Column (3) shows that, with a one standard deviation increase in portfolio concentration (a 6.12% increase in HHI_{ft}), the marginal effect of similarity on $Divest$ decreases by 0.06 p.p. (in correspondence to the -0.01 coefficient in Column (3) of Panel A), and the marginal effect of similarity on $\Delta Exposure$ increases by 0.06 p.p. (in correspondence to the 0.01 coefficient in Column (3) of Panel B). The coefficient associated with $Similarity_{fit-1} \times HHI_{ft-1}$ is of similar magnitude in Column (4) where we include issuer×fund fixed effects to control for time-invariant fund-issuer relationships. Consistent with a diversification-diversity trade-off, the estimates imply that the effect of similarity on fund outflows is only present for diversified funds' portfolios. To be precise, the effect of portfolio similarity on $Divest$ and on $\Delta Exposure$ goes to zero for funds with an HHI of 40%.

Consistent with the interpretation of portfolio similarity reflecting concerns over liquidity risk of an asset held in its portfolio, we expect that similarity matters more when the fund's exposure to an issuer is large. We report consistent results in Columns (5) and (6) of Table 5, where we add an interaction term $Similarity_{fit-1} \times Weight_{fit-1}$ to assess the differential ef-

[17] In particular, this result corresponds to Proposition 5 in Wagner (2011), which states that *"More diversified portfolios entail higher average liquidation costs."*

fect of similarity when the fund's portfolio share in an issuer is substantial. Consistent with this hypothesis, we find that the marginal effect of similarity increases with the fund's exposure to an issuer. For each additional one p.p. exposure in an issuer, the marginal effect of similarity increases by 0.017 p.p. on $Divest$ (in Column (5) of Panel A) and by −0.014 p.p. on $\Delta Exposure$ (in Column (5) of Panel B). We obtain similar economic magnitudes when we include fund×issuer fixed effects in Column (6). The results suggest that the response of funds to similarity is concentrated in the large exposures of the fund, for which joint liquidation costs would be sizeable. For example, when the fund's portfolio share in an issuer is about 10% (corresponding to the 90th percentile of $Weight_{fit}$), the divestment probability increases by 1.27 p.p. and the percentage flows by −2.16 p.p. for a one standard deviation increase in portfolio similarity.

Additionally, Appendix Table SI-6 shows that ownership concentration and portfolio similarity represent distinct but reinforcing channels of fragility. Unlike portfolio concentration in Table 5, which measures diversification across a fund's holdings, ownership concentration refers to the share of an issuer's total unsecured funding provided by a given fund. Consistent with Giannetti and Jotikasthira (2024), funds with large positions in an issuer limit their own sales to reduce the exposure and cost of (systemic) joint liquidation, since divesting could trigger large price impacts. At the same time, after controlling for ownership concentration, we find that funds still reduce their exposure to assets co-held by similar funds, as these assets are especially costly to liquidate in the event of joint sales. The interaction terms further suggest that similarity amplifies divestment pressures even for concentrated positions, indicating that both channels can coexist and reinforce each other.

Overall, we find that the effect of portfolio similarity on funds' portfolio allocation decisions is not confounded by portfolio diversification measures. In addition, consistent with a trade-off between portfolio diversity and portfolio diversification, we find that the decision to divest from assets funded by similar investors is driven by diversified funds, suggesting that

the concern of joint liquidation costs due to similarity is mostly present for diversified funds. Finally, funds that have a large exposure in an issuer react more to an increase in similarity, indicating that the response to similarity is proportionate to the extent the fund is exposed to an issuer. To summarize, when similarity increases, funds reduce their exposure to an issuer when the initial portfolio weight in the issuer is large but the rest of the fund's portfolio is diversified.

3.6 Robustness and Additional Analyses

In this section, we discuss robustness tests and additional analyses. We propose an instrumental variable for portfolio similarity in Section 3.6.1. We analyze the robustness of our results to potential delays in the public disclosure of MMFs' portfolio holdings in Section 3.6.2. We then discuss additional results reported in the Appendix in Section 3.6.3.

3.6.1 Exogenous Variation in Fund Similarity

We address potential endogeneity concerns related to the definition of our portfolio similarity measure, and propose an instrumental variable (IV) for it. Specifically, the concern we are trying to address with the IV approach is a reverse causality or reflection problem where similarity is the result of a fund's past investment decisions. Indeed, portfolio similarity is the result of previous portfolio decisions of fund f and all other funds φ investing in issuer i. At the same time, our outcome variables capture a portfolio decision of fund f relative to issuer i. While we already address endogeneity concerns pertaining to issuer i by removing it from the portfolios when we derive similarity, the measure is still based on the portfolio decisions of fund f in the other issuers $j \neq i$ that could affect the decision of fund f to divest from issuer i in the future.

To mitigate this concern, we propose an instrumental variable in the spirit of a Bartik in-

strument, focusing on variation in our similarity measure that is the result of exogenous shocks to the other funds' portfolios (Borusyak et al., 2022). We define our instrumental variable as:

$$Z_{fit} = \sum_{\varphi=1,\varphi\neq f}^{F_t} w_{\varphi it} g_{\varphi t} \tag{4}$$

where $g_{\varphi t}$ is an exogenous shock at fund $\varphi \neq f$. We propose three definitions of $g_{\varphi t}$: (i) the net redemptions at fund φ scaled by fund φ size ($Redemption_{\varphi t}$); (ii) the idiosyncratic redemptions at fund φ that are the residuals of a regression of $Redemption_{\varphi t}$ on month fixed effects ($Redemption^{idio}_{\varphi t}$); and (iii) the idiosyncratic redemptions multiplied by fund φ's exposure to issuers in the euro area ($EurExp_{\varphi t} \times Redemption^{idio}_{\varphi t}$) as an indicator of the severity of the European sovereign debt crisis for that fund.

To ensure that the exclusion condition holds, we restrict the sample to funds that do not have net redemptions at time t. We also control in all specifications for the average exposure of the other funds investing in issuer i to euro area issuers, defined as $EurExp_{fit-1} = \sum_{\varphi=1,\varphi\neq f}^{F_t} w_{\varphi it-1} EurExp_{\varphi t-1}$, given that this variable is not exogenous. This ensures that the instrument is only related to fund f's allocation decisions through its effect on portfolio similarity with fund f. The relevance condition is tested in the first stage of the two-stage least squares estimation procedure.

The results of the IV regressions are reported in Table 6 where Columns (1) and (4) refer to the IV definition (i), Columns (2) and (5) refer to the IV definition (ii), and Columns (3) and (6) to the IV definition (iii). In Panel A, we report the first-stage estimation results relative to the dependent variable $Divest$ in Columns (1)-(3), and relative to $\Delta Exposure$ in Columns (4)-(6). In all specifications, the instrument is positively correlated with portfolio similarity and is significant at the 1% level with portfolio similarity. The results suggest that similarity with fund f increases when other funds have to reallocate their portfolios following redemptions.

Consistent with this result, we report, in Appendix Table SI-3, an increasing average portfolio similarity following the crisis period, during which funds exposed to the euro area experienced significant redemptions (Chernenko and Sunderam, 2014). In addition, portfolio similarity of non-euro area exposed funds increased even more (by 3 p.p.) compared to the portfolio similarity of funds exposed to euro area issuers in June 2011 (1 p.p. increase). These results further corroborate the intuition that some funds might not be exposed to euro area issuers or might not experience redemptions, but their portfolio similarity still increases due to other funds facing redemptions from their investors and reallocating their portfolio away from euro area issuers.

[INSERT TABLE 6 HERE]

In Panel B of Table 6, we report the coefficient estimates obtained in the second stage. The signs of the IV estimates are consistent with the OLS estimates obtained in our baseline results, and the IV estimates are all statistically significant at least at the 10% level. These estimates, focusing on exogenous variation in similarity coming from redemptions at other funds, support our previous evidence that funds divest from issuers exposed to similar funds.

3.6.2 Portfolio Composition Disclosure Timing

In this section, we address the concern that the portfolio composition of MMFs is not immediately public information, and therefore, that funds cannot observe the portfolio composition of other funds in real time. The reporting frequency of the N-MFP forms we use in our analysis is monthly. Over the sample period from November 2010 until August 2014, MMFs can report up to 5 days after the end of the month to the SEC. Then, there is a 60 day delay before the SEC publicly discloses the N-MFP form. In addition, MMFs may file an amendment to a previously

filed N-MFP form at any time, including an amendment to correct a previously filed form.[18]

Our empirical strategy in Section 3.1 instead assumes that, while making investment decisions in month t, funds observe the latest exposure of other funds at the end of month $t-1$, suggesting real time public disclosure. If we consider the 60 day delay in public disclosure by the SEC, we should instead use exposures in month $t-3$ to measure portfolio similarity ($Similarity_{fit-3}$) to reflect the information on portfolio similarity available to fund f in month t. Then, adding the allowed delay of 5 days after the end of the month to report, and the potential additional delays due to amendments to the initial reporting, we should eventually consider exposures at the end of month $t-4$ ($Similarity_{fit-4}$) as public information for funds to compare their exposures with other funds and make portfolio adjustments in month t.

[INSERT TABLE 7 HERE]

In Table 7 we consider the portfolio allocation response of funds to portfolio similarity lagged by one (Column (1)) to six months (Column (6)), as well as the joint effect of all lags of portfolio similarity in Column (7). Panel A reports the results relative to $Divest$ and Panel B reports the results for $\Delta Exposure$. We restrict the sample to observations for which the one-month up to the six-month lagged similarity measures are available, which reduces the overall sample by more than half. We keep the issuer×month fixed effects and the fund fixed effects, but do not include other control variables due to the different timing of measurement between similarity and the control variables. The results in both Panels A and B indicate that the portfolio similarity effect on fund allocation decisions increases with the lag in Columns (1) to (4) up to a lag of four months, after which similarity does not affect portfolio decisions anymore

[18] Source: https://www.sec.gov/files/formn-mfp.pdf. Note, however, that this 60 day delay requirement was removed in August 2014: *"Because we are removing this 60-day delay, we are also requiring funds to make the market-based value of their portfolio securities available on the fund Web site at the same time that this information becomes public on Form N–MFP."* A Rule by the Securities and Exchange Commission on 08/14/2014. Source: https://www.federalregister.gov/documents/2014/08/14/2014-17747/money-market-fund-reform-amendments-to-form-pf#h-99, visited on 05/03/2024.

(the coefficients associated with higher lags are not statistically significant at the 10% level in Columns (5) and (6)). In addition, consistent with the institutional details on the public disclosure timing of MMFs' portfolio composition, we find that $Similarity_{fit-3}$ (in Column (3)) and $Similarity_{fit-4}$ (in Column (4)) have the largest impact on portfolio allocation decisions.

Finally, the joint regression in Column (7) demonstrates that the effect of similarity is indeed driven by the fourth lag, while $Similarity_{fit-1}$ has a high correlation with $Similarity_{fit-4}$ (0.86). We, therefore, interpret $Similarity_{fit-1}$ as a covariate of $Similarity_{fit-4}$, resulting, to some degree, from persistence in portfolio similarity. While it is not a perfect measure of new information about portfolio similarity available at the time of fund allocation decisions, it correlates positively with $Similarity_{fit-4}$ and allows us to keep a larger sample of observations and avoid some selection bias based on fund-issuer relationship length in our baseline analyses.

3.6.3 Additional Analyses

In the Appendix, we provide additional tests to complement our main findings and reduce the scope for alternative interpretations. For example, we investigate the possibility that the effect of fund similarity on fund flows is the result of funds following the same benchmark index. Including additional fund controls, fund cluster×time fixed effects, or even fund×time fixed effects does not qualitatively alter our results. We further control for the correlation in investor flows across funds, and show that it does not subsume the effect of portfolio similarity. This confirms that our mechanism reflects similarity in portfolio composition, as in Wagner (2011), rather than similarities in fund flows or performance. We also show that the effect of fund similarity is reversed for secured securities, where joint liquidation costs are less of a concern. We find that the effect of portfolio similarity is amplified for riskier issuers, and that this effect is even stronger during a crisis. Additionally, we replicate the results after consolidating data at the fund complex level, since funds might have an interest in reducing the exposure to liquidity

risk of other funds in the same complex, and not only at the individual fund level. We also control for funds complexes' affiliation with banks and show that this does not significantly affect our main results. Lastly, we use alternative similarity measures and show that our portfolio similarity measure outperforms other measures in predicting fund's portfolio allocation decisions.

4 Investors Similarity and Issuer's Funding Fragility

In this section, we study the effect of the portfolio similarity of the funds of an issuer on the issuer's outcomes. An issuer can resort to multiple funds to diversify its liabilities and strengthen its balance sheet. However, if all funds of an issuer have the same portfolios, funding fragility increases as the diversification benefits from resorting to multiple funds attenuate. In Section 4.1, we examine the effect of fund similarity on funding quantities—specifically, the percentage change in the principal amount lent to the issuer and the incidence of correlated outflows. In Section 4.2, we assess whether these similarity-driven outflows translate into higher yields, shedding light on the pricing consequences of concentrated funding structures.

4.1 Issuer's Access to Funding

Issuers relying on more similar funds on average might have a more fragile funding structure, in the sense that they might not be able to substitute the loss of funding from similar investors when the similar investors are hit by a common shock. In order to assess potential substitution effects, we study access to funding at the issuer level. Note that this analysis does not require the sample to be restricted to issuers borrowing from at least three MMFs, but we still need the issuer to borrow from at least two MMFs to compute the similarity of the portfolios of funds exposed to an issuer.

We estimate the following specification to predict outcomes of issuer i in month t:

$$y_{it} = \alpha_i + \alpha_t + \beta Similarity_{it-1} + \delta Controls_{it-1} + \varepsilon_{it}, \tag{5}$$

where y_{it} is the percentage fund flows to issuer i at time t ($\Delta Outstanding_{it}$), or the fraction of funds exposed to issuer i at time $t-1$ that divest from issuer i at time t ($CorrOutflows_{it}$), and α_i and α_t are respectively issuer and time fixed effects. The average similarity of funds investing in issuer i at time t is $Similarity_{it} = \sum_f w_{fit} Similarity_{fit}$, where the weights are given by $w_{fit} = Amount_{fit}/Amount_{it}$ with $Amount_{it} = \sum_f Amount_{fit}$ defining the total unsecured principal amount borrowed by issuer i in U.S. money markets. The control variables $Controls_{it}$ include issuer-specific controls, as well as the weighted average maturity and yield of securities of the issuer (using the same weights as for the issuer's average similarity). In particular, issuer controls include variables capturing the issuer's liabilities diversification (i.e., the number of funds holding securities from an issuer, and the issuer's funding HHI).

Financial institutions typically rely more on short-term funding and have a more fragile funding structure than their non-financial counterparts. As a consequence, concerns over the liability diversification of an issuer might be more important when the issuer is a financial institution. To reflect this, we report the results of this test separately for financial and non-financial institutions in Table 8.[19] All regressions include issuer fixed effects, time fixed effects, and we control for the average maturity and yield of securities. We also control for standard measures of concentration in the issuer's liabilities in Columns (2), (4), (6), and (8).

[INSERT TABLE 8 HERE]

[19] The panel of issuer-month observations counts 12,516 observations for 301 issuers. As our analysis requires issuers to borrow unsecured from two U.S. MMFs to derive the average similarity of the funds of an issuer, and during two consecutive years given the definition of the dependent variables, our final sample contains 4,590 observations.

In Columns (1) to (4), the dependent variable is the percentage change in the total unsecured principal amount lent by MMFs to issuer i ($\Delta Outstanding$). We find that the average fund similarity of an issuer predicts the fund flows to financial firms in the following month, but the effect is only statistically significant when we control for other concentration measures such as the HHI and the number of funds lending to the firm. In contrast, we do not find an effect of the average fund similarity on fund flows of non-financial issuers. The results reported in Columns (5) to (8) for the fraction of funds that simultaneously divest from an issuer ($CorrOutflows$) show a similar contrast between financial and non-financial issuers. The average fund similarity of an issuer predicts an increase in correlated outflows for financial issuers (Columns (5) and (6)), but the effect is reversed for non-financial issuers (Columns (7) and (8)).

In the Appendix, we additionally report the results for fund flows ($\Delta Outstanding$) from similar and and non-similar funds separately in Table SI-12, and find that non-similar funds do not compensate for the loss of funding from similar funds. We also assess the relevance of the average similarity of funds as a predictor of fund flows in a crisis in Table SI-13, and find that the negative effect of average fund similarity on fund flows is larger in economic magnitude during a crisis. Finally, we report the regression results of equation (6), adding issuer×year fixed effects in Table SI-14 to reduce the scope for omitted variable bias, and find that this alternative specification does not qualitatively alter our results. Importantly, in all these additional tests, the coefficient estimates are statistically significant only for financial institutions.

To illustrate our findings, Figure 3 depicts the implications of fund similarity in terms of access to funding and stock valuations of financial institutions borrowing in money markets. The figure shows the percentage change in unsecured principal amounts since June 2011 of financial institutions borrowing from similar funds (solid line) versus financial institutions borrowing from non-similar funds (dashed line). The figure shows opposite trends in issuers' fund flows depending on the similarity of their funds. Financial institutions that rely on similar funds

lost about 20% of their funding permanently, while financial institutions borrowing from non-similar funds increased funding by more than 50% over our sample period.

[INSERT FIGURE 3 HERE]

4.2 Issuer's Average Yield

We now assess whether issuers borrowing from similar funds face higher funding costs, particularly during periods of systemic financial stress. U.S. MMFs report on N-MFP forms the ex-ante yield of the securities they hold, together with the title of each issue. These unsecured and uninsured yields, reported at issuance, provide a forward-looking measure of the issuer's perceived credit risk. Controlling for maturity, a higher yield reflects a higher cost of funding. We test whether borrowing from more similar funds is associated with higher yields.

The underlying hypothesis is that portfolio similarity among lenders increases the cost of funding only during periods of aggregate stress. As shown in the previous section, similarity consistently predicts higher outflows from issuers. However, these outflows only translate into higher yields when systemic conditions deteriorate and liquidity becomes scarce. In normal times, issuers may offset withdrawals by raising funds from other sources. During stress episodes, however, similarity-driven outflows are harder to absorb, forcing issuers to offer higher yields. Thus, while similarity consistently predicts fund flows, its impact on pricing arises only when the broader financial sector is under strain.

To test this hypothesis, we estimate the following specification to predict the average yield

of issuer i in month t:

$$Yield_{it} = \alpha_i + \alpha_t + \beta_1 Similarity_{it-1} + \beta_2 Similarity_{it-1} \times AggregateStress_t + \delta Controls + \varepsilon_{it}, \tag{6}$$

where $Yield_{it}$ is the weighted average ex-ante yield on unsecured securities of issuer i held by U.S. MMFs in month t. The regression includes issuer and time fixed effects. Control variables include the weighted average maturity of the issuer's unsecured securities and lagged variables that capture the issuer's liability diversification, such as the number of funds lending to the issuer and the HHI of the issuer's MMF liabilities. We also control for flow-induced price pressure (FIPP), a variable that captures the potential yield impact of MMF investor redemptions. FIPP is constructed following Edmans et al. (2012): it measures the hypothetical increase in yields if funds were to liquidate their portfolios pro rata in response to large redemptions.[20] After controlling for FIPP, the effect of portfolio similarity corresponds to a yield increase that is above and beyond what would be expected if funds simply liquidated their portfolios proportionally during redemptions.

As proxies for systemic stress ($AggregateStress_t$), we use three alternative measures: a crisis indicator variable (equal to one from June to December 2011), and two systemic risk indicators, SRISK (Acharya et al., 2017; Brownlees and Engle, 2017) and ΔCoVaR (Adrian and Brunnermeier, 2016). SRISK measures the aggregate capital shortfall of the U.S. financial sector, scaled by its total market capitalization; ΔCoVaR captures the loss to the financial system when individual financial institutions are in distress relative to their median state.[21] Both indicators capture spillovers or externalities imposed by U.S. financial institutions with publicly traded stocks and therefore exclude MMFs. As such, they reflect systemic risk in the alternative

[20] In our setting, we adapt this measure by scaling with the issuer's outstanding principal rather than trading volume, given data limitations. Formally, $FIPP_{it} = \sum_{f, outflow_{ft} \geq 5\%} \frac{Amount_{fit-1}}{Amount_{it}} \times outflow_{ft}$, where $outflow_{ft}$ are the net investor outflows from fund f in month t scaled by the size of the fund in the previous month.

[21] The two measures are derived from the stock returns of U.S. financial institutions listed in CRSP. See Acharya et al. (2025) for details.

funding sources available to the issuers in our sample. For ease of interpretation, we transform the two systemic risk variables into indicators: an indicator for high SRISK months (defined as those in the top 10% of the distribution, i.e., when the ratio of aggregate SRISK to total market capitalization exceeds 48.5%), and an indicator for high ΔCoVaR months (top 30% of the distribution, i.e., ΔCoVaR above 4.2 p.p.).[22]

[INSERT TABLE 9 HERE]

The results are reported in Table 9. In Column (1), we find no statistically significant effect of average fund similarity on the issuer's funding cost across the full sample. In Column (2), we interact similarity with the crisis indicator. The coefficient estimate on the interaction term (β_2) is positive and significant at the 5% level, suggesting that similarity only increases yields when economic conditions deteriorate. The interaction becomes more economically and statistically significant when we replace the crisis dummy with high SRISK and high ΔCoVaR indicators in Columns (3) and (4). When SRISK is elevated, a one standard deviation increase in average similarity—roughly 8 p.p.—is associated with a $0.17 \times 8 = 1.36$ basis point increase in the average yield, relative to an average yield of 27 basis points. The effect under high ΔCoVaR is similar in magnitude and also significant. The effect of potential proportional liquidations due to investor outflows, captured by the flow-induced price pressure variable (FIPP), is positive across all specifications, as expected. FIPP is also interacted with the systemic stress indicators, but these interaction coefficients are not statistically significant, consistent with the interpretation that redemptions already intensify during stress periods. In addition, the results are robust to excluding FIPP from the specification.

In Columns (5) to (8), we focus on the subset of most similar funds to an issuer using the

[22] Appendix Table SI-15 shows that the results are not sensitive to the threshold used to define high systemic risk. Instead of using indicators, we interact similarity with continuous measures of systemic stress: the ratio of total SRISK to market capitalization of the U.S. financial sector and the level of ΔCoVaR. The results confirm that the effects are driven by the level of systemic stress and not by arbitrary cutoffs.

variable $Similarity_{it}^{95\%}$, which captures the minimum similarity among the top 5% most similar funds investing in the issuer. These regressions confirm that yield effects are concentrated among the most similar lenders. The interaction terms with the crisis, SRISK, and ΔCoVaR indicators are statistically significant and economically larger than for the average similarity measure. Under high SRISK, the coefficient estimate is 0.20, indicating that a one standard deviation increase in the similarity of the 5% most similar funds raises yields by 1.6 basis points. These results reinforce the interpretation that under aggregate stress, the level of portfolio similarity of the most similar investors of an issuer generates funding outflows that can impact the issuer's security prices.

In Appendix Table SI-16,we provide additional evidence supporting our focus on the 95% similarity quintile. The table shows that fund flows to an issuer are significantly associated with the portfolio similarity of the 5% most similar funds, but not with the similarity of the 5% least similar funds. The dispersion in similarity, measured by the standard deviation, also predicts fund flows: greater dispersion is associated with larger funding losses. These findings are consistent with our fund-issuer-level analysis, where results are driven by within-issuer variation in portfolio similarity—that is, variation across funds investing in the same issuer at the same time. Thus, while the average level of similarity predicts outflows and higher yields, these effects are primarily driven by the most similar investors.

Overall, the results indicate that the portfolio similarity of investors—particularly among the most similar ones—can raise the cost of funding for issuers during periods of systemic financial stress, underscoring the importance of investor composition in assessing vulnerability to funding pressure.

5 Conclusion

Building on the theoretical literature on endogenous liquidation costs, we test the prediction that investors divest from an asset in anticipation of large liquidation costs when their portfolio similarity with other asset holders is high. Empirically testing for endogenous liquidation costs is challenging, as it requires observing both the identity of asset holders and the full composition of their portfolios. To address these challenges, we rely on detailed data on the securities held by U.S. money market funds (MMFs) and develop a measure of portfolio similarity among funds exposed to the same security.

Using panel regressions with high-dimensional fixed effects to control for all fundamental characteristics of a security issuer, we find that MMFs divest from a security when their portfolio similarity with other holders of the same security is high. Comparing the differential responses to portfolio similarity among multiple holders of the same security at the same time is central to our empirical strategy, as it allows us to disentangle fundamental risk from the endogenous liquidity risk associated with the security.

Consistent with funds divesting in anticipation of higher liquidation costs, portfolio similarity has a stronger impact on divestment for ex-post illiquid securities, more illiquid and diversified funds, and is only present for institutional funds. We validate our interpretation using an instrument that exploits variation in portfolio similarity driven by idiosyncratic redemptions from other funds. Moreover, we find that portfolio similarity predicts simultaneous divestments by multiple funds from financial institutions borrowing in money markets, and also raises security yields when aggregate systemic risk is high.

Our results connect with the regulatory debate on the rise of shadow banking and its implications for financial stability. Given the reliance of large international banks on MMFs for their short-term funding needs, disruptions in money markets can have far-reaching conse-

quences. In particular, the Financial Stability Board (2021) and Bouveret and Danielli (2021) specifically highlight MMFs' portfolio similarity in certain securities as a key challenge for liquidity, potentially hindering the simultaneous sale of these securities. Our results point to a beneficial effect of publicly disclosing MMFs' portfolio composition, and suggest that regulatory intervention may not be necessary for some institutional prime MMFs, as long as they internalize this risk in their holdings of unsecured debt securities.

References

Acharya, V.V., Brunnermeier, M.K., Pierret, D., 2025. Systemic risk measures: From the panic of 1907 to the banking stress of 2023. Annu. Rev. Financ. Econ. 17.

Acharya, V.V., Pedersen, L.H., Philippon, T., Richardson, M., 2017. Measuring systemic risk. The Review of Financial Studies 30, 2–47.

Adrian, T., Brunnermeier, M.K., 2016. CoVaR. The American Economic Review 106, 1705–1741.

Aldasoro, I., Balke, F., Barth, A., Eren, E., 2022. Spillovers of funding dry-ups. Journal of International Economics 137, 103622.

Allen, F., Babus, A., Carletti, E., 2012. Asset commonality, debt maturity and systemic risk. Journal of Financial Economics 104, 519–534.

Allen, F., Gale, D., 1994. Limited market participation and volatility of asset prices. The American Economic Review 84, 933–955.

Altonji, J.G., Elder, T.E., Taber, C.R., 2005. Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools. Journal of Political Economy 113, 151–184.

Baghai, R.P., Giannetti, M., Jäger, I., 2022. Liability structure and risk taking: Evidence from the money market fund industry. Journal of Financial and Quantitative Analysis 57, 1771–1804.

Bongaerts, D., Mazzola, F., Wagner, W., 2021. Fire Sale Risk and Credit. Working Paper.

Borusyak, K., Hull, P., Jaravel, X., 2022. Quasi-experimental shift-share research designs. The Review of Economic Studies 89, 181–213.

Bouveret, A., Danielli, L., 2021. Vulnerabilities in Money Market Funds. ESMA Working Paper.

Bouveret, A., Martin, A., McCabe, P.E., 2022. Money Market Fund Vulnerabilities: A Global Perspective. FEDS Working Paper No. 2022-12.

Brownlees, C., Engle, R.F., 2017. SRISK: A conditional capital shortfall measure of systemic risk. The Review of Financial Studies 30, 48–79.

Cai, J., Eidam, F., Saunders, A., Steffen, S., 2018. Syndication, interconnectedness, and systemic risk. Journal of Financial Stability 34, 105–120.

Chaderina, M., Mürmann, A., Scheuch, C., 2022. The dark side of liquid bonds in fire sales. Working Paper.

Chernenko, S., Sunderam, A., 2014. Frictions in shadow banking: Evidence from the lending behavior of money market mutual funds. The Review of Financial Studies 27, 1717–1750.

Chernenko, S., Sunderam, A., 2020. Do fire sales create externalities? Journal of Financial Economics 135, 602–628.

Cipriani, M., La Spada, G., 2018. Investors' appetite for money-like assets: The money market fund industry after the 2014 regulatory reform. Federal Reserve Bank of New York Staff Reports No. 816.

Cipriani, M., La Spada, G., 2024. Sophisticated and Unsophisticated Runs. Federal Reserve Bank of New York Staff Reports No. 956.

Coval, J., Stafford, E., 2007. Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86, 479–512.

Diamond, D., Rajan, R., 2011. Fear of fire sales, illiquidity seeking, and credit freezes. The Quarterly Journal of Economics 126, 557–591.

Doerr, S., 2024. Bank Geographic Diversification and Funding Stability. Working Paper. Bank for International Settlements.

Duygan-Bump, B., Parkinson, P., Rosengren, E., Suarez, G.A., Willen, P., 2013. How effective were the federal reserve emergency liquidity facilities? evidence from the asset-backed commercial paper money market mutual fund liquidity facility. The Journal of Finance 68, 715–737.

Edmans, A., Goldstein, I., Jiang, W., 2012. The real effects of financial markets: The impact of prices on takeovers. The Journal of Finance 67, 933–971.

Ellul, A., Jotikasthira, P., Lundblad, C.T., 2011. Regulatory pressure and fire sales in the corporate bond market. Journal of Financial Economics 101, 596–620.

Falato, A., Goldstein, I., Hortaçsu, A., 2021. Financial fragility in the covid-19 crisis: The case of investment funds in corporate bond markets. Journal of Monetary Economics 123, 35–52.

Favara, G., Giannetti, M., 2017. Forced asset sales and the concentration of outstanding debt: Evidence from the mortgage market. The Journal of Finance 72, 1081–1118.

Financial Stability Board, 2021. Policy Proposals to Enhance Money Market Fund Resilience. Report. Financial Stability Board.

Gallagher, E.A., Schmidt, L.D., Timmermann, A., Wermers, R., 2020. Investor information acquisition and money market fund risk rebalancing during the 2011-2012 eurozone crisis. The Review of Financial Studies 33, 1445–1483.

Gandhi, P., Purnanandam, A., 2023. United They Fall: Bank Risk after the Financial Crisis. Working Paper.

Giannetti, M., Jotikasthira, C., 2024. Bond price fragility and the structure of the mutual fund industry. The Review of Financial Studies 37, 2063–2109.

Giannetti, M., Saidi, F., 2019. Shock propagation and banking structure. The Review of Financial Studies 32, 2499–2540.

Girardi, G., Hanley, K.W., Nikolova, S., Pelizzon, L., Sherman, M.G., 2021. Portfolio similarity and asset liquidation in the insurance industry. Journal of Financial Economics 142, 69–96.

Gorton, G., Metrick, A., 2010. Regulating the shadow banking system. Brookings Papers on Economic Activity (Fall 2010), 261–312.

Greenwood, R., Landier, A., Thesmar, D., 2015. Vulnerable banks. Journal of Financial Economics 115, 471–485.

Greenwood, R., Thesmar, D., 2011. Stock price fragility. Journal of Financial Economics 102, 471–490.

Gromb, D., Vayanos, D., 2002. Equilibrium and welfare in markets with financially constrained arbitrageurs. Journal of Financial Economics 66, 361–407.

Hanson, S., Scharfstein, D., Sunderam, A., 2015. An evaluation of money market fund reform proposals. IMF Economic Review 63, 984–1023.

Kacperczyk, M., Schnabl, P., 2013. How safe are money market funds? The Quarterly Journal of Economics 128, 1073–1122.

Khwaja, A.I., Mian, A., 2008. Tracing the impact of bank liquidity shocks: Evidence from an emerging market. The American Economic Review 98, 1413–1442.

Krishnamurthy, A., 2010. Amplification mechanisms in liquidity crises. American Economic Journal: Macroeconomics 2, 1–30.

Li, L., Li, Y., Macchiavelli, M., Zhou, X.A., 2021. Liquidity restrictions, runs, and central bank interventions: Evidence from money market funds. The Review of Financial Studies 34, 5402–5437.

Manconi, A., Massa, M., Yasuda, A., 2012. The role of institutional investors in propagating the crisis of 2007–2008. Journal of Financial Economics 104, 491–518.

Manconi, A., Massa, M., Zhang, L., 2016. Bondholder concentration and credit risk: Evidence from a natural experiment. Review of Finance 20, 127–159.

Oster, E., 2019. Unobservable selection and coefficient stability: theory and evidence. Journal of Business & Economic Statistics 37, 187–204.

Schmidt, L., Timmermann, A., Wermers, R., 2016. Runs on money market mutual funds. The American Economic Review 106, 2625–2657.

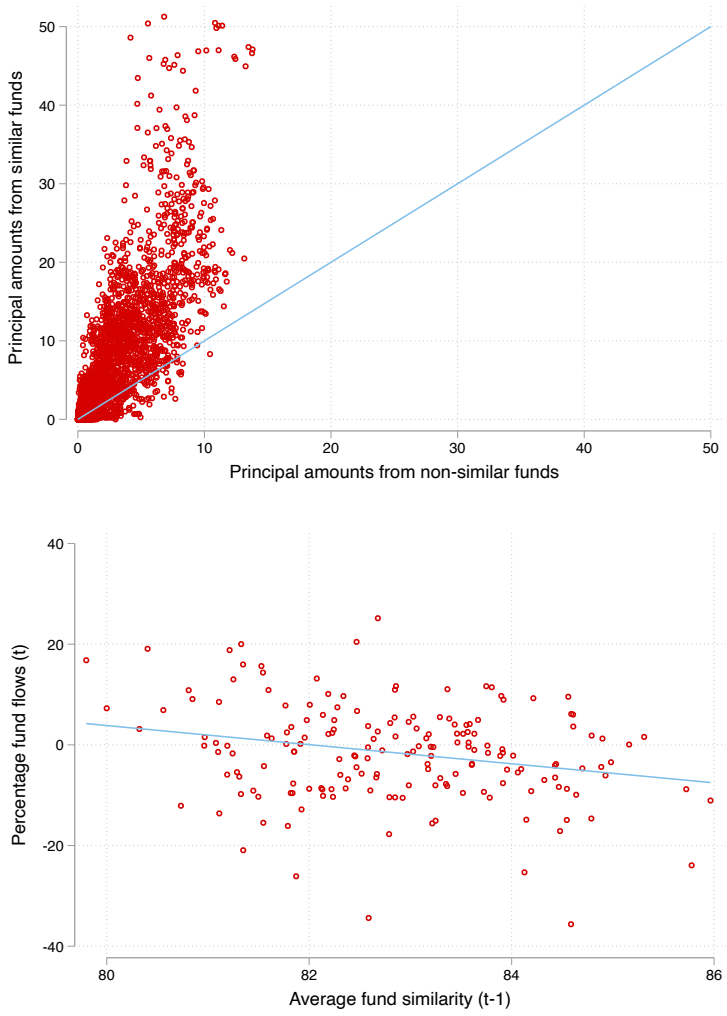
Shleifer, A., Vishny, R., 1992. Liquidation values and debt capacity: A market equilibrium approach. The Journal of Finance 47, 1343–1366.

Shleifer, A., Vishny, R., 1997. The limits to arbitrage. The Journal of Finance 52, 35–55.

Wagner, W., 2011. Systemic liquidation risk and the diversity–diversification trade-off. The Journal of Finance 66, 1141–1175.

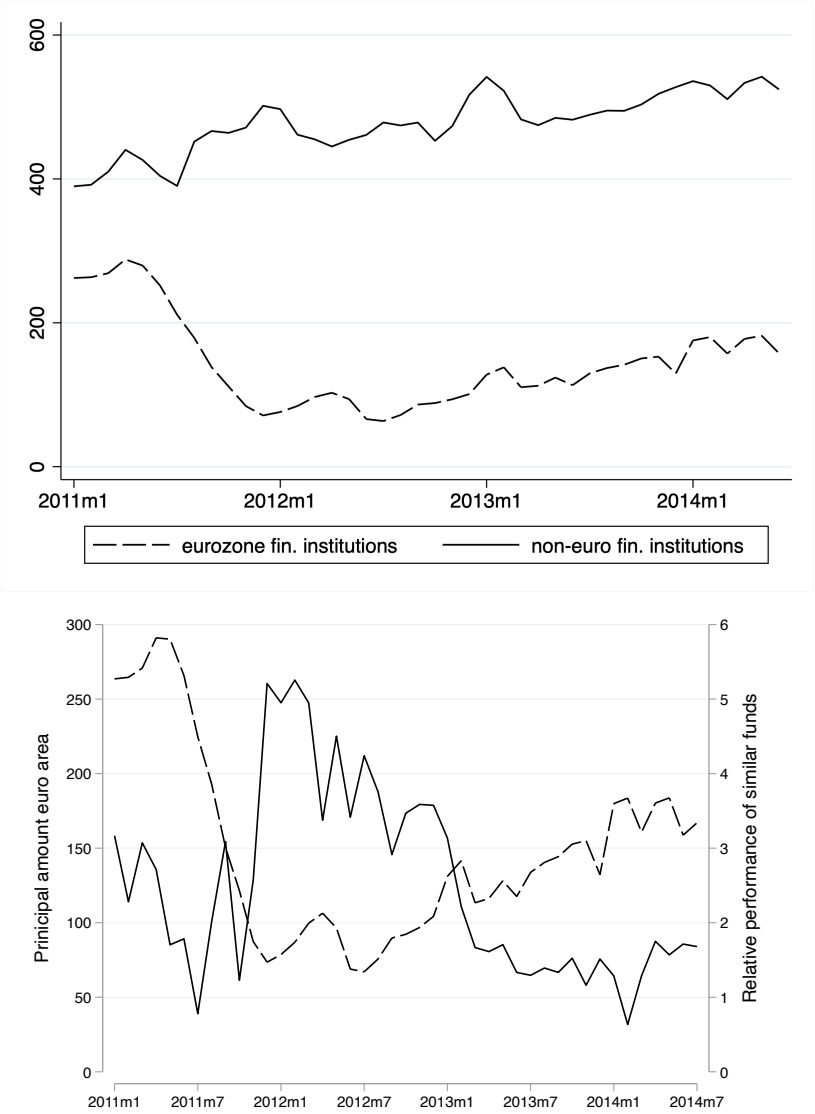
A Figures

Figure 1: Reliance on Similar MMFs, Portfolio Similarity, and Fund Flows.



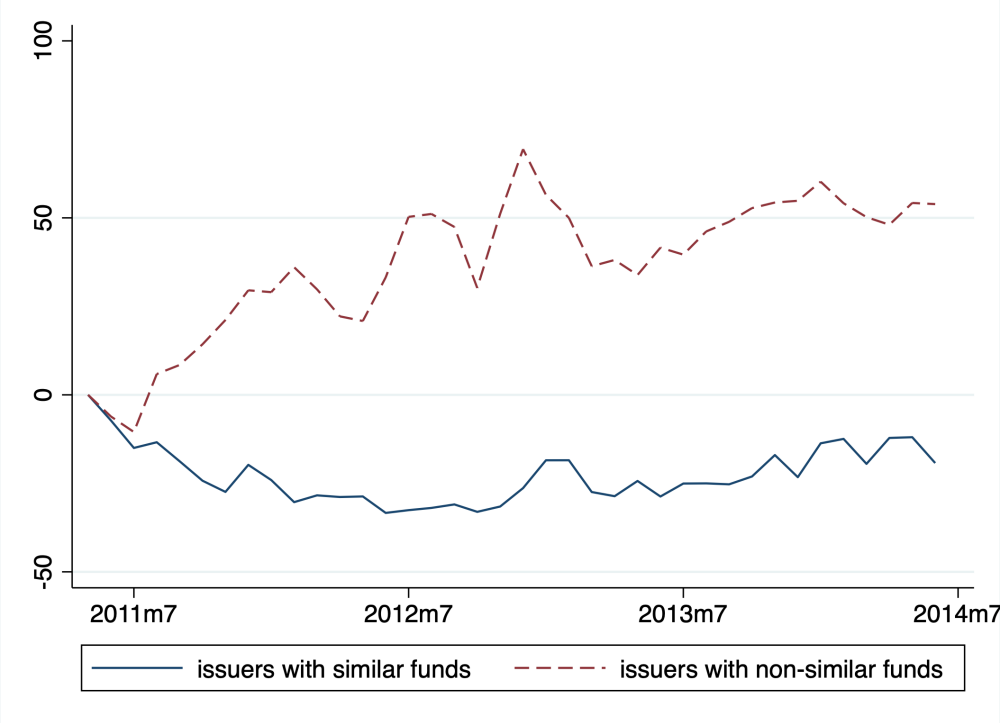
This figure illustrates the relationship between unsecured principal amounts (in $ million) lent by similar funds and non-similar funds in Panel A for each issuer-month observation, and the relationship between average portfolio similarity (in %) and monthly percentage change in unsecured principal amounts lent by MMFs (in p.p.) in Panel B for each "diversified" issuer-month observation. A fund is considered similar for a given issuer in a given month if its portfolio similarity is larger than the median similarity of all funds lending to the issuer in the same month. Issuers are considered diversified if they borrow unsecured from at least 90 MMFs and have the 10% lowest HHI. The blue line is the 45 degree line in Panel A, and the regression line of fund flows on fund portfolio similarity in Panel B.

Figure 2: U.S. MMFs' Investments in Financial Institutions and the Relative Performance of Similar Funds.



This figure shows the total unsecured principal amounts (in $ billion) invested by U.S. MMFs in euro area (dashed line) versus non-euro area financial institutions (solid line) in Panel A. Panel B presents the same dashed line as in Panel A (left scale, in $ billion), together with the relative performance of similar MMFs (right scale, in basis points). The relative performance of similar funds is the difference in the 7-day simple yield between similar funds and non-similar funds. A fund is classified as similar in a given month if its average portfolio similarity is above the median average portfolio similarity of all funds in that month.

Figure 3: MMF Fund Flows Since June 2011: Financial Institutions Exposed to Similar Funds versus Financial Institutions Exposed to Non-similar Funds.



This figure shows the percentage change in unsecured principal amounts lent by U.S. MMFs since June 2011 for financial institutions borrowing from similar MMFs (solid line) versus financial institutions borrowing from non-similar MMFs (dashed line). An issuer is considered to borrow from similar funds if its average similarity measure across its funds is greater than or equal to the median average similarity measure of all issuers, and is considered to rely on non-similar funds otherwise.

B Tables

Table 1: Descriptive statistics.
This table provides descriptive statistics of U.S. MMFs' unsecured securities. We report descriptive statistics of variables at the issuer level in Panel A, at the level of individual securities in Panel B, and at the fund level in Panel C. Panel A: Descriptive statistics of issuers of MMF securities. $Similarity_{it}$ is the principal amount-weighted average portfolio similarity (in %) of the funds lending to issuer i at time t. $Amount_{it}$ is the unsecured principal amount (in $ 1'000) borrowed by issuer i at date t. $\Delta Outstanding_{it}$ is the percentage change in the unsecured principal amount. $CorrOutflows_{it}$ is the fraction of funds divesting from issuer i in month t. $Yield_{it}$ and $Maturity_{it}$ are respectively the average yield (in p.p.) and the average maturity (in days) of unsecured securities of an issuer. (Unsecured) $Funds_{it}$ is the number of funds lending (unsecured) to an issuer in the same month. $IssuerHHI_{it}$ is the Hirschman-Herfindahl Index (in %) measured on MMF liabilities of issuer i at date t. Sample: Issuers of securities that borrow from at least two funds in the same month.

Panel A: Descriptive statistics of issuers of MMF securities

	Obs.	Mean	Std. Dev.	Min	Max
$Similarity_{it}$	4,078	83.87	8.04	24.16	100
$Amount_{it}$	4,078	7,238	10,063	2.22	61,526
$\Delta Outstanding_{it}$	3,574	0.33	28.84	-100	99
$CorrOutflows_{it}$	3,744	0.23	0.20	0	1
$Yield_{it}$	4,078	0.27	0.12	0	1.2
$Maturity_{it}$	4,078	45.97	31.37	1	288
$Funds_{it}$	4,078	39.58	42.44	2	189
$Unsecured\ Funds_{it}$	4,078	31.77	33.65	2	135
$IssuerHHI_{it}$	4,078	27.54	24.68	2.44	100
Number of issuers	171				
of which, fin. institutions	115				
of which, banks	87				
of which, euro area banks	26				

Panel B: Descriptive statistics of MMF securities. $Similarity_{fit}$ is the portfolio similarity of fund f to other funds exposed to issuer i at time t (in %). $Amount_{fit}$ is the principal amount (in $ 1'000) borrowed by issuer i from fund f at time t. $\Delta Exposure_{fit}$ is the percentage change in fund f's exposure to issuer i at time t. $Divest_{fit}$ is the probability that fund f reduces its unsecured exposure to issuer i at time t. $Yield_{fit}$ and $Maturity_{fit}$ are respectively the average yield (in p.p.) and average maturity (in days) of securities issued by issuer i and held by fund f at time t. The sample is restricted to issuers that simultaneously borrow from at least three U.S. MMFs.

Panel B: Descriptive statistics of MMF securities

	Obs.	Mean	Std. Dev.	Min	Max
$Similarity_{fit}$	146,876	82.07	6.19	23.48	100
$Amount_{fit}$	150,579	201	451	0.001	10,461
$\Delta Exposure_{fit}$	123,711	-0.28	28.95	-100	100
$Divest_{fit}$	131,273	0.24	0.43	0	1
$Yield_{fit}$	141,895	0.29	0.15	0	5.51
$Maturity_{fit}$	150,556	50.23	44.77	0.63	391
Number of funds	213				
Number of issuers	144				

Panel C: Descriptive statistics of MMFs. $Similarity_{ft}$ (in %) is the weighted average of $Similarity_{fit}$, where weights correspond to fund's f portfolio weights. HHI_{ft} is the HHI (in %) on fund's f portfolio weights, $Issuers_{ft}$ is the number of issuers a fund invests during the same month. $FundSize_{ft}$ is the size (in $ 1'000) of the unsecured portfolio of the fund. 7-day simple $Yield_{ft}$ is a SEC-approved yield (in basis points) that describes the annualized income that the fund investors earned over the last seven days. $NetFundFlows_{ft}$ (in p.p.) are the fund's subscriptions minus its redemptions scaled by its net assets, WAL_{ft} is the weighted average life (in days) of the fund's portfolio, WAM_{ft} is the weighted average maturity (in days) of the fund's portfolio, $Euro\ area\ exposure_{ft}$ is the fraction (in p.p.) of the fund's unsecured portfolio invested in euro area issuers. This panel shows averages for all funds, institutional funds, retail funds, similar funds, and non-similar funds separately. A fund classifies as "similar" if its average similarity is above the median average similarity of all funds in a given month.

Panel C: Descriptive statistics of MMFs

	All funds	Institutional	Retail	Similar	Non-similar
$Similarity_{ft}$	77.48	78.95	75.99	83.46	71.60
HHI_{ft}	12.96	11.17	14.97	8.36	17.48
$Issuers_{ft}$	18.02	19.70	16.15	24.94	11.21
$FundSize_{ft}$	4,792	6,770	2,419	8,077	1,562
7-day simple $Yield_{ft}$	4.44	6.93	1.35	5.70	3.18
$NetFundFlows_{ft}$	-2.51	-3.25	-1.59	-2.40	-2.62
WAL_{ft}	59.36	58.61	60.28	62.82	55.91
WAM_{ft}	38.28	36.52	40.46	38.50	38.06
$Euro\ area\ exposure_{ft}$	18.18	19.79	16.26	20.21	16.18
Number of observations	7,191	3,930	3,174	3,565	3,626
Number of funds	212	115	94	179	173

Table 2: Funds' portfolio allocation decisions and portfolio similarity.
This table reports the regression estimates on portfolio similarity, where the dependent variable is $Divest_{fit}$, an indicator variable equal to one if a fund f reduced its exposure to issuer i during month t in Columns (1) to (4), and $\Delta Exposure_{fit}$, the percentage change in the unsecured exposure of fund f to issuer i during month t in Columns (5) to (8). $Similarity_{fit}$ is the portfolio similarity of fund f to the other funds exposed to issuer i at time t. Columns (1) and (5) report the results of our baseline specification including issuer×time fixed effects, fund controls, fund fixed effects, and controls for the weighted average maturity and weighted average yield of issuer i's securities held by fund f. Columns (2) and (6) exclude control variables (i.e., fund size and average yield and maturity of securities). Columns (3) and (7) include issuer×funds fixed effects. Columns (4) and (8) exclude observations for which the average maturity is less than 30 days. Coefficient estimates on $Divest$ are multiplied by 100 ($Divest$ is a probability taking values between 0 and 1). t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

	$Divest_{fit}$				$\Delta Exposure_{fit}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{fit-1}$	0.11**	0.08	0.11**	0.48***	-0.14***	-0.15***	-0.22***	-0.11**
	(2.32)	(1.58)	(1.97)	(6.85)	(-3.83)	(-4.36)	(-5.15)	(-2.29)
Observations	120,815	120,815	120,313	60,499	102,538	102,538	102,115	57,489
R-squared	0.21	0.13	0.26	0.19	0.10	0.09	0.14	0.15
Issuer×time FE	Y	Y	Y	Y	Y	Y	Y	Y
Issuer×fund FE	N	N	Y	N	N	N	Y	N
Fund FE	Y	Y	N	Y	Y	Y	N	Y
Security controls	Y	N	Y	Y	Y	N	Y	Y
Avg.Mat.≥30d	N	N	N	Y	N	N	N	Y

Table 3: Funds' portfolio allocation decisions and portfolio similarity: Relation to ex-post illiquidity.

Panel A shows the differential effect of portfolio similarity when a fund reports a security as illiquid ex post. $IlliquidSec_{fit}$ takes the value of one if a fund f reports at least one security issued by issuer i as illiquid at time t. A security is considered illiquid according to the definition in Rule 2a-7. The dependent variable in Panel A is $Divest_{fit}$ in Columns (1)-(2), and $\Delta Exposure_{fit}$ in Columns (3)-(4). Panel B shows the differential effect of portfolio similarity for different measures of the fund's sensitivity to liquidity risk: the fund's weighted average life (WAL_{ft}) as a measure of its sensitivity to changes in liquidity and/or credit risk, the fund's weighted average maturity (WAM_{ft}) as a measure of its sensitivity to interest rate changes, and an indicator variable that takes the value of one for a fund exposed to euro area issuers in June 2011 ($EurExp_f$). The dependent variable in Panel B is $Divest_{fit}$ in Columns (1)-(2)-(3), and $\Delta Exposure_{fit}$ in Columns (4)-(5)-(6). $Divest_{fit}$, $\Delta Exposure_{fit}$, $Similarity_{fit}$, control variables, and fixed effects are defined in Table 2. Coefficient estimates on $Divest$ are multiplied by 100. t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

Panel A: Ex-post illiquid securities

	$Divest_{fit}$		$\Delta Exposure_{fit}$	
	(1)	(2)	(3)	(4)
$Similarity_{fit-1}$	0.11**	0.11**	-0.13***	-0.14***
	(2.14)	(2.24)	(-3.69)	(-3.76)
$Similarity_{fit-1} \times IlliquidSec_{fit}$	3.74***		-1.58***	
	(7.91)		(-4.15)	
$IlliquidSec_{fit}$	-3.12***		133.89***	
	(-8.17)		(4.33)	
$Similarity_{fit-1} \times IlliquidSec_{fit+1}$		2.97***		-0.74*
		(5.82)		(-1.83)
$IlliquidSec_{fit+1}$		-2.54***		63.91*
		(-6.13)		(1.96)
Observations	120,815	117,240	102,538	99,542
R-squared	0.21	0.21	0.10	0.10
Issuer×time FE	Y	Y	Y	Y
Fund FE and controls	Y	Y	Y	Y
Security controls	Y	Y	Y	Y

Panel B: Fund's sensitivity to liquidity risk

	$Divest_{fit}$			$\Delta Exposure_{fit}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Similarity_{fit-1}$	-0.08	-0.08	-0.35***	0.05	-0.12	0.12
	(-0.79)	(-0.75)	(-3.32)	(0.67)	(-1.40)	(1.48)
$Similarity_{fit-1} \times WAL_{ft-1}$	0.35**			-0.29***		
	(2.44)			(-2.86)		
$Similarity_{fit-1} \times WAM_{ft-1}$		0.49*			0.00	
		(1.90)			(0.02)	
$Similarity_{fit-1} \times EurExp_f$			0.57***			-0.30***
			(4.91)			(-3.49)
WAL_{ft-1}	-0.31***			20.06**		
	(-2.66)			(2.40)		
WAM_{ft-1}		-0.33			-11.81	
		(-1.58)			(-0.76)	
Observations	120,108	120,108	120,815	101,921	101,921	102,538
R-squared	0.21	0.21	0.21	0.10	0.10	0.10
Issuer×time FE	Y	Y	Y	Y	Y	Y
Fund FE and controls	Y	Y	Y	Y	Y	Y
Security controls	Y	Y	Y	Y	Y	Y

Table 4: Funds' portfolio allocation decisions and portfolio similarity: Institutional funds versus retail funds.

This table reports the regression estimates on portfolio similarity, separately for the sample of institutional funds (Columns (1) to (4)) and retail funds (Columns (5) to (8)). Funds are classified as retail or institutional depending on their reported category on Form N-MFP. The dependent variable is $Divest_{fit}$ in Columns (1)-(2) and (5)-(6), and $\Delta Exposure_{fit}$ in Columns (3)-(4) and (7)-(8). $Divest_{fit}$, $\Delta Exposure_{fit}$, $Similarity_{fit}$, control variables, and fixed effects are defined in Table 2. Coefficient estimates on $Divest$ are multiplied by 100. t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

	Institutional funds				Retail funds			
	$Divest_{fit}$		$\Delta Exposure_{fit}$		$Divest_{fit}$		$\Delta Exposure_{fit}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{fit-1}$	0.21***	0.19**	-0.23***	-0.31***	-0.00	0.02	-0.03	-0.11*
	(2.82)	(2.25)	(-4.25)	(-5.02)	(-0.03)	(0.29)	(-0.63)	(-1.79)
Observations	71,579	71,301	61,168	60,917	47,496	47,267	40,039	39,851
R-squared	0.21	0.26	0.11	0.15	0.26	0.31	0.16	0.19
Issuer×time FE	Y	Y	Y	Y	Y	Y	Y	Y
Issuer×fund FE	N	Y	N	Y	N	Y	N	Y
Fund FE and controls	Y	N	Y	N	Y	N	Y	N
Security controls	Y	Y	Y	Y	Y	Y	Y	Y

Table 5: Funds' portfolio allocation decisions according to portfolio similarity and portfolio concentration.

This table reports the regression estimates on portfolio similarity and portfolio concentration measures. The dependent variable is $Divest_{fit}$ in Panel A, and $\Delta Exposure_{fit}$ in Panel B. Fund's portfolio concentration is measured by the fund's portfolio HHI (HHI_{ft}) and the fraction of the portfolio of fund f invested in issuer i ($Weight_{fit}$). $Divest_{fit}$, $\Delta Exposure_{fit}$, $Similarity_{fit}$, control variables, and fixed effects are defined in Table 2. Coefficient estimates on $Divest$ are multiplied by 100. t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

Panel A: Portfolio similarity, portfolio concentration, and the probability to divest

	$Divest_{fit}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Similarity_{fit-1}$	0.11*	0.28***	0.23***	0.30***	0.04	0.31***
	(1.72)	(3.20)	(3.11)	(3.38)	(0.56)	(3.58)
HHI_{ft-1}	-0.91***	-0.98***	0.35**	0.51***		
	(-15.36)	(-13.25)	(2.37)	(3.12)		
$Weight_{fit-1}$	1.64***	2.33***			0.16	1.04***
	(33.68)	(32.59)			(1.10)	(5.73)
$Similarity_{fit-1} \times HHI_{ft-1}$			-0.01***	-0.01***		
			(-3.08)	(-3.60)		
$Similarity_{fit-1} \times Weight_{fit-1}$					0.02***	0.01***
					(7.72)	(5.07)
Observations	120,815	120,313	120,815	120,313	120,815	120,313
R-squared	0.22	0.28	0.21	0.26	0.22	0.28
Issuer×time FE	Y	Y	Y	Y	Y	Y
Issuer×fund FE	N	Y	N	Y	N	Y
Fund FE and controls	Y	N	Y	N	Y	N
Security controls	Y	Y	Y	Y	Y	Y

Panel B: Portfolio similarity, portfolio concentration, and the fund's exposure

	$\Delta Exposure_{fit}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Similarity_{fit-1}$	-0.18***	-0.58***	-0.25***	-0.38***	-0.21***	-0.68***
	(-3.08)	(-5.86)	(-4.60)	(-5.81)	(-3.71)	(-8.82)
HHI_{ft-1}	0.85***	0.99***	-0.38***	-0.50***		
	(15.92)	(13.31)	(-3.91)	(-4.60)		
$Weight_{fit-1}$	-1.54***	-2.55***			-0.26**	-1.29***
	(-35.15)	(-30.19)			(-2.03)	(-6.81)
$Similarity_{fit-1} \times HHI_{ft-1}$			0.01***	0.01***		
			(5.32)	(5.88)		
$Similarity_{fit-1} \times Weight_{fit-1}$					-0.01***	-0.01***
					(-7.10)	(-4.53)
Observations	102,538	102,115	102,538	102,115	102,538	102,115
R-squared	0.13	0.19	0.10	0.14	0.13	0.18
Issuer×time FE	Y	Y	Y	Y	Y	Y
Issuer×fund FE	N	Y	N	Y	N	Y
Fund FE and controls	Y	N	Y	N	Y	N
Security controls	Y	Y	Y	Y	Y	Y

Table 6: Funds' portfolio allocation decisions and portfolio similarity: IV estimation results. Panel A (resp. Panel B) reports the first-stage (resp. second-stage) estimation results. The dependent variable in Panel B is $Divest_{fit}$ in Columns (1)-(3), and $\Delta Exposure_{fit}$ in Columns (4)-(6). The IV is $Z_{fit} = \sum_{\varphi=1,\varphi\neq f}^{F_t} w_{\varphi it} g_{\varphi t}$, where $g_{\varphi t} = Redemption_{\varphi t}$ in Columns (1) and (4), $g_{\varphi t} = Redemption_{\varphi t}^{idio}$ in Columns (2) and (5), and $g_{\varphi t} = EurExp_{\varphi t} * Redemption_{\varphi t}^{idio}$ in Columns (3) and (6). $Similarity_{fit-1}^{inst}$ is the instrumented portfolio similarity of fund f in issuer i. $EurExp_{fit}$ captures the average euro area exposure of the other funds other than fund f investing in issuer i at time t. $Divest_{fit}$, $\Delta Exposure_{fit}$, $Similarity_{fit}$, other control variables, and fixed effects are defined in Table 2. The difference in results reported in Panel A, between Columns (1) and (4), Columns (2) and (5), and Columns (3) and (6), arises from the different samples corresponding to the two dependent variables ($Divest_{fit}$ for Columns (1) to (3), and $\Delta Exposure_{fit}$ for Columns (4) to (6)). Coefficient estimates on $Divest$ are multiplied by 100. t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

Panel A: First-stage estimation results

	$Similarity_{fit}$			$Similarity_{fit}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Z_{fit-1}	0.11***	0.11***	0.14***	0.12***	0.12***	<0.01***
	(3.28)	(3.37)	(3.80)	(3.42)	(3.46)	(3.75)
$EurExp_{fit-1}$	0.24***	0.24***	0.24***	0.24***	0.24***	0.24***
	(9.18)	(9.20)	(9.28)	(7.37)	(7.38)	(7.42)
Observations	21,646	21,646	21,646	18,349	18,349	18,349
Issuer×time FE	Y	Y	Y	Y	Y	Y
Fund FE and controls	Y	Y	Y	Y	Y	Y
Security controls	Y	Y	Y	Y	Y	Y

Panel B: Second-stage estimation results

	$Divest_{fit}$			$\Delta Exposure_{fit}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Similarity^{inst}_{fit-1}$	7.15*	6.75*	6.19**	-5.53**	-5.44**	-5.33***
	(1.81)	(1.79)	(2.01)	(-2.36)	(-2.38)	(-2.67)
$EurExp_{fit-1}$	-1.62*	-1.53*	-1.40*	1.35**	1.33**	1.30**
	(-1.69)	(-1.67)	(-1.82)	(2.23)	(2.24)	(2.45)
Observations	21,646	21,646	21,646	18,349	18,349	18,349
R-squared	-0.01	0.00	0.02	-0.06	-0.06	-0.05
Issuer×time FE	Y	Y	Y	Y	Y	Y
Fund FE and controls	Y	Y	Y	Y	Y	Y
Security controls	Y	Y	Y	Y	Y	Y

Table 7: Funds' portfolio allocation decisions and portfolio similarity: Delays in portfolio composition disclosure.

This table reports the regression estimates on portfolio similarity lagged by one (Column (1)) to six months (Column (6)), where the dependent variable is $Divest_{fit}$ in Panel A, and $\Delta Exposure_{fit}$ in Panel B. The reported regression results control for issuer×time fixed effects and fund fixed effects. $Divest_{fit}$, $\Delta Exposure_{fit}$, $Similarity_{fit}$ are defined in Table 2. Coefficient estimates on $Divest$ are multiplied by 100. t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

Panel A: Lagged effect of portfolio similarity on the probability to divest

	$Divest_{fit}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Similarity_{fit-1}$	0.31***						-0.11
	(2.94)						(-0.64)
$Similarity_{fit-2}$		0.40***					-0.01
		(3.56)					(-0.07)
$Similarity_{fit-3}$			0.51***				0.26
			(4.45)				(1.28)
$Similarity_{fit-4}$				0.60***			0.60***
				(5.25)			(3.26)
$Similarity_{fit-5}$					0.16		-0.41**
					(1.26)		(-2.09)
$Similarity_{fit-6}$						0.03	-0.05
						(0.27)	(-0.32)
Observations	55,764	53,002	50,215	47,407	44,482	41,521	41,521
R-squared	0.12	0.12	0.12	0.12	0.12	0.12	0.12
Issuer×time FE	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y
Other controls	N	N	N	N	N	N	N

Panel B: Lagged effect of portfolio similarity on the fund's exposure

	$\Delta Exposure_{fit}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Similarity_{fit-1}$	-0.17***						-0.04
	(-2.70)						(-0.43)
$Similarity_{fit-2}$		-0.20***					-0.09
		(-3.06)					(-0.75)
$Similarity_{fit-3}$			-0.21***				0.01
			(-3.24)				(0.11)
$Similarity_{fit-4}$				-0.29***			-0.42***
				(-4.35)			(-3.85)
$Similarity_{fit-5}$					-0.03		0.28**
					(-0.39)		(2.37)
$Similarity_{fit-6}$						-0.04	-0.00
						(-0.51)	(-0.00)
Observations	48,623	46,221	43,726	41,268	38,660	36,283	36,283
R-squared	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Issuer×time FE	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y
Other controls	N	N	N	N	N	N	N

Table 8: Issuer's funding liquidity risk and issuer's average fund similarity.
This table shows the effect of the average fund portfolio similarity of an issuer on the issuer's total unsecured funding from MMFs. $\Delta Outstanding_{it}$ is the percentage change in the total principal amount of issuer i at time t. $CorrOutflows_{it}$ is the fraction of funds reducing their exposure to issuer i at time t. $Similarity_{it}$ is the average similarity of the funds exposed to issuer i at time t. The table reports the results for financial institutions and non-financial institutions separately, controlling for issuer and time fixed effects, and issuer controls that include the weighted average maturity and weighted average yield of the securities of issuer i held by MMFs in the previous month. In addition, Columns (2), (4), (6), and (8) control for additional concentration measures such as the number of funds lending to an issuer and the HHI of the issuer's MMF liabilities. Coefficient estimates on $CorrOutflows_{it}$ are multiplied by 100. t-statistics based on standard errors clustered at the issuer level are reported in parentheses.

	$\Delta Outstanding_{it}$				$CorrOutflows_{it}$			
	Financial		Non Financial		Financial		Non Financial	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{it-1}$	-0.18	-0.43**	-0.76	-0.74	0.30***	0.34***	-0.32**	-0.32***
	(-0.75)	(-2.44)	(-1.11)	(-1.12)	(3.36)	(3.81)	(-2.62)	(-2.81)
$IssuerHHI_{it-1}$		0.35***		0.06		-0.04		-0.05
		(2.90)		(0.20)		(-1.10)		(-0.79)
$Funds_{it-1}$		-0.34***		-1.16**		0.07***		0.23
		(-4.28)		(-2.05)		(3.06)		(1.66)
Observations	3,057	3,057	680	680	3,057	3,057	680	680
R-squared	0.07	0.09	0.16	0.17	0.18	0.19	0.30	0.30
Issuer and time FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y

Table 9: Issuer's average yield and fund portfolio similarity.
This table shows the effect of the portfolio similarity of the funds of an issuer on the issuer's average yield. $Yield_{it}$ is the weighted average ex-ante yield on unsecured securities of issuer i held by U.S. MMFs at time t. Sim_{it} is the average similarity of the funds exposed to issuer i at time t ($Similarity_{it}$) in Columns (1) to (4), and the minimum similarity of the 5% most similar funds exposed to issuer i at time t ($Similarity_{it}^{95\%}$) in Columns (5) to (8). The flow-induced price pressure variable $FIPP_{it}$ (Edmans et al., 2012) is a measure of price pressure induced by funds' investors net flows. $FIPP_{it}$ is interacted with the same stress indicators as Sim_{it-1} in all specifications, but these interaction coefficients are not statistically significant and therefore not reported in the table. $Crisis_t$ is an indicator variable for the period from June 2011 until December 2011. $SRISK_t$ and $\Delta CoVaR_t$ are systemic risk indicators, taking the value of one for the months were SRISK (Acharya et al., 2017; Brownlees and Engle, 2017), resp. ΔCoVaR (Adrian and Brunnermeier, 2016), are the highest. The table reports the results controlling for issuer and time fixed effects, and controlling for the weighted average maturity of the unsecured securities of issuer i held by U.S. MMFs at time t, and lagged variables capturing the issuer's liabilities diversification (i.e., the number of funds holding securities from an issuer, and the issuer's funding HHI). t-statistics based on standard errors clustered at the issuer level are reported in parentheses.

	$Yield_{it}$							
	$Sim_{it} = Similarity_{it}$ (Average)				$Sim_{it} = Similarity_{it}^{95\%}$ (95th percentile)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fund similarity (Sim_{it-1})	0.01	-0.02	-0.04	-0.06	0.03	-0.02	-0.04	-0.05
	(0.27)	(-0.39)	(-0.70)	(-1.34)	(0.45)	(-0.31)	(-0.66)	(-0.98)
$Sim_{it-1} \times Crisis_t$		0.13**	0.08*	0.05		0.19***	0.16***	0.10
		(2.46)	(1.78)	(0.90)		(2.94)	(2.74)	(1.31)
$Sim_{it-1} \times SRISK_t$			0.17***				0.20***	
			(3.97)				(3.28)	
$Sim_{it-1} \times \Delta CoVaR_t$				0.15***				0.16**
				(2.70)				(2.09)
Flow-induced price	7.10***	7.13**	6.88**	9.59***	7.14***	7.11**	6.80**	9.76***
pressure ($FIPP_{it}$)	(2.82)	(2.31)	(2.18)	(2.64)	(2.87)	(2.31)	(2.15)	(2.73)
Observations	3,702	3,702	3,702	3,702	3,702	3,702	3,702	3,702
R-squared	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72
Issuer & Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y

C Internet Appendix

In Section C.1, we provide an illustrative example to build intuition for the similarity measure presented in the paper. In Section C.2, we present an additional figure illustrating the unsecured exposure of U.S. money market funds to euro area financial institutions during our sample period. We report additional descriptive statistics in Section C.3, including an analysis of the relationship between our portfolio similarity measure and other fund characteristics. Finally, in Section C.4, we discuss additional robustness checks and analyses.

C.1 An Example to Illustrate the Portfolio Similarity Measure

To illustrate the $Similarity_{fit}$ measure, consider the following simple example. There are three funds, f_1, f_2, and f_3 investing in three issuers i_1, i_2, and i_3 at a given date (we omit the subscript t for simplicity) as follows:

		i_1	i_2	i_3
f_1	=	1	1	1
f_2	=	1	1	1
f_3	=	1	0	1

Funds f_1 and f_2 have exactly the same portfolios. Fund f_1 observes that i_2 is only exposed to f_2, which holds the same portfolio as fund f_1 itself. Therefore, issuer i_2 is riskier compared to the other two issuers from fund f_1's perspective. Funds f_1 and f_2 are *similar investors*.

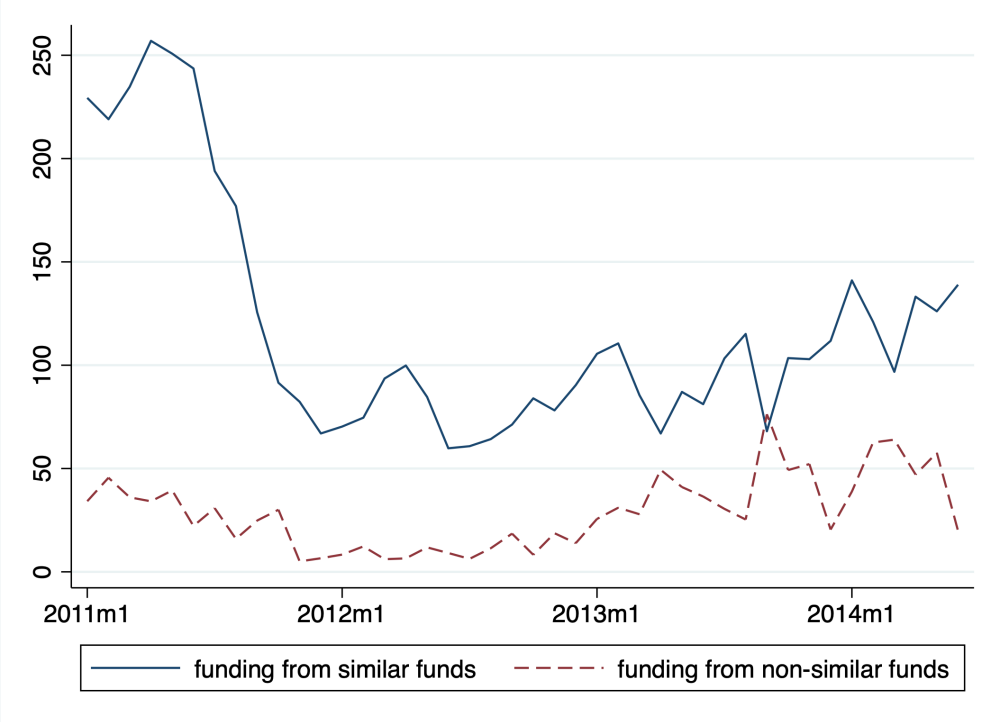
Closer to our empirical methodology, we compare the portfolio similarity of several funds lending to the same issuer. When considering rolling over funding to issuer i_1, since the portfolio of fund f_3 is the most different compared to the other funds lending to issuer i_1, fund f_3 is less likely to withdraw.

For fund f_1's decision to roll over funding to issuer i_1, the relevant pairwise Euclidean distances in funds' portfolio holdings are $d_{f_1,f_2} = 0$ and $d_{f_1,f_3} = 0.707$. Ignoring funding from fund f_1, issuer i_1 relies for 50% on fund f_2 and 50% on fund f_3. Therefore, the weights are $w_{f_2,i_1} = w_{f_3,i_1} = 1/2$, and the average distance of fund f_1 in issuer i_1 is $Distance_{f_1,i_1} = 1/2 \cdot 0 + 1/2 \cdot 0.707 = 0.354$, which converts into a similarity measure of $Similarity_{f_1,i_1} = 75\%$. We obtain the same portfolio similarity measure for fund f_2 in issuer i_1, i.e., $Similarity_{f_2,i_1} = 75\%$.

Similarly, for fund f_3's decision to roll over funding to issuer i_1, the relevant pairwise Euclidean distances in funds' portfolio holdings are $d_{f_3,f_1} = 0.707$ and $d_{f_3,f_2} = 0.707$, and the weights are $w_{f_1,i_1} = w_{f_2,i_1} = 1/2$. The average distance of fund f_3 in issuer i_1 to other funds is $Distance_{f_3,i_1} = 1/2 \cdot 0.707 + 1/2 \cdot 0.707 = 0.707$, which converts into a similarity measure of $Similarity_{f_3,i_1} = 50\%$.

C.2 Additional Figures

Figure 4: Similar versus Non-similar Funds' Investments in Euro Area Financial Institutions.



This figure shows the total unsecured principal amount invested by similar U.S. MMFs (solid line) and non-similar U.S. MMFs (dashed line) at euro area financial institutions in $ billion. A fund is considered similar if its average similarity measure is greater than or equal to the median average similarity measure of all funds.

C.3 Additional Descriptive Statistics

In this section, we report additional descriptive statistics at the issuer level in Table SI-1, at the MMF security level in Table SI-2, and at the fund level in Table SI-3. In Table SI-4, we decompose the variation in the portfolio similarity measure as a function of other fund characteristics.

Table SI-1: Descriptive statistics of issuers of MMF securities.
This table provides descriptive statistics of issuers of U.S. MMFs' securities. Panel A provides descriptive statistics that are not restricted to unsecured securities, and that are not restricted to issuers that borrow from at least two funds at the same time. In Panel B, we restrict the sample to unsecured securities, but unlike in Table 1, the sample is not restricted to issuers that borrow from at least two funds at the same time. Panel C reports average variables on different sample splits. $Amount_{it}$ is the total principal amount of secured and unsecured securities (in $ 1'000) borrowed by issuer i at date t. $\Delta Outstanding_{it}$ is the percentage change in the unsecured principal amount. $CorrOutflows_{it}$ is the fraction of funds divesting from issuer i in month t. $ShareUnsecured_{it}$ is the percentage of total securities issued that are unsecured. $Yield_{it}$ and $Maturity_{it}$ are respectively the average yield (in p.p.) and the average maturity (in days) of unsecured securities of an issuer. (Unsecured) $Funds_{it}$ is the number of funds lending (unsecured) to an issuer in the same month. The $IssuerHHI_{it}$ is the Hirschman-Herfindahl Index (in %) measured on MMF liabilities of issuer i at date t. Before crisis: 2010-12 - 2011-05, During crisis: 2011-06 - 2011-12, After crisis: 2014-08.

Panel A: Issuers' descriptive statistics (secured and unsecured securities)

$Amount_{it}$	5,941	7,762	14,256	0.24	281,874
$\Delta Outstanding_{it}$	5,061	0.09	28.72	-99.85	99.85
$ShareUnsecured_{it}$	5,941	85.34	31.17	0	100
$Yield_{it}$	5,941	0.25	0.15	0	6
$Maturity_{it}$	5,941	52.67	63.76	1	395
$Funds_{it}$	5,941	29.31	39.88	1	189
Unsecured $Funds_{it}$	5,941	22.59	31.54	0	135
$IssuerHHI_{it}$	5,941	44.88	38.88	1.24	100
Number of issuers	311				
of which, fin. institutions	213				
of which, banks	161				
of which, euro area banks	28				

Panel B: Issuers' descriptive statistics limited to unsecured securities

$Amount_{it}$	5,563	5,450	9,267	0.24	61,526
$\Delta Outstanding_{it}$	4,691	0.13	28.90	-100	99
$CorrOutflows_{it}$	5,032	0.21	0.24	0	1
$Yield_{it}$	5,563	0.28	0.17	0	4.5
$Maturity_{it}$	5,563	59.90	64.12	1	395
$Funds_{it}$	5,563	30.35	40.50	1	189
Unsecured $Funds_{it}$	5,563	24.13	32.02	1	135
$IssuerHHI_{it}$	5,563	44.11	38.32	1.91	100
Number of issuers	297				
of which, fin. institutions	203				
of which, banks	155				
of which, euro area banks	27				

Panel C: Issuers' descriptive statistics on subsamples (unsecured securities)

	Amount	ΔOut	Yield	Maturity	Sim	Funds	Funds unsec.	HHI
Non-financial inst.	3,384	-1.27	0.22	53.55	81.35	16.06	16.01	42.89
Financial inst.	8,186	0.68	0.28	44.11	84.49	45.37	35.65	23.77
Banks	9,613	0.87	0.29	44.94	85.31	52.92	41.17	19.82
Before crisis	8,013	-0.95	0.33	46.18	83.88	40.05	33.47	25.04
During crisis	6,993	-2.20	0.28	36.95	82.89	39.58	31.53	27.72
After crisis	7,171	1.04	0.26	47.95	84.08	39.51	31.56	27.89
Euro area banks	7,689	0.58	0.29	41.90	85.63	45.54	31.20	22.48
Non-euro area banks	10,317	0.97	0.30	46.05	85.20	55.61	44.82	18.84

Note: ΔOut stands for $\Delta Outstanding_{it}$, Sim for $Similarity_{it}$, and Funds (unsec.) for (Unsecured) $Funds_{it}$.

Table SI-2: Descriptive statistics of MMF securities.
This table provides descriptive statistics of U.S. MMFs' securities. Panel A presents descriptive statistics for all unsecured securities, not limited to issuers that borrow from at least three funds. Panel B presents descriptive statistics of all securities, including secured ones (i.e., repurchase agreements), and also not limited to issuers that borrow from at least three funds. $Amount_{fit}$ is the principal amount (in $ 1'000) borrowed by issuer i from fund f at time t. $\Delta Exposure_{fit}$ is the percentage change in fund f's exposure to issuer i at time t. $Divest_{fit}$ is the probability that fund f reduces its unsecured exposure to issuer i at time t. $Yield_{fit}$ and $Maturity_{fit}$ are respectively the average yield (in p.p.) and the average maturity (in days) of securities issued by issuer i and held by fund f at time t. $Similarity_{fit}$ is the portfolio similarity of fund f to other funds exposed to issuer i at time t (in %).

Panel A: Full sample of unsecured securities

	Obs.	Mean	Std. Dev.	Min	Max
$Amount_{fit}$	152,785	198	448	0.001	10,461
$\Delta Exposure_{fit}$	125,203	-0.28	28.95	-100	100
$Divest_{fit}$	132,879	0.24	0.43	0	1
$Yield_{fit}$	143,995	0.29	0.15	0	5.51
$Maturity_{fit}$	152,762	50.63	45.97	0.63	395
$Similarity_{fit}$	149,002	82.25	6.47	23.48	100
Number of funds	214				
Number of issuers	297				

Panel B: Full sample of securities

	Obs.	Mean	Std. Dev.	Min	Max
$Amount_{fit}$	203,321	227	484	0.001	10.461
$\Delta Exposure_{fit}$	158,523	-0.25	31.54	-100	100
$Divest_{fit}$	172,644	0.28	0.45	0	1
$Yield_{fit}$	191,030	0.25	0.15	0	6
$Maturity_{fit}$	203,298	38.73	44.98	0.63	395
$Similarity_{fit}$	167,432	81.96	6.78	23.48	100
Number of funds	332				
Number of issuers	311				

Table SI-3: Descriptive statistics of MMFs.
This table provides descriptive statistics of U.S. MMFs. The table reports average variables separately for euro-exposed funds and non-euro exposed funds. A fund is considered "Euro-exposed" if its exposure to euro area issuers is greater than zero in June 2011, a fund is considered "Non-euro exposed" if its portfolio size is greater than zero and its exposure to euro area issuers is equal to zero in June 2011. $Similarity_{ft}$ is the average similarity of fund f to all other funds with common exposures at date t (in %). HHI_{ft} is the HHI (in %) on the fund's unsecured portfolio, $Issuers_{ft}$ is the number of issuers a fund invests during the same month. $FundSize_{ft}$ is the size (in $ 1'000) of the unsecured portfolio of the fund. 7-day simple $Yield_{ft}$ is a SEC-approved yield (in basis points) that describes the annualized income that the fund investors earned over the last seven days. WAL_{ft} is the weighted average life (in days) of the fund's portfolio, WAM_{ft} is the weighted average maturity (in days) of the fund's portfolio, and $Euro\ area\ exposure_{ft}$ is the fraction (in p.p.) of the fund's unsecured portfolio invested in euro area issuers. "Before": 2010-12 – 2011-05, "After": 2012-01 – 2014-08, and "Change" is the difference between the values in the column "After" and the column "Before."

	Non-euro exposed funds			Euro-exposed funds		
	Before	After	Change	Before	After	Change
$Similarity_{ft}$	60.60	63.55	2.95	78.13	79.05	0.92
HHI_{ft}	49.05	34.31	-14.74	11.44	10.35	-1.08
$Issuers_{ft}$	3.38	5.02	1.64	18.86	19.54	0.69
$FundSize_{ft}$	88	188	100	5,251	5,410	159
7-day simple $Yield_{ft}$	1.29	1.23	-0.05	6.54	4.20	-2.34
WAL_{ft}	49.51	48.90	-0.62	61.60	61.17	-0.43
WAM_{ft}	38.06	39.17	1.11	38.32	39.49	1.17
$Euro\ area\ exposure_{ft}$	0.63	3.57	2.94	35.03	16.37	-18.66
Number of funds	16	15	-1	165	158	-7
Number of observations	73	342	269	807	4,468	3661

Table SI-4: Decomposition of the variation in portfolio similarity.
This table shows the relationship between portfolio similarity ($Similarity_{fit}$), portfolio concentration ($Weight_{fit}$ and HHI_{ft}), fund size ($Size_{ft}$), and the weighted average maturity of securities issued by issuer i and held by fund f ($Maturity_{fit}$). $Similarity_{fit}$ is the similarity of fund f to the other funds exposed to issuer i at time t. w_{fit} is the fraction of the portfolio of fund f invested in issuer i at time t. HHI_{ft} measures the portfolio concentration of the fund. The reported regression results control for issuer×time fixed effects and fund fixed effects in Columns (2), (4), and (6). Additionally, Columns (5) and (6) control for cross-product terms of independent variables. t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

	Similarity					
	(1)	(2)	(3)	(4)	(5)	(6)
$Weight_{fit}$	-19.73***	-1.68	-45.13***	-20.35***	-52.44***	-23.45***
	(-4.01)	(-0.63)	(-10.83)	(-8.44)	(-10.54)	(-8.15)
$Weight^2_{fit}$			42.19***	31.77***	65.64***	41.47***
			(5.80)	(6.42)	(7.15)	(6.05)
HHI_{ft}	-0.53***	-0.34***	-0.99***	-0.81***	-1.05***	-0.86***
	(-9.19)	(-7.64)	(-15.31)	(-15.65)	(-14.09)	(-14.78)
HHI^2_{ft}			0.01***	0.01***	0.01***	0.01***
			(8.58)	(11.11)	(5.91)	(9.70)
$Size_{ft}$	0.52***	0.73***	0.49**	1.69***	-0.21	0.68*
	(4.56)	(3.02)	(2.20)	(4.60)	(-0.44)	(1.67)
$Size^2_{ft}$			-0.05*	-0.16***	-0.02	-0.11***
			(-1.67)	(-4.79)	(-0.64)	(-3.76)
$Maturity_{fit}$	0.22**	0.09***	0.69***	0.59***	-0.22	0.51***
	(2.04)	(3.76)	(3.23)	(11.22)	(-1.10)	(6.35)
$Maturity^2_{fit}$			-0.29***	-0.28***	-0.36***	-0.30***
			(-2.80)	(-11.23)	(-3.68)	(-9.46)
Observations	147,648	147,647	147,648	147,647	147,648	147,647
R-squared	0.50	0.84	0.64	0.88	0.65	0.88
Issuer×time FE	N	Y	N	Y	N	Y
Fund FE	N	Y	N	Y	N	Y
Cross-product controls	N	N	N	N	Y	Y

C.4 Additional Robustness and Analyses

In this section, we discuss several additional robustness checks and analyses to complement our main findings. First, we show that our results remain qualitatively unchanged when considering that funds with similar investment strategies (e.g., follow the same index), may not be concerned about portfolio similarity. Second, we document that the effect of portfolio similarity is reversed for secured funding, where joint liquidation costs are less of a concern. Third, we show that fund divestments are exacerbated for riskier issuers with more similar funds and that this effect becomes even more pronounced during crises. Fourth, we consolidate funds belonging to the same fund complex, as funds may aim to reduce the exposure to joint liquidation costs faced by other funds in the same complex rather than only at the individual fund level. We also control for funds complexes' affiliation with banks and show that this does not significantly affect our main results. We use several alternative fund similarity measures and document that our measure outperforms others in predicting future fund allocation decisions. Finally, we show that our results are the issuer level are robust to the inclusion of issuer×year fixed effects, reducing the scope for omitted variable bias in these regressions.

C.4.1 Similar Investment Strategies

We investigate an alternative explanation for our results, namely the concern that funds' decisions to divest from some issuers are the result of funds following similar investment strategies rather than being the result of concerns over portfolio similarity. In Table SI-5, we investigate the possibility that the effect of portfolio similarity on fund divestment arises from funds following the same benchmark index in their portfolio allocation decisions. To account for this, all specifications include a control for the correlation between a fund's net investor flows and the net flows of other funds exposed to the same issuer. This variable is constructed analogously to 1, but replacing pairwise Euclidean distances with pairwise correlations in net investor flows. We refer to this measure as net flow similarity ($FlowCor_{fit}$), which also captures similarities in fund performance, since funds with correlated flows are likely to exhibit correlated returns.

We introduce additional controls and fixed effects to control for observed and unobserved heterogeneity in fund characteristics. In Columns (1) and (5), we control for a fund's performance, average liquidity and average maturity. These fund controls absorb the heterogeneity in fund performance, liquidity and maturity, making funds more comparable and more likely to

follow the same investment strategy. In Columns (2) and (6), we add fund cluster×time fixed effects. Fund clusters are obtained from a principal component analysis on fund performance.[23] The fund cluster×time fixed effects absorb the common component of funds following the same index. In Columns (3) and (7), we add fund complex×time fixed effects. The fixed effects in this case absorb the common component of funds belonging to the same fund complex. Finally, we add fund×time fixed effects in Columns (4) and (8), which absorb all heterogeneity in funds' investments decisions except for their issuer-specific similarity. We can therefore assess how a fund will tilt its portfolio towards issuers whose other investors are less similar to the fund, while controlling for all observed and unobserved characteristics of the fund.

In all regressions, we obtain the same sign for the estimates of the effect of portfolio similarity, and the estimates remain significant at the 10% level, indicating that our interpretations remain qualitatively unchanged. By contrast, the variable capturing similarity in net investor flows ($FlowCor_{fit}$) does not subsume the effect of portfolio similarity: while its coefficients generally have the expected signs, their statistical significance is not consistent, and they never eliminate the role of portfolio similarity. This underscores that our mechanism is primarily about similarity in portfolio composition, as in Wagner (2011), rather than about similarities in investor flows or fund performance.

C.4.2 Portfolio Similarity and Ownership Concentration

Table SI-6 reports regressions of divestment (Columns (1)–(4)) and changes in exposure (Columns (5)–(8)) on portfolio similarity and ownership concentration. Ownership concentration is measured using the definition of Giannetti and Jotikasthira (2024), where $topdecile_{fit}$ equals one if a position is in the top decile of a fund's share of a given issuer's total unsecured principal. Consistent with their findings, top-decile positions are less likely to be divested and experience smaller reductions in exposure, reflecting that large holders internalize fire-sale externalities. By contrast, portfolio similarity remains statistically significant across all specifications: funds are more likely to divest, and reduce exposures more strongly, when they are similar to other holders of the issuer's securities. The interaction terms between similarity and $topdecile_{fit}$

[23] We compute the first five principal components of monthly fund performance to explicitly account for the possibility that different funds follow the same index. We then regress a fund's monthly performance on the principal components and create five indicator variables equal to one if a fund has a significant loading on a principal component. This results in $2^5 = 32$ possible combinations of indicator variables per fund. Finally, we cluster all funds with the same combination of indicator variables into one cluster.

are also significant: for top-decile positions, similarity increases the probability of divestment for top-decile positions, higher similarity further increases the probability of divestment and amplifies the reduction in exposure. Importantly, portfolio similarity ($Similarity_{fit-1}$) remains statistically significant in predicting both divestment and changes in exposure, even after controlling for ownership concentration. This suggests that our similarity channel is distinct from ownership-concentration effects and reflects anticipatory concerns about joint liquidation costs.

C.4.3 Secured Versus Unsecured Funding

In Table SI-7, we test whether portfolio similarity has the same effect on fund portfolio decisions irrespective of whether the securities are secured or not. Specifically, we limit the sample of issuers to those that borrow from at least three funds, but not necessarily in the form of unsecured securities. In other words, the issuer may also borrow via repurchase agreements (repos) from U.S. MMFs. We report the results for $Divest$ in Columns (1) to (3) and for $\Delta Exposure$ in Columns (4) to (6). In Columns (1) and (4), we report the effect of portfolio similarity for the whole sample, which includes both secured and unsecured debt securities, which include certificates of deposit, financial commercial paper, government agency repos, and treasury repos. We also report the results separately for secured securities in Columns (2) and (5), and for unsecured securities in Columns (3) and (6). We observe the contrasting effect of portfolio similarity on the decisions of funds to divest from secured versus unsecured securities of an issuer by comparing Columns (2) and (3) for $Divest$, and Columns (5) and (6) for $\Delta Exposure$. The effect of portfolio similarity on divestment decisions is reversed for secured funding. Government agency repos and treasury repos are secured by the highest quality collateral. Issuers holding eligible collateral and having access to secured funding markets can substitute the loss of funding from similar investors in unsecured markets with repurchase agreements. It is plausible that investor similarity and exposure to joint liquidation costs are less of a concern for secured securities, where concerns over the collateral's endogenous illiquidity might be better captured by considering the similarity between all investors exposed to the same collateral (rather than the group of investors investing in a specific issuer's security secured by the collateral).

C.4.4 Issuer Risk

We study the interaction of similarity with issuer stock price volatility. Joint liquidation costs are likely to be more of a concern for riskier issuers because they are more prone to default on repayment when multiple funds divest. While our regression design absorbs all variation in fund divestment related to issuer risk through issuer×time fixed effects, this design still allows us to investigate whether funds' response to similarity is stronger for riskier issuers by using interaction terms with a proxy for issuer risk. To measure risk, we construct the stock return volatility variable $Risk_{it}$ for the sample of issuers that are public firms. We then include the interaction term $Similarity_{fit-1} \times Risk_{it-1}$ in our baseline regression. We report the results in Panel A of Table SI-8.

Columns (1) to (3) show the results for $Divest$ and Columns (4) to (6) present the results for $\Delta Exposure$. Columns (1) and (4) replicate the baseline results of Table 2 for the restricted sample of issuers for which stock price data are available. Columns (2) and (5) include an interaction term $Similarity_{fit-1} \times Risk_{it-1}$, and Columns (3) and (6) include an additional interaction term with the crisis period indicator variable, which equals one for the period from June 2011 until December 2011.

We find that the effect of portfolio similarity on the divestment probability does not depend on issuer risk or the crisis period indicator in Column (2) and (3). In contrast, Column (5) shows that funds divest significantly more from issuers with similar investors when these issuers are riskier. Column (6) shows that the effect of portfolio similarity on fund divestment from these risky issuers is even stronger during the crisis period. In summary, the probability that a fund divests based on similarity does not increase with issuer risk, but the reduction in the funds' exposure is larger when they do divest, particularly during stressed periods.

C.4.5 Fund Complex and Bank-Affiliated Funds

In Table SI-9, we replicate the results of Table 2 at the fund complex level. Funds that belong to the same fund complex are sponsored by a single provider who typically also manages the group of funds (Schmidt et al., 2016). Given that the funds within the same fund complex have common management, they have an interest in reducing the exposure to joint liquidation costs faced by other funds in the same complex, not just at the individual fund level. To address this concern, we replicate the results of our baseline regression at the fund complex level, and

report the results in Table SI-9. Compared to the results in Table 2, the economic magnitude of the effect of portfolio similarity is the same for the percentage change in the fund's exposure ($\Delta Exposure$), but almost doubles for the probability of divestment ($Divest$). In other words, fund complexes that are more similar to other fund complexes exposed to the same issuer, are twice as likely to reduce their exposure to the issuer compared to individual funds.

In addition, some fund complexes are affiliated with banks. For example, JPMorgan Prime MMF/Capital is a fund of J.P. Morgan Asset Management, which is the asset management business of JPMorgan Chase & Co. Another example is HSBC Prime Money Market Fund from HSBC Global Asset Management (USA) Inc., a subsidiary of a bank holding company. Almost half of the sample consists of bank-affiliated funds. In Table SI-10, we investigate whether our results on similarity-associated divestments change if the MMF is affiliated with a bank. Column (1) of Table SI-10 shows that the effect of similarity on the divestment probability is neutralized when the fund is affiliated with a bank. However, the differential effect is no longer statistically significant when we control for time-invariant fund-bank relationships by including fund×issuer fixed effects in Column (2). This result is expected as the affiliation of a fund to a bank rarely changes over time. Likewise, the differential effect of similarity for bank-affiliated funds is not statistically significant for $\Delta Exposure$ in Columns (3) and (4).

C.4.6 Alternative Similarity Measures

In this section, we compare our portfolio portfolio similarity measure with other measures of portfolio similarity used in the literature. We show evidence that $Similarity_{fit}$ outperforms other measures of similarity in predicting future fund portfolio allocation decisions in Table SI-11. In the table, Columns (1) and (5) report the results for $Similarity_{fit}$ as defined in equations (1) and (2). Columns (2) and (6) report the results for $Similarity^{\ni i}_{fit-1}$, which differs from $Similarity_{fit}$ because it does not exclude the exposure to issuer i from funds' portfolios in the computation of the Euclidean distances in equation (1).[24] Comparing Column (1) to Column (2), and Column (5) with Column (6), we can identify and measure the bias due to including exposures to issuer i in the definition of the similarity measure. We observe that the coefficient magnitude increases considerably when the exposure to issuer i is included in the computation of portfolio similarity ($Similarity^{\ni i}_{fit-1}$).

[24] Note that the Euclidean distances for $Similarity_{fit}$ are derived from sub-portfolios of the funds, excluding their exposure to issuer i to avoid endogeneity concerns.

Following the literature on asset commonality (Cai et al., 2018), we compute the similarity of a fund to all other funds in our sample. In other words, instead of averaging portfolio similarity only over funds investing in a particular issuer, we do so across all other funds. We report the results in Columns (3) and (7) for $Similarity_{ft-1}^{conv,u}$ (the unweighted average similarity between fund f and all other funds in the sample), and in Columns (4) and (8) for $Similarity_{ft-1}^{conv,w}$ (the weighted average similarity between fund f and all other funds in the sample, with weights proportional to fund size). We find that the measures $Similarity_{ft-1}^{conv,u}$ and $Similarity_{ft-1}^{conv,w}$ do not predict the probability of divestment in Columns (3) and (4), and are only significant at the 10% level when predicting the percentage change in a fund's exposure in Columns (7) and (8).

C.4.7 Investors Similarity and Issuer's Funding Fragility

In Table SI-12, we investigate whether issuers can compensate for outflows with funding from non-similar investors. In particular, if there are material concerns about the liquidity of the securities of financial institutions, non-similar investors could play a role in stabilizing the institutions' access to funding. To test the substitution effects between similar and non-similar investors, we split our dependent variable describing the percentage fund flows to an issuer into two separate dependent variables: (i) the percentage fund flows to an issuer from similar investors, and (ii) the percentage fund flows to an issuer from non-similar investors. Funds are labeled as similar when their similarity measure is above the median similarity measure of funds in a given month.

Table SI-12 reports regression results separately for fund flows ($\Delta Outstanding$) from similar funds (Columns (1), (3), (5) and (7)) and non-similar funds (Columns (2), (4), (6) and (8)). As in Table 8, we also report the results for financial and non-financial issuers separately, controlling for issuer and month fixed effects, and controls that include the average maturity and average yield of securities of an issuer. In addition, Columns (2), (4), (6) and (8) control for conventional concentration measures (HHI and number of funds). We find a significant decrease in fund flows from similar investors associated with an increase in fund similarity (Columns (1) and (3)), while the effect of fund similarity is not statistically significant for fund flows from non-similar investors (Columns (2) and (4)). That is, non-similar investors do not compensate for the loss of funding from similar investors. The estimate of -2.22 in Column (3) translates into an average 40% decrease of an issuer's outstanding amount from similar investors as a result of a one standard deviation increase in the issuer's average fund similarity, and this loss of funds

is not compensated for by non-similar investors. In contrast, there is no effect of similarity on fund flows to non-financial issuers (Columns (5) to (8)), independently of whether fund flows are from similar or non-similar investors.

In Table SI-13, we assess the relevance of the average similarity of funds as a predictor of fund flows in a crisis. To do so, we estimate the effect of similarity during the crisis period from June 2011 until December 2011 ($Crisis_t$), and compare it to the effect of fund similarity outside the crisis months. The results are again reported separately for financial and non-financial issuers and for the two dependent variables $\Delta Outstanding$ and $CorrOutflows$. The results in the table show that the negative effect of average fund similarity on fund flows is larger in economic magnitude during the crisis for financial firms. As in Table 8, the effect on fund flows is only significant when we control for other concentration measures. The effect of average fund similarity is, however, stable for correlated outflows and does not change substantially between the two periods. Finally, and consistent with the previous results, the effect of fund similarity on funding liquidity is only relevant for financial institutions.

To reduce concerns about omitted variable bias in the issuer level regressions, we replicate the results of this table, replacing issuer and time fixed effects by issuer×year and time (month) fixed effects in Table SI-14. We find that the alternative specifications do not qualitatively change our results.

Table SI-15 confirms that the effects of portfolio similarity on yields are not driven by arbitrary thresholds for systemic risk. Using continuous measures of SRISK and ΔCoVaR, we find that the interaction between fund similarity and systemic stress remains statistically and economically significant, reinforcing that pricing effects emerge when aggregate financial conditions deteriorate.

Finally, Table SI-16 shows that funding outflows are primarily driven by the most similar investors. The similarity of the 5% most similar funds significantly predicts decreases in the total amount lent to issuers, while the similarity of the 5% least similar funds does not. Dispersion in similarity, measured by the standard deviation, is also associated with larger funding losses, supporting the relevance of within-issuer variation in similarity.

Table SI-5: Funds' portfolio allocation decision and portfolio similarity: Similar investment strategies.

This table shows the effect of portfolio similarity on funds' decision to divest from an issuer, controlling for a common investment strategy among funds following the same index. Net flows similarity ($FlowCor_{fit-1}$) is the weighted average of pairwise correlations of fund f's net investors flows with the net investor flows other funds exposed to issuer i. All other variables are defined in Table 2. Coefficient estimates on $Divest$ are multiplied by 100. t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

	$Divest_{fit}$				$\Delta Exposure_{fit}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Portfolio similarity	0.11**	0.10*	0.14*	0.70***	-0.11***	-0.15***	-0.20***	-0.71***
($Similarity_{fit-1}$)	(2.15)	(1.84)	(1.92)	(6.03)	(-3.06)	(-3.55)	(-3.63)	(-7.42)
Net flows similarity	0.02*	0.01	0.01	0.02	-0.81	-1.13*	-1.33**	-1.32*
($FlowCor_{fit-1}$)	(1.91)	(1.36)	(1.26)	(1.59)	(-1.42)	(-1.76)	(-2.32)	(-1.65)
Observations	119,877	101,020	119,446	120,402	101,711	86,141	101,701	102,138
R-squared	0.21	0.22	0.25	0.27	0.10	0.13	0.14	0.17
Issuer*month FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund controls	Y	N	N	N	Y	N	N	N
Fund cluster*month FE	N	Y	N	N	N	Y	N	N
Fund complex*month FE	N	N	Y	N	N	N	Y	N
Fund*month FE	N	N	N	Y	N	N	N	Y
Fund FE	Y	Y	Y	N	Y	Y	Y	N
Security controls	Y	Y	Y	Y	Y	Y	Y	Y

Table SI-6: Funds' portfolio allocation decisions according to portfolio similarity and ownership concentration.

This table reports the regression estimates on portfolio similarity and ownership concentration measures. The dependent variable is $Divest_{fit}$ in Columns (1) to (4), and $\Delta Exposure_{fit}$ in Columns (5) to (8). Fund's ownership concentration is measured as in Giannetti and Jotikasthira (2024): $Topdecile_{fit}$ equals to one if a position is in the top decile of our fund-issuer-time data set. $Divest_{fit}$, $\Delta Exposure_{fit}$, $Similarity_{fit}$, control variables, and fixed effects are defined in Table 2. Coefficient estimates on $Similarity_{fit-1}$ are multiplied by 100 in Columns (1) to (4). t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

	$Divest_{fit}$				$\Delta Exposure_{fit}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{fit-1}$	0.17***	0.17***	0.13**	0.12**	-0.17***	-0.25***	-0.15***	-0.22***
	(3.49)	(2.96)	(2.55)	(2.07)	(-4.83)	(-5.93)	(-4.12)	(-5.23)
Ownership concentration	-0.17***	-0.23***	-0.61***	-0.78***	11.01***	15.44***	29.07***	42.36***
($Topdecile_{fit}$)	(-35.53)	(-40.79)	(-8.15)	(-8.67)	(31.02)	(33.18)	(5.09)	(5.75)
$Similarity_{fit-1} \times Topdecile_{fit}$			0.53***	0.66***			-0.22***	-0.32***
			(5.86)	(6.11)			(-3.18)	(-3.67)
Observations	120,815	120,313	120,815	120,313	102,538	102,115	102,538	102,115
R-squared	0.22	0.27	0.22	0.27	0.11	0.15	0.11	0.15
Issuer*month FE	Y	Y	Y	Y	Y	Y	Y	Y
Issuer*fund FE	N	Y	N	Y	N	Y	N	Y
Fund FE	Y	N	Y	N	Y	N	Y	N
Security controls	Y	Y	Y	Y	Y	Y	Y	Y

Table SI-7: Funds' portfolio allocation decision and portfolio similarity: Secured versus unsecured funding.

This table compares the effect of portfolio similarity on fund divestment depending on whether the securities lent to an issuer are secured or not. All variables are defined in Table 2. Coefficient estimates on $Divest$ are multiplied by 100. t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

	$Divest_{fit}$			$\Delta Exposure_{fit}$		
	All	Secured	Unsecured	All	Secured	Unsecured
	(1)	(2)	(3)	(4)	(5)	(6)
$Similarity_{fit-1}$	0.04	-0.40***	0.11**	-0.10***	0.24*	-0.14***
	(0.77)	(-2.93)	(2.32)	(-2.76)	(1.79)	(-3.84)
Observations	129,826	15,664	120,949	108,153	9,855	102,550
R-squared	0.20	0.18	0.21	0.09	0.15	0.10
Issuer×time FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Security controls	Y	Y	Y	Y	Y	Y

Table SI-8: Funds' portfolio allocation decision and portfolio similarity: Issuer risk.
This table shows the joint effect of portfolio similarity and issuer risk on fund divestment. Issuer risk is measured by the past squared stock return of issuer i ($Risk_{it-1}$). $Crisis_t$ denotes the period from June 2011 until December 2011. The other variables are defined in Table 2. Coefficient estimates on $Divest$ are multiplied by 100. t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

	$Divest_{fit}$			$\Delta Exposure_{fit}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Similarity_{fit-1}$	0.16**	0.14**	0.14**	-0.13***	-0.08*	-0.09*
	(2.57)	(2.19)	(2.20)	(-2.96)	(-1.81)	(-1.94)
$Similarity_{fit-1} \times Risk_{it-1}$		0.03	-0.02		-0.08***	-0.02
		(1.23)	(-0.50)		(-4.10)	(-0.83)
$Similarity_{fit-1} \times Risk_{it-1} \times Crisis_t$			0.08			-0.11***
			(1.57)			(-2.99)
$Similarity_{fit-1} \times Crisis_t$			0.00			0.02
			(0.04)			(0.24)
Observations	85,310	85,310	85,310	72,464	72,464	72,464
R-squared	0.20	0.20	0.20	0.09	0.09	0.09
Issuer×time FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Security controls	Y	Y	Y	Y	Y	Y

Table SI-9: Funds' portfolio allocation decision and portfolio similarity: Results at the fund family level.

This table replicates Table 2 at the fund complex level. Coefficient estimates on $Divest$ are multiplied by 100. t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

	$Divest_{fit}$				$\Delta Exposure_{fit}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{fit-1}$	0.23***	0.17**	0.24***	0.52***	-0.13**	-0.16***	-0.22***	-0.16**
	(3.17)	(2.00)	(2.89)	(4.70)	(-2.46)	(-2.61)	(-3.53)	(-2.17)
Observations	44,283	39,081	44,123	22,229	38,108	34,190	37,928	21,214
R-squared	0.20	0.15	0.25	0.21	0.12	0.12	0.16	0.17
Issuer×time FE	Y	Y	Y	Y	Y	Y	Y	Y
Issuer×fund complex FE	N	N	Y	N	N	N	Y	N
Fund complex and time FE	Y	Y	Y	Y	Y	Y	Y	Y
Security controls	Y	N	Y	Y	Y	N	Y	Y
drops avgmat<30days	N	N	N	Y	N	N	N	Y

Table SI-10: Funds' portfolio allocation decision and portfolio similarity: Bank-affiliated funds.

This table assesses the differential effect of portfolio similarity on fund divestment when the fund parent company is a bank. The variable $parentbank_f$ is an indicator variable equal to one if the parent company of fund f is a bank and is zero otherwise. The other variables are defined in Table 2. Coefficient estimates on $Divest$ are multiplied by 100. t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

	$Divest_{fit}$		$\Delta Exposure_{fit}$	
	(1)	(2)	(3)	(4)
$Similarity_{fit-1}$	0.19***	0.18**	-0.14***	-0.24***
	(3.05)	(2.38)	(-2.86)	(-3.98)
$Similarity_{fit-1} \times parentbank_f$	-0.17**	-0.13	-0.00	0.03
	(-2.07)	(-1.27)	(-0.05)	(0.43)
Observations	119,767	119,267	102,004	101,581
R-squared	0.21	0.26	0.10	0.14
Issuer×time FE	Y	Y	Y	Y
Issuer×fund FE	N	Y	N	Y
Fund FE	Y	N	Y	N
Security controls	Y	Y	Y	Y

Table SI-11: Funds' portfolio allocation decision and portfolio similarity: Alternative measures of similarity.

This table shows the effect of different measures of portfolio similarity on fund divestment. $Similarity_{fit}$ is the similarity of fund f to the other funds exposed to issuer i at time t as defined in equations (1) and (2). $Similarity^{\ni i}_{fit-1}$ differs from $Similarity_{fit}$ because it excludes the exposure to issuer i from funds' portfolios in the computation of the Euclidean distances in equation (1). $Similarity^{conv,u}_{ft-1}$ is the unweighted average similarity between fund f and all other funds in the sample at time t. $Similarity^{conv,w}_{ft-1}$ is the weighted average similarity between fund f and all other funds in the sample at time t, where the weights are proportional to the fund size. The other variables are defined in Table 2. Coefficient estimates on $Divest$are multiplied by 100. t-statistics based on standard errors clustered at the fund×time level are reported in parentheses.

	$Divest_{fit}$				$\Delta Exposure_{fit}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{fit-1}$	0.11**				-0.15***			
	(1.98)				(-3.82)			
$Similarity^{\ni i}_{fit-1}$		0.57***				-0.51***		
		(9.41)				(-12.35)		
$Similarity^{conv,u}_{ft-1}$			0.01				-0.10*	
			(0.07)				(-1.70)	
$Similarity^{conv,w}_{ft-1}$				0.00				-0.10*
				(0.01)				(-1.93)
Observations	106,297	106,297	106,297	106,297	91,457	91,457	91,457	91,457
R-squared	0.20	0.21	0.20	0.20	0.11	0.11	0.11	0.11
Issuer×time FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y
Security controls	Y	Y	Y	Y	Y	Y	Y	Y

Table SI-12: Issuer's funding liquidity risk and issuer's average fund similarity: Fund flows from similar versus non-similar investors.

This table reports the effect of the average fund similarity of an issuer on the issuer's total unsecured funding from similar versus non-similar MMFs. A fund is labeled "similar" when its portfolio similarity is above the median similarity of funds in a given month. The table reports regression results separately for the percentage change in fund flows to an issuer ($\Delta Outstanding_{it}$) from "similar" (Columns (1), (3), (5), (7)) versus "non-similar" investors (Columns(2), (4), (6), (8)). $\Delta Outstanding_{it}$ is the percentage change in the total principal amount of issuer i at time t. $Similarity_{it}$ is the average similarity of the funds exposed to issuer i at time t. As in Table 8, this table reports the results for financial institutions and non-financial institutions separately, controlling for issuer and time fixed effects, and issuer controls that include the weighted average maturity and weighted average yield of the securities of issuer i held by MMFs in the previous month. In addition, Columns (3), (4), (7), and (8) control for additional concentration measures such as the number of funds lending to an issuer and the HHI of the issuer's MMF liabilities. Coefficient estimates on $CorrOutflows_{it}$ are multiplied by 100. t-statistics based on standard errors clustered at the issuer level are reported in parentheses.

	Financial				Non Financial			
	Similar	Non-Sim.	Similar	Non-Sim.	Similar	Non-Sim.	Similar	Non-Sim.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{it-1}$	-1.68***	0.53	-2.22***	0.41	0.19	-0.37	0.24	-0.36
	(-2.87)	(1.25)	(-4.41)	(1.02)	(0.21)	(-0.75)	(0.29)	(-0.74)
$IssuerHHI_{it-1}$			1.08***	0.17			0.78	-0.08
			(5.21)	(1.09)			(1.45)	(-0.25)
$Funds_{it-1}$			-0.34***	-0.15*			-1.12	-0.88*
			(-3.15)	(-1.85)			(-1.32)	(-1.97)
Observations	2,847	3,057	2,847	3,057	541	680	541	680
R-squared	0.06	0.04	0.10	0.04	0.15	0.13	0.17	0.13
Issuer and time FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y

Table SI-13: Issuer's funding liquidity risk and issuer's average fund similarity during a crisis. This table reports the differential effect of portfolio similarity and concentration measures during a crisis, where $Crisis_t$ denotes the period from June 2011 until December 2011.$\Delta Outstanding_{it}$ is the percentage change in the total principal amount of issuer i at time t. $CorrOutflows_{it}$ is the fraction of funds reducing their exposure to issuer i at time t. $Similarity_{it}$ is the average similarity of the funds exposed to issuer i at time t. The table reports the results for financial institutions and non-financial institutions separately, controlling for issuer and time fixed effects, and issuer controls that include the weighted average maturity and weighted average yield of the securities of issuer i held by MMFs in the previous month. In addition, Columns (2), (4), (6), and (8) control for additional concentration measures such as the number of funds lending to an issuer and the HHI of the issuer's MMF liabilities. Coefficient estimates on $CorrOutflows$ are multiplied by 100. t-statistics based on standard errors clustered at the issuer level are reported in parentheses.

	$\Delta Outstanding_{it}$				$CorrOutflows_{it}$			
	Financial		Non Financial		Financial		Non Financial	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{it-1} \times (1 - Crisis_t)$	-0.13	-0.41**	-0.79	-0.75	0.31***	0.36***	-0.41**	-0.41***
	(-0.52)	(-2.06)	(-1.13)	(-1.09)	(3.27)	(3.77)	(-2.65)	(-2.87)
$Similarity_{it-1} \times Crisis_t$	-0.31	-0.64**	-0.63	-0.57	0.27**	0.31**	0.02	-0.03
	(-0.87)	(-2.36)	(-0.79)	(-0.71)	(2.17)	(2.37)	(0.07)	(-0.15)
$IssuerHHI_{it-1} \times (1 - Crisis_t)$		0.28**		0.08		-0.03		-0.08
		(2.25)		(0.24)		(-0.63)		(-1.03)
$IssuerHHI_{it-1} \times Crisis_t$		0.69***		-0.19		-0.13*		0.12
		(2.71)		(-0.61)		(-1.92)		(1.16)
$Funds_{it-1} \times (1 - Crisis_t)$		-0.40***		-1.33**		0.07***		0.29**
		(-4.72)		(-2.29)		(2.77)		(2.05)
$Funds_{it-1} \times Crisis_t$		-0.14		-1.79**		0.07**		0.48**
		(-1.35)		(-2.51)		(2.11)		(2.25)
Observations	3,057	3,057	680	680	3,057	3,057	680	680
R-squared	0.07	0.09	0.16	0.17	0.18	0.19	0.31	0.31
Issuer and time FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y

Table SI-14: Issuer's funding liquidity risk and issuer's average fund similarity: Including issuer×year fixed effects.

This table replicates Table 8 including issuer×year fixed effects to address potential concerns about omitted variable bias at the issuer level. Coefficient estimates on $CorrOutflows$ are multiplied by 100. t-statistics based on standard errors clustered at the issuer level are reported in parentheses.

	$\Delta Outstanding_{it}$				$CorrOutflows_{it}$			
	Financial		Non Financial		Financial		Non Financial	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{it-1}$	-0.18	-0.59***	-0.76	-1.47	0.30***	0.28**	-0.32***	-0.33**
	(-0.71)	(-2.78)	(-1.38)	(-1.40)	(2.67)	(2.55)	(-2.82)	(-2.52)
$IssuerHHI_{it-1}$		0.65***		0.39		-0.01		0.00
		(2.99)		(0.88)		(-0.17)		(0.00)
$Funds_{it-1}$		-0.37**		-3.15***		0.09***		0.16
		(-2.08)		(-2.87)		(2.66)		(1.04)
Observations	3,057	3,050	680	667	3,057	3,050	680	667
R-squared	0.07	0.16	0.16	0.24	0.18	0.28	0.30	0.35
Issuer×year and month FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y

Table SI-15: Issuer's average yield and fund portfolio similarity: continuous systemic risk. This table shows the effect of the portfolio similarity of the funds of an issuer on the issuer's average yield. $Yield_{it}$ is the weighted average ex-ante yield on unsecured securities of issuer i held by U.S. MMFs at time t. Sim_{it} is the average similarity of the funds exposed to issuer i at time t ($Similarity_{it}$) in Columns (1) to (4), and the minimum similarity of the 5% most similar funds exposed to issuer i at time t ($Similarity_{it}^{95\%}$) in Columns (5) to (8). The flow-induced price pressure variable $FIPP_{it}$ (Edmans et al., 2012) is a measure of price pressure induced by funds' investors net flows. $FIPP_{it}$ is interacted with the same stress indicators as Sim_{it-1} in all specifications, but these interaction coefficients are not statistically significant and therefore not reported in the table. $Crisis_t$ is an indicator variable for the period from June 2011 until December 2011. $SRISK_t^{cont.}$ and $\Delta CoVaR_t^{cont.}$ are continuous systemic risk indicators: $SRISK_t^{cont.}$ is the ratio of total SRISK (Acharya et al., 2017; Brownlees and Engle, 2017) to total market capitalization of the U.S. financial sector, $\Delta CoVaR_t^{cont.}$ is ΔCoVaR (Adrian and Brunnermeier, 2016) of the U.S. financial sector. The table reports the results controlling for issuer and time fixed effects, and controlling for the weighted average maturity of the unsecured securities of issuer i held by U.S. MMFs at time t, and lagged variables capturing the issuer's liabilities diversification (i.e., the number of funds holding securities from an issuer, and the issuer's funding HHI). t-statistics based on standard errors clustered at the issuer level are reported in parentheses.

	$Yield_{it}$							
	$Sim_{it} = Similarity_{it}$ (Average)				$Sim_{it} = Similarity_{it}^{95\%}$ (95th percentile)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fund similarity (Sim_{it-1})	-0.48***	-0.47***	-3.43***	-3.14***	-0.54***	-0.51***	-4.23***	-3.67***
	(-5.23)	(-5.38)	(-3.92)	(-3.61)	(-5.04)	(-4.97)	(-3.70)	(-3.06)
$Sim_{it-1} \times SRISK_t^{cont.}$	0.01***	0.01***			0.01***	0.01***		
	(5.88)	(5.85)			(5.25)	(4.89)		
$Sim_{it-1} \times \Delta CoVaR_t^{cont.}$			0.83***	0.75***			1.03***	0.89***
			(3.89)	(3.55)			(3.67)	(3.01)
$Sim_{it-1} \times Crisis_t$		0.01		0.07		0.07		0.11
		(0.19)		(1.32)		(1.05)		(1.59)
Flow-induced price pressure ($FIPP_{it}$)	9.22	9.17	60.22	60.59	8.97	9.13	55.69	58.64
	(0.55)	(0.53)	(0.44)	(0.44)	(0.55)	(0.53)	(0.41)	(0.43)
Observations	3,702	3,702	3,702	3,702	3,702	3,702	3,702	3,702
R-squared	0.73	0.73	0.72	0.72	0.73	0.73	0.72	0.72
Issuer & Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y

Table SI-16: Issuer's funding liquidity risk and issuer's extreme fund similarity
This table shows the effect of the portfolio similarity of the funds of an issuer on the issuer's total unsecured funding from MMFs. $\Delta Outstanding_{it}$ is the percentage change in the total principal amount of issuer i at time t. $Similarity_{it}$ is the average similarity of the funds exposed to issuer i at time t. $Similarity_{it}^{Std.Dev}$ is the standard deviation of portfolio similarity of the funds exposed to issuer i at time t. $Similarity_{it}^{95\%}$ is the minimum similarity of the 5% most similar funds exposed to issuer i at time t. $Similarity_{it}^{5\%}$ is the maximum similarity of the 5% least similar funds exposed to issuer i at time t. The table reports the results controlling for issuer and time fixed effects, and controlling for the weighted average yield and maturity of the unsecured securities of issuer i in the previous month, the number of funds lending to an issuer and the HHI of the issuer's MMF liabilities. t-statistics based on standard errors clustered at the issuer level are reported in parentheses.

	$\Delta Outstanding_{it}$			
	(1)	(2)	(3)	(4)
$Similarity_{it-1}$	-0.59**	-0.65**		
	(-2.19)	(-2.50)		
$Similarity_{it-1}^{Std.Dev}$		-0.88**		
		(-2.55)		
$Similarity_{it-1}^{95\%}$			-0.81**	
			(-2.05)	
$Similarity_{it-1}^{5\%}$				0.13
				(1.42)
Observations	3,737	3,737	3,737	3,737
R-squared	0.09	0.09	0.09	0.09
Issuer & Time FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y