Similar Investors *

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Abstract

With the failure of Silicon Valley Bank in March 2023, the concentration risk in bank liabilities has come under scrutiny. We use detailed security-level holdings of U.S. Money Market Mutual Funds (MMFs) that fund banks to introduce a novel measure of portfolio similarity among investors. Our findings suggest that MMFs actively manage their asset holdings based on the similarity of their portfolios with those of other investors. Specifically, when portfolios are more similar, investors are less likely to roll over investments, anticipating higher expected joint liquidation costs when portfolios are more similar. At the issuer bank level, the average similarity of its investors' portfolios is a reliable predictor of the bank's total funding in the following period. Importantly, banks are unable to fully compensate for the loss of funding when similar investors withdraw.

Keywords: concentration risk, institutional investors, liquidity risk, wholesale funding.

JEL Classification: G1, G21

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1 Introduction

The concentration of bank deposits has become a critical issue in the wake of recent developments in lending markets. The bank run that occurred in March 2023 at Silicon Valley Bank (SVB), a financial institution specializing in high-tech startups and venture capital, highlighted the potential risks associated with such concentration. This event demonstrated that SVB's deposits were heavily tied to tech startups. In this paper, we investigate whether investors internalize concentration risk in bank liabilities using detailed data on money market funds (MMFs) as a laboratory.

The possibility of investors internalizing concentration risk in bank liabilities is in line with the theoretical predictions in Wagner (2011)). In the absence of frictions that affect liquidation costs, full diversification is optimal and might lead to investors holding similar portfolios. However, when faced with systemic liquidation costs, investors have a preference for holding different portfolios to distinguish themselves from other investors. Consequently, investors face a trade-off in their investment decisions between liquidation costs and diversification benefits, that we refer to as the "diversity-diversification trade-off".[1] A key feature of this model is that joint liquidation costs arise endogenously and depend on investors and their portfolio similarity.

Analyzing bank funding diversity and investor similarity might be challenging. To overcome these challenges, we rely on detailed data on the securities held by U.S. MMFs and introduce a novel measure of portfolio similarity. U.S. MMFs therefore serve as a laboratory to investigate whether investors consider the "diversity-diversification trade-off" while investing in bank liabilities. MMFs invest unsecured in banks and are not covered by deposit insurance.

[1] One reason for systemic liquidation costs are fire sales (Shleifer and Vishny, 2011). Empirical studies show that the cost of fire sales can be large in equity markets (Coval and Stafford, 2007) and in corporate bond markets (Ellul et al., 2011). Fire-sale amplifications are also discussed in, for example, Kiyotaki and Moore (1997), Brunnermeier and Pedersen (2009), Allen et al. (2012) and Greenwood et al. (2015).

They are also constrained by regulations regarding the type of assets they can invest in. Importantly, U.S. MMFs can observe the portfolio holdings of other MMFs due to post-crisis regulation in the U.S. requiring the Securities and Exchange Commission (SEC) to collect and publicly disclose the portfolio holdings of MMFs on a monthly basis.

Our analysis starts by focusing on a critical prediction from Wagner (2011) that investors, all else being equal, prefer to decrease their exposure to an asset owned by other investors with similar portfolio holdings. To test this prediction, we examine changes in the investments of several MMFs, acting as investors, that invest in the same security issued by a particular issuer, the asset. These MMFs vary in their degree of portfolio similarity. For our analysis, we use security-level data that contains both the fund name and the issuer name. We account for all the observed and unobserved heterogeneity in fund flows originating from issuer characteristics such as funding demands and fundamental risks by including issuer*month fixed effects in our regressions.[2] We consider two variables to describe the investment decisions of funds once they become aware of their similarity to other investors: the likelihood of decreasing exposure to a security issuer (*Outflow*), and the percentage change in exposure to a security issuer (Δ*Outstanding*).

Additionally, we examine the relationship between bank funding diversity and bank funding liquidity risk. Specifically, we investigate whether issuers can substitute the loss of funding from similar investors with new funds from non-similar investors. To do this, we test whether an issuer's average fund similarity predicts the percentage change in the issuer's total funding in the following month.

We collect detailed information on the universe of investments of U.S. money market funds from iMoneyNet. Our dataset includes monthly information from the SEC about the outstanding amount a money market fund invests in a single issuer's security, the maturity, the

[2]This fixed effect saturation follows Khwaja and Mian (2008), Schnabl (2012), Jiménez et al. (2012, 2014).

security rate, as well as the type of security (repurchase agreements, certificates of deposits, etc.) from November 2010 until August 2014. Our analysis focuses on unsecured funding provided through certificates of deposit and financial commercial papers, as opposed to repurchase agreements to abstract from concerns regarding the quality of collateral backing the securities.[3] After a manual consolidation procedure, our sample comprises 295 distinct issuers and 213 MMFs.

Our similarity measure is both fund and security *issuer*-specific and comprises two components: the similarity of portfolio holdings between any two funds and the funding allocation by each fund to the issuer as a proportion of the total funding. Essentially, when a fund does not invest in a particular issuer, the joint liquidation costs associated with that fund are zero. Therefore, to use fund similarity as an indicator for anticipated joint liquidation costs, we calculate the average similarity of a fund with respect to all other funds investing in the same security.

We present empirical evidence that supports the existence of a *demand for diversity*. Specifically, we find that a fund reduces its exposure to an issuer as its similarity to other funds that invest in the same issuer increases. This finding represents our first key result. More precisely, a one standard deviation increase in similarity to other funds investing in the same issuer is associated with a 2.2 percentage point (p.p.) increase in the probability of outflow (*Outflow*). This estimate is economically significant since it represents 7% of the unconditional probability of *Outflow* (33%). Furthermore, investments in an issuer (Δ*Outstanding*) decrease by 2.66 p.p. when fund similarity increases by one standard deviation. This translates to an additional $5,346$ USD monthly outflow from one fund to an issuer, relative to unconditional average monthly outflows of 503 USD between a fund and an issuer, and to an outstanding amount of $201,000$ USD for the average security contract. Our regression analysis compares different

[3] In some robustness checks we consider secured funding via repurchase agreements (repos), and find no effect of investor similarity on fund flows. For secured securities, concerns over the collateral endogenous illiquidity would be better captured by considering the similarity between all investors exposed to the same collateral asset (rather than the group of investors investing in a specific issuer's security secured by the collateral).

funds investing in the same issuer at the same time while controlling for various factors such as time-invariant fund characteristics, month fixed effects, and keeping the fund size, maturity, yield of the security contract, and security type constant.

Our findings also suggest the existence of a trade-off between diversity and diversification. Specifically, we observe that the impact of fund similarity on fund flows weakens as the concentration of a fund's portfolio increases, indicating lower average joint liquidation costs (Wagner, 2011). We measure portfolio concentration using the Hirschman-Herfindahl index (HHI) based on a fund's portfolio shares. For a fund with a median HHI of 7.73%, the effect of a one standard deviation increase in fund similarity on fund flows is -3.22 p.p. Meanwhile, for the fund with the top 10% largest HHI of 25%, the effect is -2.64 p.p. Our results also reveal that the impact of fund portfolio similarity fades away for funds with an HHI of 75%. Moreover, consistent with comparative statics in Wagner (2011), we find that funds with less stable funding from their investors (funds experiencing outflows), issuers in which funds are concentrated, and riskier issuers exhibit a stronger response to similarity.

We conduct various robustness tests and explore alternative hypotheses to validate our findings. For example, it is possible that fund outflows are not triggered by fund similarity, but rather by funds' investment strategies and constraints, such as concentration limits or following a benchmark index. We provide different tests to address this. To address this, we include control variables that measure the fraction of a fund's portfolio invested in a specific issuer. We also construct fund clusters based on a principal component analysis on fund performance and add cluster*month fixed effects to the regressions. The fixed effects absorb a common component of funds following the same index. Additionally, we saturate the regression by adding fund*month fixed effects to absorb common effects at the fund level. Finally, we considered a potential concern that fund similarity arises mechanically due to large MMF withdrawals during the sovereign debt crisis and demonstrated that all results hold for funds not exposed to eurozone issuers. Our findings remain robust even after conducting these tests.

Our second main finding demonstrates that funds' portfolio allocation decisions based on similarity have implications for an issuer's funding fragility. Specifically, the average similarity of the funds invested in a bank can affect the bank's access to funding during a crisis, such as the European sovereign debt crisis in the summer of 2011, which triggered significant redemptions from some U.S. MMFs (Chernenko and Sunderam, 2014). During this crisis period (June 2011 - December 2011), we find that a one standard deviation increase in the average similarity of funds invested in a bank leads to a 6 p.p. outflow on the bank's total unsecured outstanding funding amount from U.S. MMFs, holding the number of funds and the diversification of liabilities of the bank constant. To put this into perspective, for an average outstanding investment of USD 5.5 million, the impact of similarity translates into an additional monthly outflow of USD $330,731$.

The negative effect of similarity is due to the fact that funding from investors with similar portfolios is lost and cannot be replaced by investments from those with dissimilar portfolios. More precisely, our analysis reveals that during a crisis, a one standard deviation increase in the average fund similarity of an issuer bank leads to a 17.2% decline in funding from similar investors, without any corresponding increase in funding from non-similar investors.

Our paper contributes to multiple streams of literature. First, it is related to the literature on asset commonality and its consequences. Prior theoretical works by Allen et al. (2009), Castiglionesi and Navarro (2020), Ibragimov et al. (2011), and Wagner (2010) demonstrate that asset commonality increases systemic risk. Greenwood et al. (2015) introduce a model explaining how shocks propagate in a system of leverage-targeting banks with common asset holdings. Empirical studies by Cai et al. (2018a) find that asset commonality in banks' syndicated loan portfolios is positively correlated with systemic risk. Additionally, Wagner (2011) and Capponi and Weber (2020) model investors' portfolio decisions and their trade-off between diversification costs and benefits. Our paper is related to these papers as we investigate the portfolio choices of investors due to asset commonality. However, unlike these studies, our investors are not banks but MMFs that invest in banks, and their similarity creates concentration risk in bank liabilities.

Our paper is also related to the literature on money markets frictions and their consequences for financial stability. Chernenko and Sunderam (2014) show that security issuers maintain relationships with specific MMFs, and during the European sovereign debt crisis, issuers were not able to replace lost funds from relationship-MMFs. Gallagher et al. (2019) document that MMF managers reduced their exposure to eurozone issuers in response to investors' selective information on MMFs' risk exposures to Europe. Aldasoro et al. (2019b) find that the U.S. money market fund sector is highly concentrated and that MMFs charge markups to some issuers unrelated to credit risk. In addition, the 2016 U.S. MMF reform made government funds more attractive than prime funds, further reducing competition in unsecured money markets. [4] Our paper highlights another friction in money markets that affects MMFs' expected joint liquidation costs, making it difficult for issuers exposed to similar funds to recover funding access in a crisis.

Our study's implications go beyond the MMF industry and have implications for the broader literature on bank liquidity risk and its regulation. While the literature has mainly focused on banks' asset risk and exposure to short-term wholesale funding, our results suggest that commonality of investors also matters for banks' funding risk and financial stability. This issue has become even more relevant in light of the recent collapse of Silicon Valley Bank in March 2023, which has been attributed in part to its heavy reliance on uninsured depositors from the same industry in the same region. Our research highlights the need for further research to explore the impact of commonality of investors on bank funding risk and its regulation.

[4] Cipriani and Spada (2018), Baghai et al. (2020), Aldasoro et al. (2019a), and Anderson et al. (2019) have further studied the responses of funds and banks to recent MMF reforms and their implications for financial stability.

The rest of the paper is organized as follows. Section 2 describes our similarity measure, data and descriptive statistics of U.S. MMFs' investments. We present our empirical strategy in Section 3. We report and interpret our results in Sections 4 to 6. Section 7 concludes.

2 Conceptual Framework and Data

2.1 Conceptual Framework

Our paper shows empirical evidence for a *demand for diversity* from investors consistent with the model of Wagner (2011). In this model, the demand for diversity stems from the ex-ante risk of systemic joint liquidation costs that affect investors' portfolio choices. Liquidation costs are systemic because the liquidation costs are disproportionately higher when multiple investors jointly liquidate an asset compared to liquidation costs incurred by an individual investor who liquidates in isolation. This friction makes full portfolio diversification no longer optimal. In the case of full portfolio diversification, investors would hold the exact same portfolios, exposing them to common shocks, correlated liquidity demands and ultimately, joint liquidation costs. To hedge against the risk of (systemic) joint liquidation costs, investors prefer to hold different portfolios to distinguish themselves from each other. Investors therefore face a trade-off between the benefits of holding *diversified* portfolios versus *diverse* portfolios. An important feature of the model is that joint liquidation costs, and therefore asset illiquidity, arise endogenously depending on the portfolio composition of other investors holding the same asset.

We test the relevance of the diversity-diversification trade-off using data on money market funds. Money markets are an interesting setting to study this trade-off given the specific incentives of MMFs and the limited pool of low-risk and liquid assets MMFs can invest in. They usually roll over existing exposures, but stop rolling them over e.g. due to concerns about issuer or liquidity risk.[5] MMFs manage and monitor portfolio risk because of the mandate to invest in "money-like assets", and because regulation limits their investments to highly-rated issuers.

For the same reasons, we expect MMFs to monitor asset illiquidity and hedge against the risk of systemic liquidation costs. The absence of deposit insurance likely reduces moral hazard and risk-shifting incentives compared to banks, as MMF investors are not protected against downside risk.[6]

The intuition from a fund's perspective is straightforward: if two funds have similar portfolios, they are hit by shocks to their portfolio at the same time. Consequently, they will both experience liquidity needs in the same states of the world and are, therefore, subject to joint liquidation costs when they decide to stop rolling over funding to an issuer. Thus, they might decide to reduce their exposure to hedge against systemic joint liquidation costs. We summarize this in our first hypothesis:

H1: Investors hedge against joint liquidation costs and reduce their exposure to issuers that are exposed to similar investors.

Investors' demand for diversity likely has consequences for *issuers' funding fragility*. That is, the withdrawal of investments by similar investors might restrict an issuer's overall access to funding if she cannot fully replace it. We summarize this in our second hypothesis:

H2: Investor similarity affects an issuer's overall access to funding and increases her funding fragility.

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

[6] Another important underlying assumption is that funds can observe the portfolio composition of other funds. Note that, unlike for banks, fund portfolio information is widely available through data providers like iMoneyNet and Morningstar.

2.2 Portfolio Similarity

We introduce a novel measure of portfolio similarity that fully exploits the granular information about funds' security holdings. This measure describes the similarity of a fund's portfolio with the portfolios of other funds investing in the same issuer.

In our definition, I denotes the total number of assets available to investors. We represent a portfolio as a vector in an I dimensional space where each "direction" corresponds to a different asset. A fund f's portfolio naturally corresponds to a vector in this space. The average distance of fund f to other funds investing in security issuer i at time t is:

$$\text{Wgt.Avg.Distance}_{fi,t} = \sum_{\varphi \neq f} w_{\varphi i,t} d_{f\varphi,t} = \sum_{\varphi \neq f} w_{\varphi i,t} \sqrt{\sum_{i=1}^{I} \left(\frac{\text{Amount}_{fi,t}}{\text{FundSize}_{f,t}} - \frac{\text{Amount}_{\varphi i,t}}{\text{FundSize}_{\varphi,t}} \right)^2}, \tag{1}$$

where I is the total number of securities in a fund's portfolio at time t, $\text{Amount}_{fi,t}$ is the outstanding amount invested by fund f in issuer i at time t, and the fund size is $\text{FundSize}_{f,t} = \sum_{i=1}^{I} \text{Amount}_{fi,t}$.

The measure in equation (1) can be decomposed into two elements: (i) a distance describing the similarity in portfolio holdings between fund f and another fund φ denoted $d_{f\varphi,t}$ (pairwise distance), and (ii) a weighting function denoted $w_{\varphi i,t}$ that aggregates the pairwise fund distances into an average distance for fund f. That is, we average the pairwise distances of fund f using a weighting function that selects all other funds (except fund f) investing in a specific issuer i. The weight allocated to the *other* fund φ is based on fund φ's share of issuer i's funding relative to all other funds investing in i.

$$w_{\varphi i,t} := \frac{\text{Amount}_{\varphi i,t}}{\sum_{\varphi \neq f} \text{Amount}_{\varphi i,t}} \in [0,1].$$

The total amount of funding security issuer i receives from all other funds (except f) at time t

is given by $\sum_{\varphi \neq f} \text{Amount}_{\varphi i,t}$.

Intuitively, if fund φ provides no funding to issuer i (i.e. $\text{Amount}_{\varphi i,t} = 0$), it cannot withdraw any funding from that issuer and thus its weight will be zero. However, if fund φ provides all other funding to issuer i (in addition to the funding from fund f), $w_{\varphi i,t} = 1$, i.e. only the portfolio overlap between funds φ and f matters.

The average distance of fund f in issuer i in equation (1) can be expressed 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 "average" similarity of fund f to other funds investing in security issuer i at time t is:

$$\text{Similarity}_{fi,t} = 100 \times \left(1 - \frac{1}{\sqrt{2}} \text{Wgt.Avg.Distance}_{fi,t}\right) \in [0, 100], \tag{2}$$

which we simply call "similarity" for brevity in the rest of this paper.

Based on this definition, it is obvious that $\text{Similarity}_{fi,t}$ can change for two reasons: (i) because of changes in portfolio holdings that will be reflected in pairwise Euclidean distances $d_{f\varphi,t}$, and (ii) because of changes in the weighting function $w_{\varphi i,t}$ when other funds stop rolling over funding or when new funds start investing in issuer i.

We are ultimately interested in comparing the similarity of one fund to the similarity of other funds in a given security issuer i. This restricts our sample to issuers that borrow from at least three funds. In Appendix A (and in Online Appendix D.1) we illustrate the similarity measure for the two instructive examples shown in Figure 1 to build an intuition for our measure.

[INSERT FIGURE 1 HERE]

2.3 Data and Descriptive Statistics

Our main data source for U.S. money market funds are the regulatory N-MFP forms which cover monthly information about MMFs' exposures collected by the U.S. Securities Exchange Commission (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 $10,619$ securities held by U.S. MMFs (including certificates of deposits, 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 $10,619$ securities was necessary. This resulted in a total of 308 individual security issuers, of which 213 are financial institutions (including 161 banks).

We focus our work on *unsecured* securities of MMFs — namely, certificates of deposits and financial commercial papers — as we expect joint liquidation costs to be less of a concern for securities secured by high quality collateral like Treasury repos or Government Agency repos.[7] Confining our research to unsecured funding automatically centers our analysis on prime MMFs as opposed to government MMFs. MMFs have different investment patterns for the same issuer depending on whether the security is secured or not. We illustrate this differential trend in MMFs' secured and unsecured investments in eurozone banks during the European sovereign debt crisis in Figure 2. The figure shows the total principal amounts invested in eurozone banks by U.S. MMFs. MMFs only massively withdrew unsecured funding (about 200 USD billion) from eurozone banks in the summer of 2011 (between June 2011 and December 2011) — a period that we label the "crisis" throughout. In contrast, some eurozone banks were able

[7] We, however, test the effect of similarity on funds' decisions by security type in the robustness section.

to substitute the loss in unsecured funding with repos from U.S. MMFs during the same crisis period.

[INSERT FIGURE 2 HERE]

We report descriptive statistics for unsecured investments of U.S. MMFs in Table 1.[8] The data are collected for 295 issuers; among those, 203 are financial institutions, 155 are banks, and 39 banks are located in the European Union. In Panel A of Table 1, we report descriptive statistics at the issuer level. The average fund similarity of an issuer is 89.1%, with a standard deviation of 8.76%. The average principal amount invested in an issuer is 5.5 USD million, and the standard deviation around the average is 9.3 USD million. Average total monthly unsecured fund flows to an issuer are 0.19%, and the standard deviation of flows is 29%. The average yield is 0.26 basis points, the average maturity is 60 days, and issuers have access to 30 funds on average.

[INSERT TABLE 1 HERE]

In Panel B of Table 1, we report descriptive statistics at the security level. We apply an additional filter in this panel, requiring issuers to receive unsecured funding from at least three different U.S. MMF names each month. As a consequence, we are reporting the descriptive statistics for a subsample of securities of 144 issuers. The similarity of a fund to the other funds investing in the same issuer is 84.7% on average, with a standard deviation of 5.6%. The average amount a fund invests in an issuer through a security is 201,000 USD, with a standard deviation of 451,000 USD. Monthly security flows between a fund and an issuer are -0.28% on average, with a standard deviation of 29%. The average yield of a security contract is 0.29 basis points,

[8] We report the same descriptive statistics for unsecured and *secured* investments of U.S. MMFs in Table SI-1 in the Appendix. Note that 85% of the amount U.S. MMFs invest is composed of unsecured investments on average, with a standard deviation of 31%.

and the average maturity is 50 days. The average fund portfolio size is 7.9 USD million, and a fund invests in 24 different issuer names on average.

In Panel C of Table 1, we decompose the descriptive statistics at the issuer level for different subsamples. For example, the average principal amount is larger for banks (7.8 USD million) than non-banks (1.8 USD million), and is the largest for non-EU banks (7.9 USD million). We find negative average total fund flows to an issuer during the crisis (-3%), for non-bank (including non-bank financial institutions) issuers (-0.85%), and for banks in Greece, Ireland, Italy, Portugal and Spain (GIIPS) (-0.82%). The average yield was the largest before the crisis (34 bps), and for GIIPS banks (35 bps). The average maturity increased from 39 to 65 days after the crisis, and is the largest for non-EU banks (70 days). Banks have access to more funds on average than non-banks (43 and 9, respectively), but have a comparable average fund similarity (86.6% versus 86.2% for non-banks).

[INSERT FIGURE 3 HERE]

Figure 3 shows a breakdown of unsecured funding to eurozone banks from similar and non-similar U.S. MMFs. We observe in this figure that most U.S. MMFs exposed to eurozone banks were similar funds (where a fund is considered "similar" if its similarity is above the median U.S. MMF similarity in a given month). At the same time, we observe in Figure 4 that the average of the average fund similarity of issuers increased from 86% to 92%, reflecting a potential reduction in the set of eligible investments for U.S. MMFs.

[INSERT FIGURE 4 HERE]

3 Empirical Strategy

3.1 Fund Similarity

Our first hypothesis (H1) implies that fund similarity to other investors in the same security issuer predicts the decision of a fund to roll over funding to an issuer in the next period. Testing this hypothesis involves two empirical challenges: (i) investors funding supply shocks and issuers funding demand shocks might be correlated, which calls for the identification of funding outflows that are the result of funds' decisions and not the result of issuers' heterogeneous funding demands, (ii) funds make investment decisions on the basis of issuer fundamental risk such that an additional identification challenge comes from the potential correlation between issuer fundamental risk and endogenous issuer security illiquidity arising from the similarity of his investors.

To address both empirical challenges, we study changes in the funding supply of several funds investing in the same issuer where the funds differ by their degree of similarity to the other funds investing in that issuer. We absorb all the heterogeneity in funding flows coming from observed and unobserved issuer characteristics (e.g. issuers' funding demands, issuers' fundamental risk) by including issuer fixed effects interacted with month fixed effects in our regressions. To ensure heterogeneity in funds' similarity within an issuer, note that we need at least three funds investing in the same issuer at time t. Our regressions are therefore based on a restricted sample of issuers who have access to funding in money markets from at least three different fund names. The hypothesis also entails the assumption that the fund can observe other funds' investments one month after reporting. The fund similarity measure is lagged by one month, implying that this information is known by the fund when the fund makes its investment decisions at time t.[9]

[9]The information about funds' exposures is publicly available from iMoneyNet and the N-MFP forms, the same

We consider two dependent variables that describe the investment decisions of funds after learning of their similarity to other investors: the probability of reducing the exposure to a security issuer (*Outflow*), and the percentage change in the exposure to a security issuer (Δ*Outstanding*). As we control for the level of demand of funding at the issuer level, both measures are interpreted as capturing a fund's decision to roll over funding to an issuer.

We test the effect of fund similarity on the fund's decision to roll over funding to an issuer ($Fund\,rollover_{fit}$) with the following regression:

$$\begin{aligned} Fund\,rollover_{fit} &= \beta_{it} + \beta_f + \beta_t + \gamma Similarity_{fit-1} \\ &\quad + \delta controls_{fit-1} + \varepsilon_{fit} \end{aligned} \tag{3}$$

where β_{it} are issuer*month fixed effects, β_f are fund fixed effects, and β_t are month fixed effects, $Similarity_{fit}$ is the similarity of fund f to the other funds investing in issuer i at time t. The control variables $controls_{fit}$ are security-specific characteristics (e.g. maturity, yield) and fund-specific control variables (e.g. fund size).

The dependent variable $Fund\,rollover_{fit}$ is defined as one of two variables:

- *Outflow*: a indicator variable equal to one if a fund f was investing in issuer i at time $t-1$ and invests less in issuer i at time t than it was investing in issuer i at time $t-1$, and equal to zero otherwise. The sample is restricted to fund-issuer pairs with a non-zero exposure at time $t-1$. The parameter γ describes a change in the probability of a fund to reducing its exposure to an issuer when the similarity of the fund is one p.p. higher.

- Δ*Outstanding*: the percentage change in the security exposure of fund f to issuer i between time $t-1$ and time t given by $\log(vol_{fit}/vol_{fit-1}) * 100$, excluding observations outside the $[-100\%, 100\%]$ range. This is similar to Chernenko and Sunderam (2014), who

data source we use in our analyses.

use the percentage change in the average exposure of fund f to issuer i. The parameter γ describes a change in the funding flow from a fund to an issuer when the similarity of the fund is one p.p higher.

As mentioned above, the unobserved heterogeneity in issuer funding demands is absorbed by issuer*month fixed effects. In addition, we repeat the regressions adding *fund*issuer* fixed effects in order to exploit the funding supply variation within the same fund-issuer pair over time, controlling for observable and unobservable time-invariant fund-issuer pairs characteristics (such as relationship, or distance). As a robustness test, we include both issuer*month and *fund*month* fixed effects, such that we also absorb all unobserved time-varying heterogeneity in funds' characteristics outside their similarity to other funds in an issuer. In this regression, we look at relative/compositional changes in the portfolio of the fund — holding the fund portfolio growth constant — depending on the fund similarity to other funds investing in an issuer.

To study the diversification-diversity trade-off, we also consider (in a specification without fund*month fixed effects) the fund portfolio concentration as measured by the Hirschman-Herfindahl index (HHI). The fund HHI is constructed from the fund's portfolio shares in issuers and captures the concentration of the fund portfolio between 0% (full diversification) to 100% (full concentration). We will use the fund's HHI both as a control variable in regression (3), and as an interaction term with the fund similarity measure to study the heterogeneous effects of fund similarity depending on the level of fund portfolio concentration.

3.2 Issuer Access to Funding

Our second hypothesis (H2) focuses on the issuer and his overall access to funding. Issuers with more-similar funds on average potentially 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 they are hit by a common shock.

In order to assess potential substitution effects when an issuer loses funding from its similar investors, we study access to funding at the aggregate issuer level. Our dependent variable is the percentage change in an issuer's total outstanding amount from MMFs during a month. Note that this test is not required to be restricted to a sample of issuers having access to U.S. MMFs via at least three funds. We therefore consider all unsecured fund flows from U.S. MMFs. This test, however, does not exclude the possibility of substituting the loss in unsecured funding from U.S. MMFs with secured funding or funding other than from MMFs. Finally, the possibility for an issuer to substitute funding away from similar investors might be harder during a crisis. To account for this, we estimate the differential effect of the average similarity of funds of an issuer on its fund flows during crisis months.

We consider the following regression for the total unsecured fund flows to issuer i during month t:

$$\begin{aligned}\log(Amount_{it}/Amount_{it-1}) &= \beta_i + \beta_t + \gamma_1 Similarity_{it-1} + \gamma_2 Similarity_{it-1} * Crisis_t \\ &\quad + \delta controls_{it-1} + \varepsilon_{it},\end{aligned} \tag{4}$$

where β_i are issuer fixed effects, β_t are month fixed effects, $Similarity_{it} = \sum_f w_{fit} Similarity_{fit}$ is the average similarity of funds investing in issuer i at time t (similarity with other funds that also invested in issuer i at time t), $Amount_{it} = \sum_f Amount_{fit}$ is the total outstanding amount invested by all U.S. MMFs in issuer i, $Crisis_t$ is a dummy variable equal to one during the European sovereign debt crisis months (from June 2011 until December 2011), and the weights for the different funds investing in issuer i are given by $w_{fit} = Amount_{fit}/\sum_f Amount_{fit}$. 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 measure). In particular, issuer controls include variables capturing the issuer's diversification of his funding sources (e.g. the number of funds buying securities from an issuer, and the issuer's funding HHI). The parameter γ_1 describes the change in total fund flows of an issuer (outside crisis months) when the average similarity of funds of the issuer is one p.p. higher. During crisis months, the effect of the average similarity on fund flows is $\gamma_1 + \gamma_2$. Therefore, the parameter γ_2 captures the extent to which funding liquidity risk increases due to the similarity of the investors of an issuer during a crisis.

4 Results

In this section, we present the results of tests related to our first hypothesis (H1) about funds' rollover decisions as a function of their similarity to other funds. Results are reported in Subsection 4.1 where we provide empirical evidence consistent with a demand for diversity (Subsection 4.1.1), and a diversity-diversification trade-off (Subsection 4.1.2). We rule out alternative hypotheses in Subsection 4.2.

4.1 Fund Similarity and Rollover Decisions

4.1.1 Baseline Results

We first investigate the effect of similarity of investors on their investment (i.e. rollover) decisions using regression equation (3) and the methodology outlined in the previous section. We report the results in Table 2.[10]

[10] Out of 668,022 observations describing a fund's exposure though a security contract to an issuer, we drop observations for issuers who have funding contracts with fewer than three funds (605,720 remaining observations), and security contracts that are secured by collateral (436,808 remaining observations). The analysis of *Outflow* requires funds to have a non-zero exposure to an issuer at time $t-1$. The analysis of Δ*Outstanding* requires funds to

[INSERT TABLE 2 HERE]

All regressions include issuer*month fixed effects, as well as fund and month fixed effects, and also control for fund size. Columns (1) to (4) of Panel A of Table 2 report the effect of the fund similarity on the probability of a fund reducing its exposure to an issuer (*Outflow*). The last four columns report the effect of fund similarity on the percentage change of a fund's exposure to an issuer (Δ*Outstanding*). Columns (1) and (5) report the results of our benchmark regressions, controlling for maturity and yield of the contract, as well as for security type (certificate of deposit or financial commercial paper). Columns (2) and (6) assess the effect of fund similarity without control variables. Columns (3) and (7) include issuer*funds fixed effects to control for different incentives of funds based on their relationship with an issuer. Columns (4) and (8) exclude expiring contracts (i.e., contracts expiring within the next 30 days) to mitigate concerns that the effect of fund similarity we find is only due to simultaneously expiring contracts.

In Column (1), we document that the probability that a fund will reduce its exposure to an issuer (*Outflow*) increases by 2.2 p.p. with a one standard deviation increase in the similarity of the fund to other funds that invest in the same issuer. A 2.2 p.p. increase is economically non-negligible given that the estimate, obtained after controlling for all observed and unobserved heterogeneity in issuers, represents 7% of the unconditional probability of *Outflow* (33%). In this regression, we compare different funds investing in the same issuer on the same date including the control variables described above. This estimate remains unchanged without control variables (Column (2)) while the R^2 drops from 22% to 13%, emphasizing the stability of our parameter estimates (Altonji et al. (2005) and Oster (2019)). Our estimate increases somewhat to 3.3 p.p. after including fund*issuer fixed effects (Column (3)), and to 5.58 p.p. when consid-

have a non-zero exposure at time t and $t-1$. Out of 436,808 observations for unsecured securities, we have 149,561 non-missing observations for *Outflow* and 123,748 non-missing values for Δ*Outstanding*. Additional observations are dropped in the regressions when observations for the lagged similarity measure or for the control variables are missing.

ering only contracts that expire in more than a month (Column (4)). The coefficients capturing the effect of fund similarity on *Outflow* are all statistically significant at the 1% level.

Fund flows to an issuer (Δ*Outstanding*) are 2.66 p.p. lower when *Similarity* increases by one standard deviation (Column (5)). In absolute dollar amounts, the estimate translates into an additional 5,346 USD monthly outflow, relative to unconditional average funding outflows of 563 USD (0.28 percentage outflow) between a fund and an issuer, and to an outstanding amount of 201,000 USD for the average security contract. Among funds investing in a specific issuer, a fund with a one standard deviation higher similarity to other funds investing in the issuer in the previous reporting month decreases its exposure to the issuer by an additional 2.66 p.p. compared to other funds. The estimate remains stable in the absence of security controls (maturity, yield and security type). The effect is even larger (-4.46 p.p.) when we absorb the heterogeneity in fund-issuer pairs (Column (7)), and fairly similar (-2.35 p.p.) when we condition on contracts that expire after more than a month (Column (8)). All the estimates obtained for the effect of fund similarity on Δ*Outstanding* in Panel A are significant at the 1% level.

4.1.2 Diversification-Diversity Trade-Off

In Panel B of Table 2, we provide evidence consistent with a diversification-diversity trade-off. In our tests, we augment the regression specifications and include both fund similarity and a proxy for fund portfolio concentration measured by the fund's HHI. We find that funds reduce their exposure to an issuer when fund similarity increases, but also when portfolio concentration increases. Our results show that, holding fund diversification constant, funds become less similar by reducing their exposure to issuers financed by similar investors. A one standard deviation increase in fund similarity increases the probability of outflow by 2.8 p.p., and reduces fund flows to an issuer by 2.99 p.p., while a one standard deviation increase in fund's concentration increases the probability of outflow by 1.5 p.p. and decreases fund flows by 1.26 p.p. The estimate of fund HHI is only significant at the 5% level for Δ*Outstanding*, while the effect of fund similarity is significant at the 1% level for both outcome variables *Outflow* and Δ*Outstanding*. In addition, the economic magnitude of the effect of fund similarity is more than twice as large than the effect of fund's concentration on Δ*Outstanding*.

Interestingly, the effect of fund similarity on rollover decisions increases with fund diversification, consistent with higher average joint liquidation costs for more diversified portfolios (Wagner (2011)).[11] Columns (2) and (4) of Panel B show that, with a one standard deviation increase in fund's concentration, the marginal effect of similarity on the outflow probability decreases by 0.1 p.p., and the marginal effect of similarity on percentage fund flows decreases by 0.09 p.p. Consistent with a diversification-diversity trade-off, we find that the effect of similarity on fund outflows attenuates for concentrated fund portfolios. More precisely, we find that the effect of fund similarity goes to zero for funds with an HHI of 75%.

4.2 Alternative Hypotheses

In this subsection, we investigate alternative explanations for our results, specifically, (i) that funds follow a similar investment strategy and (ii) funds' outflows from eurozone issuers increasing fund similarity during the European sovereign debt crisis (reverse causality).

A possible concern is that funds' decision to stop rolling over funding to some issuers is the result of funds following similar investment strategies rather than the result of concerns over portfolio similarity. For example, our results might simply reflect that funds have concentration limits and thus reduce their exposures to issuers in which they are concentrated. In Panel A, we mitigate this concern and introduce a control variable for the fraction of the fund portfolio

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

invested in issuer i ($Weight_{fi,t}$).The results are reported in Table 3.

[INSERT TABLE 3 HERE]

Three observations emerge from Panel A of Table 3: first, the effect of fund similarity is robust to controlling for a fund's concentration in an issuer. Second, in Columns (1) and (3), we provide evidence consistent with concentration limits as, e.g. funds with larger investments in a single issuer are more likely to reduce their investments. Third, in Columns (2) and (4), we find that, controlling for the fund's portfolio weight in an issuer, the sign of the estimate of fund's concentration ($HHI_{f,t}$) becomes negative. This is intuitive, once we control for a fund's investment in a single issuer i, the overall portfolio concentration of the fund measured by $HHI_{f,t}$ measures the concentration in all other issuers (except i). In other words, we find that funds are less likely to reduce funding to an issuer if the concentration of their portfolio in other issuers is high.

In Panel B of Table 3, we investigate the possibility that the effect of fund similarity on fund flows is the result of funds following the same benchmark index in their investment decisions. To address this concern, 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 all heterogeneity in fund performance, liquidity and maturity and make funds more comparable and susceptible to following the same investment strategy. In Columns (2) and (6), we add fund cluster*month fixed effects. Fund clusters are obtained from a principal component analysis on fund performance.[12] The fund cluster*month fixed effects should absorb the

[12]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 that equal one if a fund has a significant loading on a principal component. This gives $2^5 = 32$ possible combinations of indicator variables per fund. Finally, we cluster all funds with the same combination of indicator variables into one cluster.

common component of funds following the same index. In Columns (3) and (7), we add fund complex*month fixed effects. The fixed effects here absorb the common component of funds belonging to the same fund family ("fund complex"). Finally, we add fund*month fixed effect in Columns (4) and (8). In this regression, we absorb all the 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, 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 fund similarity, and the estimates are all significant at the 1% level, suggesting that our interpretations remain qualitatively unchanged after controlling for the level of funding supply of a fund.

In Panel C of Table 3, we address the issue of reverse causality. While our result is identified within an issuer-month by comparing the similarity of several funds investing in the same issuer, it is possible that our result is explained by outflows from eurozone issuers during the European sovereign debt crisis mechanically increasing the similarity of U.S. MMFs. Consequently, outflows would explain an increase in similarity (reverse causality). Indeed, as we observe in Figure 2, U.S. MMFs withdrew almost all unsecured funds from eurozone issuers in the summer of 2011. Average investor similarity increased by 6 p.p. from 86% to 92% (Figure 4) as a result of MMFs all withdrawing from the same issuers at the same time. In Panel C, we show that the marginal effect of similarity on fund flows to an issuer is not significantly different for funds that were not exposed to eurozone issuers in June 2011. The indicator variable $noeuroexp_f$ in Panel C takes the value of one for a fund that had no exposure to eurozone issuers in June 2011 and zero otherwise. The effect of similarity is not significantly different for non-exposed funds for both the outflow probability (Column (1)) and the percentage fund flows to an issuer (Column (3)). The table also shows in Columns (2) and (4) that there is no differential effect of the fund concentration on fund flows from non-exposed funds. We discuss further robustness checks to our main result in the Online Appendix D.2.

5 When Does Similarity Matter?

Our previous results are consistent with the interpretation that funds react when portfolio similarity with other funds increases. In this section, we investigate when similarity matters, exploiting the heterogeneity across funds and issuers, and report the results in Tables 4 and 5.

5.1 Fund Exposure

It is a testable hypothesis that similarity matters more when fund exposures are large. We report the results of this test in Table 4, where we add the fraction of the fund's portfolio invested in issuer i ($Weight_{fi,t}$) to our baseline regression, as well as the interaction term $Similarity_{fit-1} \times Weight_{fi,t}$ (Columns (1) and (4)) to assess the differential effect of similarity when the fund's exposure in an issuer's security is high. Consistent with our hypothesis, we find that the marginal effect of similarity increases when the fraction of the fund's portfolio invested in an issuer increases. For example, when the portfolio share of a fund in an issuer is about 10% (corresponding to the 90th percentile of $Weight_{fi,t}$ distribution), the probability of experiencing a fund outflow increases by 4.3 p.p. and the percentage flows by -4.5 p.p. for a one standard deviation increase in fund similarity.

[INSERT TABLE 4 HERE]

Funds might also react more strongly to an increase in similarity when they experience redemptions. We construct a new variable (*Redemption*), which is defined as a fund's net outflows as a percentage of the fund total portfolio in a given month. We add the interaction term

$Similarity_{fit-1} \times Redemption_{ft}$ in Columns (2) and (5) and also include the interaction term $Similarity_{fit-1} \times Weight_{fi,t}$ in Columns (3) and (6). Conditional on withdrawals, we find that funds withdraw more as a response to similarity in months with large redemptions from investors (Column (5)). The effect of a one standard deviation in fund similarity on fund flows increases from -2.32 p.p. for a fund with no redemption to -2.35 p.p. (-0.04 p.p. difference) for the fund with the 10% largest net outflows from its investors. Interestingly, the coefficient of *Redemption* is positive and significant, suggesting that MMFs shift funds from investments with high similarity into investments where similarity is low.

Taken together, funds that have more concentrated holdings in an issuer or experience higher redemptions react more strongly to an increase in similarity. This is consistent with the literature on fire sales where fire sales are more pronounced when assets are jointly held by banks that are more leveraged or closer to the regulatory constraint (Ellul et al., 2011). In our context, we observe an analogous effect in that joint liquidation costs are more of a concern for investments held by similar funds with large exposures and less stable funding structures.

5.2 Issuer Risk

In this section, we study the interaction of similarity with issuer risk. Joint liquidation costs are likely to be a concern for risky issuers as they are more prone to default on repayment when multiple funds withdraw. While our regression design absorbs all variations in fund flows that are related to issuer risk through issuer*month fixed effects, this design allows us to investigate whether funds' response to similarity is stronger for riskier issuers using interaction terms with a proxy for issuer risk. To measure risk, we construct a new variable $Volatility_{it}$ as the squared stock return of the security issuer over the past month and include an interaction term with similarity in our baseline regression.[13] We report the results in Panel A of Table 5.

[INSERT TABLE 5 HERE]

All regressions include issuer*month fixed effects, fund and month fixed effects, security controls and security types, and a control variable for the fund size. Columns (1)-(3) show the result for the outcome variable *Outflow*, and Columns (4)-(6) the results for the outcome variable Δ*Outstanding*. Columns (1) and (4) show the results of Table 2 for the restricted sample of issuers for which we have stock price data. Columns (2) and (5) include an interaction term $Similarity_{fit-1} \times Volatility_{it-1}$, and Columns (3) and (6) include an additional interaction with the crisis period.

We do not find any differential effect of fund similarity for riskier issuers on the funds' probability to withdraw funding from an issuer (Columns (2)-(3)). In contrast, Column (5) shows that funds withdraw significantly more funding from issuers with similar investors when issuers are riskier. The effect of a one standard deviation increase in fund similarity on fund flows is -2.2 p.p. for issuers with the lowest volatility, -2.3 p.p. for issuers with a median volatility, and -3.4 p.p. for issuers within the 90th percentile of stock return volatility. Column (6) shows that the effect of fund similarity on fund flows of these risky issuers is stronger (-4.6 p.p.) during the crisis period. In summary, the probability that a fund withdraws funding based on similarity does not increase with issuer risk, but outflows are larger when they do, particularly during crises.

As European banks were particularly affected during the sovereign debt crisis (Acharya and Steffen, 2015), we expect joint liquidation costs and the effect of fund similarity on fund flows to be stronger for European banks during the crisis. We construct a new variable $Bank$, which is a dummy equal to one if an issuer is a bank. We also define a new variable $EUbank$

[13]We obtain the stock price data from Bloomberg.

indicating a European bank issuer. In Columns (1) and (4) of Panel B, we include the interaction term $Similarity_{fit-1} \times Bank_i$. We find no differential effect on similarity if issuers are banks.

In a next step, we drop all non-bank issuers and compare the effect of fund similarity for banks during the crisis (Columns (2) and (6)), European banks (Columns (3) and (7)), and European banks during the crisis (Columns (4) and (8)) separately. As in Panel A, we do not find any significant differential effect of similarity on *Outflow* for any set of banks or during the crisis. We do, however, find that banks suffer larger outflows from similar funds during the crisis (Column (6)). Moreover, European banks have larger outflows from similar investors compared to non-European banks (Column (7))[14], and all banks experience even larger outflows from similar investors during crisis periods.

Overall, our results are consistent with the interpretation that investors in European banks are exposed to greater expected joint liquidation costs due to the relatively higher fragility of these banks during our sample period. In terms of economic magnitudes, the reduction in fund flows from a one standard deviation increase in fund similarity is -3.6 p.p. for banks during a crisis, compared to -2.8 p.p. outside the crisis period (Column (6)). Similarly, the effect of a one standard deviation increase in fund similarity on fund flows is -3.8 p.p. (7,693 USD outflow) for European banks, compared to -2.9 p.p. (5,800 USD outflow) for other banks (Column (7)). Combining both effects in Column (8), we find that the monthly outflow due to an increase in fund similarity of one standard deviation is about -3.9 p.p. (7,850 USD) during the European sovereign debt crisis for the securities issued by European banks.

[14]Note that the $EUbank$ dummy is dropped because of fixed effects.

6 Fund Similarity and Issuer Funding Fragility

6.1 Funding Liquidity Risk

We turn to our second hypothesis (H2) pointing to an increase in a security issuer's funding liquidity risk when his funds are more similar. An issuer can resort to multiple funds to diversify his liabilities and strengthen his balance sheet. However if all funds of an issuer have the same portfolios, funding liquidity risk increases for the issuer as diversification benefits from resorting to multiple fund names attenuates. We report the results of regression (4) describing the effect of the average fund similarity of an issuer on its total fund flows in Table 6.[15] We focus on the issuer's access to unsecured funding and aggregate our observations at the issuer level providing us with 12,516 panel observations and 301 issuers. As our analysis requires issuers to have access to unsecured funding via U.S. MMFs in two consecutive years, our final sample contains about 4,590 observations with non-missing funding flows.

[INSERT TABLE 6 HERE]

All regressions in Panel A include issuer fixed effects, month fixed effects, and security control variables. The regressions in Columns (3)-(4) and (7)-(8) also include issuer*year fixed effects to focus on the within-year variation at the issuer level. We also control for the number of funds investing in an issuer and the issuer's liability diversification with the *issuer*'s HHI index in Columns (1), (3), (5), and (7). In Columns (1) to (4), we exclude interaction terms with the crisis indicator variable from our regression. We find that average fund similarity of an issuer is not statistically significant in explaining fund flows. Only the number of funds of an issuer and the issuer's liability HHI explain the total fund flows. Fund flows are 0.3 p.p. lower for issuers with

[15] Regressions at the issuer level do not require us to restrict the sample to issuers with access to money markets via three funds. We therefore consider the entire universe of issuers with access to U.S. money market funds reporting to iMoneyNet in this section.

an additional fund relationship, and 5.7 p.p. higher for issuers with a one standard deviation higher concentration in their liabilities (Column (3)). Both coefficients are significant at the 5% level after including issuer*year fixed effects, and are relative to unconditional average fund flows of 0.2% to an issuer, and an average total outstanding amount invested by U.S. MMFs in an issuer of USD 5.5 million.

We find that the average similarity of the funds of an issuer only affect access to funding during a crisis. In Column (5), fund flows to an issuer increase by 1.1 p.p. when the average fund similarity of the issuer is one standard deviation higher. This coefficient for non-crisis months is, however, not significant at the 5% level. The effect of average fund similarity of an issuer on its fund flows decreases by 7.1 p.p. in a crisis, and fund flows to an issuer decrease by about 6 p.p. when the average fund similarity of the issuer is one standard deviation higher during crisis months. In dollar amount terms, and relative to an average outstanding investment of USD 5.5 million, the effect of a one standard deviation increase in the issuer's average fund similarity translates into a USD 330,731 additional monthly outflow during crisis months.

In Panel B, we study the heterogeneous effects of the issuer's average fund similarity depending on issuers characteristics, for banks and European banks, in particular. All regressions include issuer and month fixed effects[16], issuer control variables for the number of funds and the diversification of liabilities, as well as security control variables. We do not find any differential effect of the average fund similarity on the total fund flows of issuers when issuers are banks (Column (1)). In the subsample of bank issuers, the effect of average fund similarity of an issuer is only significant at the 1% level for European banks during the European sovereign debt crisis. The effect of an increase in the issuer's average fund similarity by one standard deviation leads to a reduction in fund flows by 7.6 p.p. for European banks during the crisis, compared to 5.4 p.p. for other banks during the crisis. Relative to an average total outstanding amount invested

[16] We do not include issuer*year fixed effects in the regressions of Panel B given the lower number of observations in subsamples.

in a bank of USD 7.8 million, a 7.6 p.p. outflow corresponds to a USD 592,404 monthly funding outflow due to a one standard deviation increase in the issuer's average fund similarity.

Overall, we find that similarity leads to substantial funding outflows at the issuer level, particularly during crises and for European banks. In a next step, we investigate whether issuers can compensate for these outflows with funding from "non-similar" investors.

6.2 Similar vs. Non-Similar Investors

If issuers can recover funding from non-similar investors when similar investors reduce funding to an issuer, then fund similarity should not have any consequence for the issuer's funding fragility. In particular, during a crisis, when concerns about expected joint liquidation costs are more important, non-similar investors could play a role in stabilizing issuers' 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 (or investors) are labelled as "similar" when their similarity measure is above the median similarity measure of funds in a given month. We show the separate effects of an increase in average fund similarity of an issuer on fund flows from similar investors (Columns (1)-(2)), and on the fund flows from non-similar investors (Columns (3)-(4)). In addition, we separate the sample between crisis months and non-crisis months ($NoCrisis_t$). Columns (1) and (2) include issuers' liability structure controls (issuer HHI and number of funds), while Columns (3) and (4) exclude the controls. The results are reported in Table 7.

[INSERT TABLE 7 HERE]

Outside the crisis period, we find that similar investors reduce their exposure to an issuer as a result of an increase in the issuer's average fund similarity, while non-similar funds increase their exposure. That is, non-similar investors compensate for the loss of funding from similar investors outside the crisis. In contrast, non-similar investors do not significantly change their exposure to an issuer following an increase in the issuer's average similarity during a crisis, while issuers experience severe outflows from similar investors. Issuers lose on average 17.2% of their outstanding amount from their similar investors during a crisis 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.

To summarize, non-similar investors do not substitute funding from similar investors, while similar investors "run" from issuers with higher average investor similarity during a crisis.[17]

7 Conclusion

We study the effect of portfolio similarity among investors on their decision to roll over funding to a security issuer. Using detailed security-level holdings of U.S. Money Market Mutual Funds (MMFs), we construct a novel measure of portfolio similarity among investors (i.e. MMFs) who are exposed to the same issuer. Consistent with theories highlighting correlated liquidity needs of more similar investors (e.g. Wagner (2011)), we find that a fund reduces the exposure to an issuer if the fund's similarity to other investors in this issuer increases. Importantly, we find that an issuer's average fund similarity predicts its total funding in the next period. In other words,

[17] In Table SI-5 in the Online Appendix, we present analogous results as in Table 6, replacing the average fund similarity measure of an issuer with the share of total U.S. MMF funding of an issuer coming from similar funds (with "similar" being defined as above). This alternative measure captures the issuer's exposure to similar funds. The results we obtain using the share of similar investors in Table SI-5 are qualitatively the same as the results obtained with the average fund similarity measure in Table 6.

issuers cannot substitute this loss in funds, particularly during crises.

While our measure and analysis are broader and not industry-specific, they do highlight concerns regarding funding liquidity risk in the banking sector. Since the 2007-09 global financial crisis, new regulations have been introduced in order to limit bank liquidity risk (e.g. Basel III liquidity coverage ratio (LCR) and net stable funding ratio (NSFR)). The friction of systemic liquidation costs arises due to limited available liquidity in the market. In the case of MMF securities, correlated funding liquidity needs of similar funds and limited available cash on the issuer's balance sheet increase expected joint liquidation costs. Regulations that improve available liquidity at issuers exposed to similar funds or at similar funds themselves can play a significant role in reducing concerns related to systemic liquidation costs.

Our results are complementary and emphasize the need for regulators to pay closer attention to the funding side of banks' balance sheets in future attempts to address banks' funding liquidity risk. It is insufficient to assess a bank's liquidity needs based on the amount of short-term funding, nor would it be sufficient to focus on the concentration of short-term depositors or assess liquidity risk as a function of bank health. Our results suggest that it would be wise to focus on the portfolio similarity among investors and their correlated liquidity needs.

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A Examples to Illustrate Portfolio Similarity

Example 1. To illustrate the $\text{Similarity}_{fi,t}$ measure, consider the following simple example. There are three funds, the first two of which each invest one unit into one of two security issuers and the third fund only invests one unit in the first issuer. The situation is depicted in Figure 1. The portfolio allocation of the three funds f_1, f_2, and f_3 and the two security issuers i_1 and i_2 is as follows:

$$\begin{array}{rcll} & & i_1 & i_2 \\ f_1 & = & 1 & 1 \\ f_2 & = & 1 & 1 \\ f_3 & = & 1 & 0 \end{array}$$

This portfolio allocation implies the corresponding fund-issuer-specific weighting vectors $w_{\varphi,i}$ for fund f_1 of:

$$\begin{array}{rccc} & & f_2 & f_3 \\ w_{f_1,i_1} & = & 1/2 & 1/2 \\ w_{f_1,i_2} & = & 1 & 0 \end{array}$$

where row i indicates the weight $w_{f_1,i}$ fund f_1 has in issuer i, and column φ is the weight fund f_1 has relative to fund φ. Weights are derived the following way: excluding funding provided by fund f_1 to issuer i_1, issuer i_1 receives two units of funding, of which one unit comes from fund f_2 and one unit comes from fund f_3. Therefore, to average pairwise distance of fund f_1 relative to issuer i_1, the pairwise distance between fund f_1 and f_2 receives a weight of 1/2, and the pairwise distance between fund f_1 and f_3 has a weight of 1/2.

For funds f_2, and f_3 we get:

$$\begin{array}{rclcr} & & (f_1 & , & f_3) \\ w_{f_2,i_1} & = & (1/2 & , & 1/2) \\ w_{f_2,i_2} & = & (1 & , & 0) \end{array}$$

$$\begin{array}{rclcr} & & (f_1 & , & f_2) \\ w_{f_3,i_1} & = & (1/2 & , & 1/2) \\ w_{f_3,i_2} & = & (1 & , & 0) \end{array}$$

In this example, the pairwise Euclidean distances in funds' portfolio holdings are $d_{f_1,f_2} = 0$, and $d_{f_1,f_3} = d_{f_2,f_3} = 0.707$. Using these pairwise distances multiplied by the corresponding weighting vectors $w_{\varphi,i}$, the weighted average fund distances are given as:

$$\begin{aligned} \text{Wgt.Avg.Distance}_{f_1} &= \text{Wgt.Avg.Distance}_{f_2} \approx (0.354, 0.0) \\ \text{Wgt.Avg.Distance}_{f_3} &\approx (0.707, 0.707) \end{aligned}$$

Using the relation between distance and similarity in equation (2), the funds' similarity measures are given by:

$$\begin{aligned} S_{f_1} = S_{f_2} &= (75, 100) \\ S_{f_3} &= (50, 50) \end{aligned}$$

Funds f_1 and f_2 are identical in this example, and fully diversified, while fund f_3 is different and specialized. Funds f_1 and f_2 have the same similarity measure since they are identical. Looking at security issuer i_2, the similarity of fund f_1 (resp. fund f_2) is 100% (the largest possible value) given that the only other fund investing in issuer i_2 is fund f_2 (resp. fund f_1) with the exact same portfolio. Looking at issuer i_1, the similarity is below 100% given that for each fund, there is at least one different fund investing in issuer i_1. Comparing the similarity of funds investing in issuer i_1, the similarity of fund f_1 and fund f_2 (75%) is relatively higher than the similarity of fund f_3 (50%), given the respective portfolio composition of the three funds (i.e., funds f_1 and f_2 are identical, while fund f_3 is different).

Example 2. In another simple example, we consider the alternative case where we have two specialized funds with the exact same portfolios, and one diversified fund that is different. Consider the following portfolio allocation:

$$\begin{array}{ccccc} & & i_1 & i_2 \\ f_1 & = & 1 & 0 \\ f_2 & = & 1 & 0 \\ f_3 & = & 1 & 1 \end{array}$$

We can show that, for issuer i_1, who gets the exact same funding allocation as in the previous example, the similarity measure of each fund remains the same. In other words, our fund similarity measure is not a function of fund diversification. In this case, the average weighted distances are:

$$\begin{aligned}
\text{Wgt.Avg.Distance}_{f_1} &= \text{Wgt.Avg.Distance}_{f_2} = (0.354, 0.707) \\
\text{Wgt.Avg.Distance}_{f_3} &= (0.707, \emptyset)
\end{aligned}$$

Consequently, the fund similarities are:

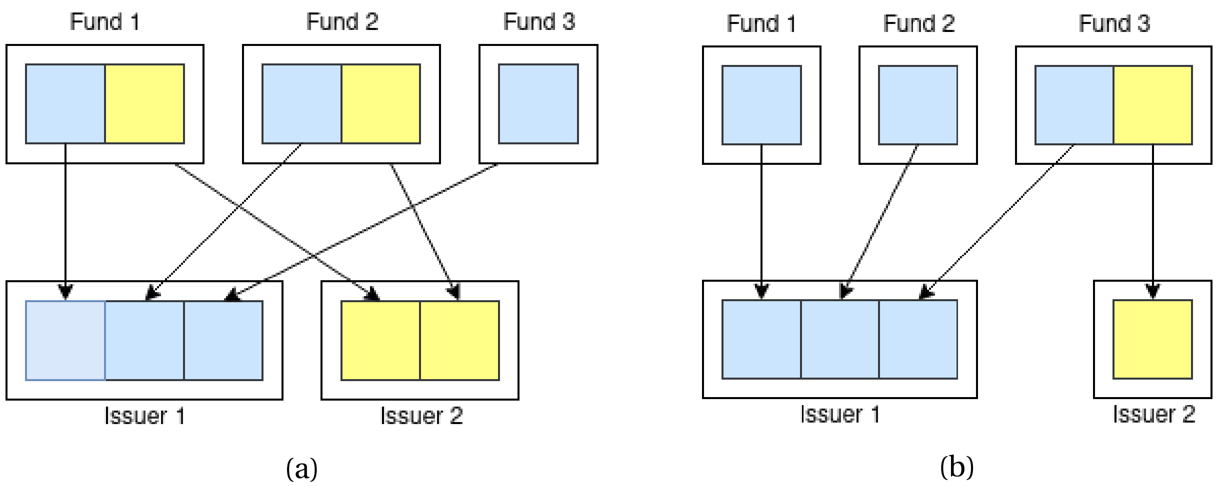
$$\begin{aligned}
S_{f_1} = S_{f_2} &= (75, 50) \\
S_{f_3} &= (50, \emptyset)
\end{aligned}$$

Note that, for issuer i_1, we obtain the same fund similarity of 75% for funds f_1 and f_2, and of 50% for fund f_3 as in the previous example where the difference in portfolio diversification between funds is reversed. The $\emptyset$ for fund f_3 in issuer i_2 appears because there is no other fund investing in this issuer. Consequently, the average distance of fund f_3 to all other funds investing in issuer i_2 is not defined.[18]

[18] An average distance of zero would mean that fund f_3 has no distance to the other funds investing in issuer i_2, i.e. that there are other funds investing in this issuer with the exact same portfolio as fund f_3.

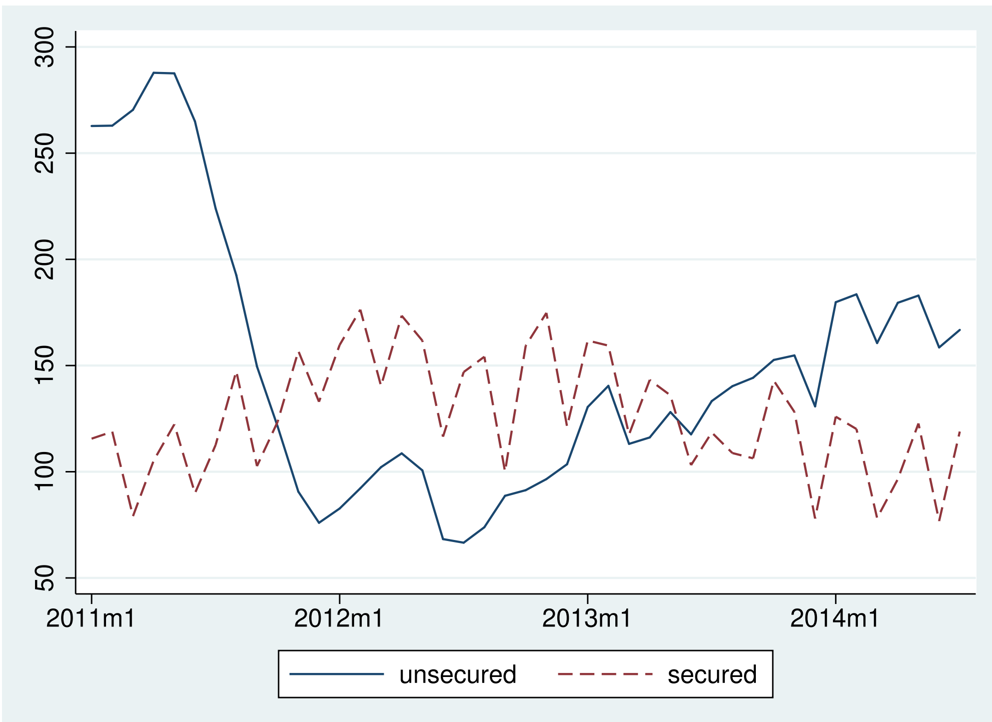
B Figures

Figure 1: Fund Portfolio Composition in Examples 1& 2



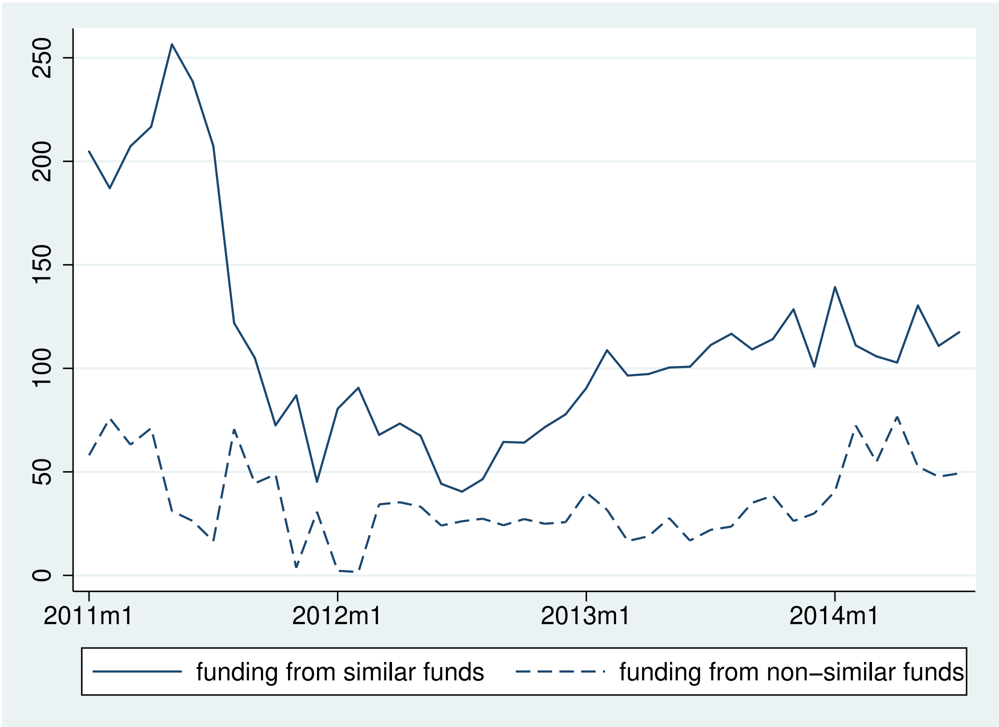
(a): Investments of funds f_1, f_2, f_3 in security issuers i_1, i_2 corresponding to Example 1. (b): Investments of funds f_1, f_2, f_3 in security issuers i_1, i_2 corresponding to Example 2. Different colors denote different security issuers. Each arrow represents an investment of 1 by a fund (top) in a security issuer (bottom).

Figure 2: U.S. Money Market Funds' Investments at European Banks



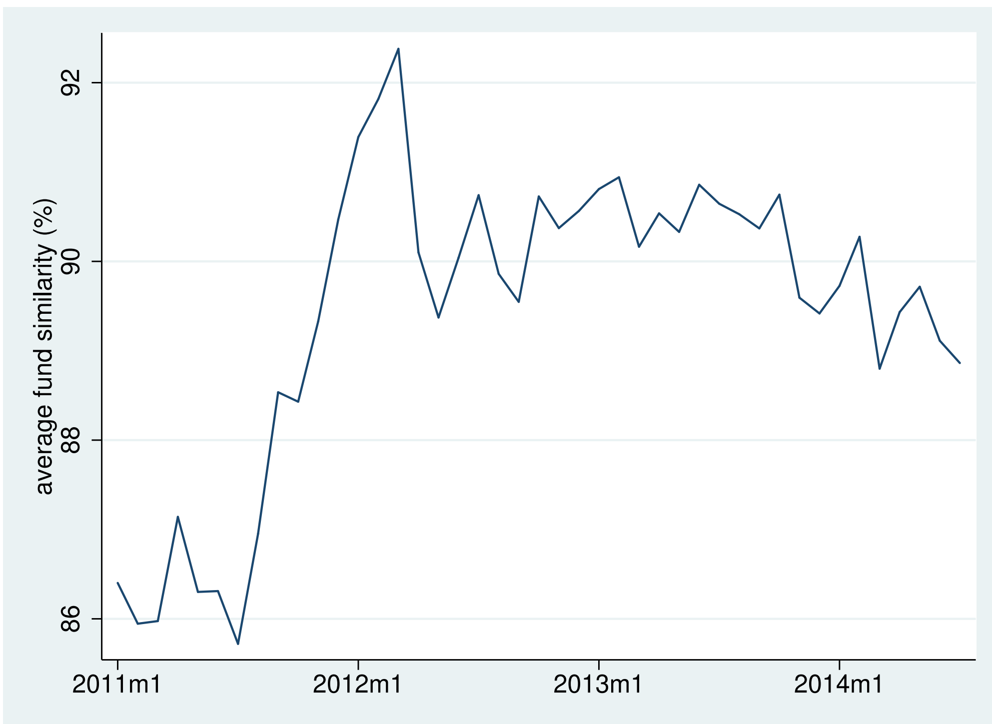
This figure shows the total principal unsecured (solid line) and secured (dashed line) amounts invested by U.S. MMFs at European (eurozone) banks in USD billion over time. Secured investments include repurchase agreements, and unsecured investments are certificates of deposit and financial commercial papers.

Figure 3: Unsecured Investments at European Banks: Similar vs. Non-similar U.S. MMFs



This figure shows the total unsecured principal amounts invested by similar funds (solid line) and non-similar funds (dashed line) at European (eurozone) banks in USD billion. A fund is considered similar to other funds if its average similarity measure across its issuers is greater than or equal to the median average similarity measure of all funds, and considered non-similar otherwise.

Figure 4: Average of Average Fund Similarity of Issuers



This figure shows the average across issuers of the average fund similarity measure (in %). The average fund similarity measure of an issuer is computed as the average similarity across funds investing in that issuer.

C Tables

Table 1: **Descriptive statistics: unsecured funding**

This table provides descriptive statistics describing U.S. MMFs' unsecured investments. Panel A reports descriptive moments of variables at the issuer level. Panel B reports descriptive moments at the security level (at the issuer-fund pair level) for the same variables on the sample of issuers who have access to U.S. MMFs via at least three funds. Panel C reports average variables at the issuer level describing unsecured funds received by issuers via U.S. MMFs on different sample splits. Panels A and C: Amount is the total unsecured principal amount invested by U.S. MMFs in an issuer. $\Delta Outstanding_{it}$ is the percentage change the unsecured amount invested by U.S. MMFs in an issuer. Yield and maturity are, respectively, the weighted average yield and maturity of an issuer on its unsecured funding, where weights are given by the relative volume of the fund investment in the issuer. $Similarity_{it}$ is the average similarity of the funds investing in an issuer. Panel B: Amount is the unsecured principal amount invested by one fund in an issuer via one security type. $\Delta Outstanding_{fit}$ is the percentage change in the amount invested by one fund in an issuer. Yield and maturity are, respectively, the yield and maturity of the security. $Similarity_{fit}$ is the similarity of a fund investing in an issuer to the other funds investing in the same issuer. Crisis: 2011-06 - 2011-12. GIIPS: Greece, Ireland, Italy, Portugal and Spain.

Panel A: Descriptive statistics at the issuer level (unsecured funding)

	Obs	Mean	Std. Dev.	Min	Max
Amount (1'000 USD)	5,468	5,544	9,325	0.00	61,526
$\Delta Outstanding_{it}$ (pct. change)	4,590	0.19	28.92	-99.48	99.39
Yield (bps)	5,468	0.26	0.17	0.00	4.50
Maturity (days)	5,468	59.99	63.92	0.00	395.00
$Similarity_{it}$ (%)	5,303	89.11	8.76	32.26	100.00
# Funds per issuer	5,468	30.25	40.39	0.00	189.00
HHI	5,467	0.44	0.38	0.02	1.00
Issuers	295				
of which, fin. institutions	203				
of which, banks	155				
of which, EU banks	39				
of which, GIIPS banks	4				

Panel B: descriptive statistics at the fund-issuer level (unsecured funding)

	Obs	Mean	Std. Dev.	Min	Max
Amount (1'000 USD)	150,631	201	451	0.00	10,461
$\Delta Outstanding_{fit}$ (pct change)	123,748	-0.28	28.95	-99.99	100.00
Yield (bps)	141,945	0.29	0.15	0.00	5.51
Maturity (days)	150,608	50.24	44.81	0.63	391.00
$Similarity_{fit}$ (%)	146,927	84.70	5.58	27.36	99.90
Fund size	150,631	7,906	13,897	0.30	86,434
# Issuers per fund	150,631	24.19	9.24	1.00	52.00
Fund HHI	150,631	7.47	6.13	2.80	100.00
Funds	213				
Issuers	144				

Panel C: Descriptive statistics at the issuer level (unsecured funding) - sample splits

	Amount	ΔOut_{it}	Yield	Maturity	Sim_{it}	#funds	HHI	Obs	Issuers
Before crisis	6,891	-0.29	0.34	50.75	88.10	33.72	0.36	485	122
Crisis	5,811	-3.01	0.29	39.14	87.81	32.69	0.38	766	160
After crisis	5,341	0.79	0.25	64.84	85.97	29.41	0.46	4,217	265
Not a bank	1,813	-0.85	0.21	53.57	86.18	9.48	0.61	2,060	140
Bank	7,800	0.73	0.30	63.87	86.56	42.80	0.34	3,408	155
Non EU bank	7,938	0.90	0.31	70.02	86.66	42.64	0.36	2,645	128
EU bank	7,801	0.20	0.26	42.98	86.47	46.25	0.23	699	27
GIIPS bank	2,086	-0.82	0.35	38.26	84.73	12.00	0.44	63	4

Note: ΔOut_{it} is $\Delta Outstanding_{it}$; Sim_{it} is $Similarity_{it}$

Table 2: **Fund rollover decision and fund similarity.**

This table shows the effect of the fund similarity on funds' decision to roll over funding to an issuer. *Outflow* is an indicator variable equal to one if a fund f was investing in issuer i at time $t-1$ and invests less in issuer i at time t, and equal to zero otherwise. Δ*Outstanding*: the percentage change in the security exposure of fund f to issuer i between time $t-1$ and time t. $Similarity_{fit}$ is the similarity of fund f to the other funds investing in issuer i at time t. Panel A reports the effect of $Similarity_{fit}$ under different specifications. Panel B shows the effect of $Similarity_{fit}$ controlling for the portfolio concentration of the fund measured by HHI_{ft}. The reported regression results control for the level of funding demand (issuer*month fixed effects), fund characteristics, fund fixed effects, and month fixed effects. Security controls and fixed effects include the weighted average maturity and weighted average yield of funding contracts between issuer i and fund f at time $t-1$, as well as fixed effects for the type of security. T-statistics based on standard errors clustered at the fund*month, issuer and month level.

Panel A: Fund rollover decision and fund similarity

	$Outflow_{fit}$				$\Delta Outstanding_{fit}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{fit-1}$	0.004***	0.004***	0.006***	0.010***	-0.477***	-0.506***	-0.799***	-0.421***
	(4.43)	(4.52)	(4.64)	(9.03)	(-6.34)	(-6.68)	(-8.85)	(-8.44)
Issuer*month FE	Y	Y	Y	Y	Y	Y	Y	Y
Issuer*fund FE	N	N	Y	N	N	N	Y	N
Fund, month FE	Y	Y	Y	Y	Y	Y	Y	Y
Security controls, FE	Y	N	Y	Y	Y	N	Y	Y
drops mat<30days	N	N	N	Y	N	N	N	Y
R^2	22.00	13.09	26.87	16.47	9.21	8.19	12.48	11.63
Adjusted R^2	19.75	10.59	20.68	13.03	6.14	5.09	3.89	7.80
Observations	136982	136982	136465	82253	113073	113073	112637	77698
Issuers*month	3575	3575	3552	3007	3449	3449	3430	2975
Funds	210	210	207	207	204	204	204	202
Months	43	43	43	43	43	43	43	43
Issuers*funds			6844				6380	

Panel B: Fund rollover decision and fund similarity, controlling for fund concentration

	$Outflow_{fit}$		$\Delta Outstanding_{fit}$	
	(1)	(2)	(3)	(4)
$Similarity_{fit-1}$	0.005***	0.006***	-0.537***	-0.623***
	(4.15)	(4.82)	(-5.41)	(-5.45)
HHI_{ft-1}	0.001	0.006***	-0.085**	-0.491***
	(0.96)	(2.90)	(-2.00)	(-3.32)
$Similarity_{fit-1} * HHI_{ft-1}$		-7.82×10^{-5}***		0.006***
		(-2.58)		(3.12)
Issuer*month FE	Y	Y	Y	Y
Fund, month FE	Y	Y	Y	Y
Security controls, FE	Y	Y	Y	Y
R^2	22.00	22.01	9.22	9.23
Adjusted R^2	19.75	19.76	6.15	6.16
Observations	136982	136982	113073	113073
Issuers*month	3575	3575	3449	3449
Funds	210	210	204	204
Months	43	43	43	43

Table 3: **Fund rollover decision and fund similarity: alternative hypotheses**

This table shows the effect of the fund similarity on funds' decision to roll over funding to an issuer, controlling for funds' concentration limits in Panel A, controlling for a common investment strategy for funds following the same index in Panel B, and controlling for a differential effect of similarity on funds not exposed to eurozone issuers before the European sovereign debt crisis in Panel C. *Outflow* is an indicator variable equal to one if a fund f was investing in issuer i at time $t-1$ and invests less in issuer i at time t, and equal to zero otherwise. Δ*Outstanding*: the percentage change in the security exposure of fund f to issuer i between time $t-1$ and time t. $Similarity_{fit}$ is the similarity of fund f to the other funds investing in issuer i at time t. $Weight_{fit}$ 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. $noeuroexp_f$ is an indicator variable equal to one for a fund that was not exposed to eurozone issuers in June 2011, and equal to zero otherwise. The reported regression results control for the level of funding demand (issuer*month fixed effects), fund characteristics, fund fixed effects, and month fixed effects. Security controls and fixed effects include the weighted average maturity and weighted average yield of funding contracts between issuer i and fund f at time $t-1$, as well as fixed effects for the type of security. T-statistics based on standard errors clustered at the fund*month, issuer and month level.

Panel A: Concentration limits

	$Outflow_{fit}$		$\Delta Outstanding_{fit}$	
	(1)	(2)	(3)	(4)
$Similarity_{fit-1}$	0.008***	0.006***	-0.851***	-0.644***
	(7.05)	(4.58)	(-7.14)	(-5.14)
$Weight_{fit-1}$	1.809***	1.897***	-157.810***	-163.575***
	(12.81)	(13.90)	(-12.46)	(-13.31)
HHI_{ft-1}		-0.004***		0.310***
		(-4.36)		(4.11)
Issuer*month FE	Y	Y	Y	Y
Fund, month FE	Y	Y	Y	Y
Security controls, FE	Y	Y	Y	Y
R^2	23.31	23.36	11.55	11.61
Adjusted R^2	21.1	21.15	8.56	8.62
Observations	136982	136982	113073	113073
Issuers*month	3575	3575	3449	3449
Funds	210	210	204	204
Months	43	43	43	43

Panel B: Funds tracking an index

	$Outflow_{fit}$				$\Delta Outstanding_{fit}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{fit-1}$	0.005***	0.005***	0.008***	0.012***	-0.488***	-0.537***	-0.830***	-1.222***
	(4.66)	(4.19)	(3.91)	(9.14)	(-6.07)	(-5.50)	(-4.12)	(-11.54)
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, month FE	Y	Y	Y	N	Y	Y	Y	N
Security controls, FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	22.04	23.39	25.8	27.6	9.21	11.17	12.82	15.01
Adjusted R^2	19.79	20.04	22.06	21.77	6.12	6.62	7.61	6.84
Observations	123575	115433	120341	136797	101509	95731	99084	112876
Issuers*months	3213	3533	3123	3570	3101	3387	3012	3436
Funds	197	141	195		191	138	189	
Months	39	43	38		39	43	38	
Fund clusters*months		1102				1099		
Fund complex*months			2408				2343	
Funds*months				6610				6455

Panel C: Eurozone exposure

	$Outflow_{fit}$		$\Delta Outstanding_{fit}$	
	(1)	(2)	(3)	(4)
$Similarity_{fit-1}$	0.005***	0.006***	-0.574***	-0.615***
	(4.36)	(4.06)	(-5.65)	(-5.06)
$Similarity_{fit-1} * noeuroexp_f$	-0.001	-0.001	0.141**	0.122*
	(-0.73)	(-0.93)	(2.10)	(1.80)
HHI_{ft-1}		0.003		-0.044
		(1.42)		(-0.48)
$HHI_{ft-1} * noeuroexp_f$		0.00		-0.04
		(-1.25)		(-0.45)
Issuer*month FE	Y	Y	Y	Y
Fund, month FE	Y	Y	Y	Y
Security controls, FE	Y	Y	Y	Y
R^2	22.00	22.00	9.22	9.22
Adjusted R^2	19.75	19.76	6.15	6.15
Observations	136982	136982	113073	113073
Issuers*month	3575	3575	3449	3449
Funds	210	210	204	204
Months	43	43	43	43

Table 4: **Fund rollover decision and fund similarity: fund's attention to similarity.**

This table shows the differential effect of fund similarity on funds' decision to roll over funding to an issuer depending on the size of a fund's exposure to an issuer, and whether the fund experiences redemptions from its investors. *Outflow* is an indicator variable equal to one if a fund f was investing in issuer i at time $t-1$ and invests less in issuer i at time t, and equal to zero otherwise. Δ*Outstanding*: the percentage change in the security exposure of fund f to issuer i between time $t-1$ and time t. $Similarity_{fit}$ is the similarity of fund f to the other funds investing in issuer i at time t. $Weight_{fit}$ is the fraction of the portfolio of fund f invested in issuer i at time t. $Redemption_{ft}$ is an indicator variable equal to one if fund f experiences redemptions at time t. The reported regression results control for the level of funding demand (issuer*month fixed effects), fund characteristics, fund fixed effects, and month fixed effects. Security controls and fixed effects include the weighted average maturity and weighted average yield of funding contracts between issuer i and fund f at time $t-1$, as well as fixed effects for the type of security. T-statistics based on standard errors clustered at the fund*month, issuer and month level.

	$Outflow_{fit}$			$\Delta Outstanding_{fit}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Similarity_{fit-1}$	0.001	0.004***	0.0001	-0.194**	-0.414***	-0.101*
	(0.76)	(4.75)	(0.17)	(-2.25)	(-7.08)	(-1.94)
$Weight_{fit-1}$	-2.699***		-2.291	261.680***		196.049***
	(-9.19)		(0.30)	(10.15)		(10.68)
$Similarity_{fit-1} * Weight_{fit-1}$	0.065***		0.065***	-5.949***		-5.409***
	(14.29)		(20.81)	(-14.67)		(-15.89)
$Similarity_{fit-1} * Redemption_{ft}$		7.55×10^{-5}	2.06×10^{-4}		-0.044**	-0.054**
		(0.11)	(0.27)		(-2.13)	(-2.54)
$Redemption_{ft}$		0.001	-0.008		3.309**	4.100**
		(0.02)	(-0.14)		(-8.84)	(2.49)
Issuer*month FE	Y	Y	Y	Y	Y	Y
Fund, month FE	Y	Y	Y	Y	Y	Y
Security controls, FE	Y	Y	Y	Y	Y	Y
R^2	23.91	22.36	24.36	12.57	9.14	12.49
Adjusted R^2	21.72	20.12	22.18	9.61	6.06	9.52
Observations	136982	120384	120384	113073	99139	99139
Issuers*month	3575	3125	3125	3449	3013	3013
Funds	210	197	197	204	191	191
Months	43	38	38	43	38	38

Table 5: **Fund rollover decision and fund similarity: issuer risk.**

This table shows the joint effect of fund similarity and issuer risk on funds' decision to roll over funding to an issuer. $Outflow_{fit}$ is an indicator variable equal to one if a fund f was investing in issuer i at time $t-1$ and invests less in issuer i at time t, and equal to zero otherwise. $\triangle Outstanding_{fit}$ is the percentage change in the security exposure of fund f to issuer i between time $t-1$ and time t. $Similarity_{fit}$ is the similarity of fund f to the other funds investing in issuer i at time t. $Crisis_t$ denotes the period from June 2011 until December 2011. In Panel A: issuer risk is measured by the past squared stock return of issuer i ($Volatility_{it-1}$). In Panel B: issuer risk depends on whether the issuer is a bank ($Bank_i$), located in the European Union ($EUbank_i$) during the sovereign debt crisis ($Crisis_t$). The reported regression results control for the level of funding demand (issuer*month fixed effects), fund characteristics, fund fixed effects, and month fixed effects. Security controls and fixed effects include the weighted average maturity and weighted average yield of funding contracts between issuer i and fund f at time $t-1$, as well as fixed effects for the type of security. T-statistics based on standard errors clustered at the fund*month, issuer and month level in parentheses.

Panel A: Fund rollover decision, fund similarity, and issuer volatility

	$Outflow_{fit}$			$\Delta Outstanding_{fit}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Similarity_{fit-1}$	0.004***	0.004***	0.004***	-0.448***	-0.396***	-0.420***
	(3.64)	(3.31)	(2.69)	(-5.45)	(-4.85)	(-4.96)
$Similarity_{fit-1} * Volatility_{it-1}$		3.78×10^{-6}	2.55×10^{-6}		-0.001***	-0.0002
		(1.02)	(0.42)		(-3.54)	(-1.00)
$Similarity_{fit-1} * Volatility_{it-1} * Crisis_t$			1.74×10^{-6}			-0.002***
			(0.18)			(-4.80)
$Similarity_{fit-1} * Crisis_t$			3.05×10^{-4}			0.072***
			(0.14)			(3.86)
Issuer*month FE	Y	Y	Y	Y	Y	Y
Fund, month FE	Y	Y	Y	Y	Y	Y
Fund and security controls, FE	Y	Y	Y	Y	Y	Y
R^2	21.37	21.37	21.37	8.04	8.06	8.07
Adjusted R^2	19.38	19.38	19.38	5.30	5.32	5.33
Observations	101207	101207	101207	83306	83306	83306
Issuers*month	2237	2237	2237	2159	2159	2159
Funds	209	209	209	204	204	204
Months	43	43	43	43	43	43

Panel B: Fund rollover decision, fund similarity, and issuer characteristics

	$Outflow_{fit}$				$\Delta Outstanding_{fit}$			
	All issuers	Bank issuers			All issuers	Bank issuers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{fit-1}$	0.005***	0.004***	0.004***	0.004***	-0.538***	-0.511***	-0.515***	-0.496***
	(3.84)	(3.05)	(3.36)	(2.81)	(-5.82)	(-8.03)	(-8.72)	(-7.48)
$Similarity_{fit-1} * Crisis_t$		<0.001		<0.001		-0.141***		-0.091**
		(0.22)		(0.20)		(-3.18)		(-2.57)
$Similarity_{fit-1} * EUbank_i$			<0.001	<0.001			-0.168**	-0.110*
			(0.46)	(0.46)			(-2.30)	(-1.87)
$Similarity_{fit-1} * EUbank_i * Crisis_t$				<0.001				-0.299
				(-0.10)				(-0.73)
Issuer*month FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund controls, fund, month FE	Y	Y	Y	Y	Y	Y	Y	Y
Security controls, FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	21.97	21.25	21.25	21.25	9.20	8.06	8.06	8.06
Adjusted R^2	19.73	19.38	19.38	19.38	6.14	5.49	5.49	5.49
Observations	137,519	120,110	120,110	120,110	113,563	99,179	99,179	99,179
Issuers*month	3,576	2,525	2,525	2,525	3,450	2,448	2,448	2,448
Funds	210	207	207	207	204	201	201	201
Months	43	43	43	43	43	43	43	43

Table 6: **Issuer funding liquidity risk and issuer's average fund similarity**

This table shows the effect of the average fund similarity of an issuer on the issuer's access to funding. $\Delta Outstanding$ is the percentage change in total funding to issuer i between time $t-1$ and time t. $Similarity_{it}$ is the average similarity of the funds investing in issuer i at time t. Panel A reports regression results controlling for issuer and month fixed effects in Columns (1)-(4), issuer*year and month fixed effects in Columns (5)-(8). Panel B reports regression results on different sample splits, controlling for the issuer's number of funds and HHI in addition to issuer and month fixed effects. *Crisis*: 2011-06 - 2011-12. *Bank* is a dummy variable equal to one if the issuer is a bank, and zero otherwise. Regressions of Columns (2)-(4) are based on a restricted sample where issuers are banks only. *EUbank* is a dummy variable equal to one if the issuer bank is located in the European Union, and zero otherwise. Security controls include the weighted average maturity and weighted average yield of funding contracts between issuer i and all funds investing in issuer i at time $t-1$. T-statistics based on standard errors clustered at the issuer level in parentheses.

Panel A: Funding liquidity risk and issuer's average fund similarity

	$\Delta Outstanding_{it}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{it-1}$	0.113	0.008	0.126	-0.055	0.212*	0.127	0.220	0.054
	(0.99)	(0.07)	(0.91)	(-0.40)	(1.74)	(0.98)	(1.49)	(0.37)
HHI_{it-1}		3.735		14.628**		1.270		13.084**
		(1.03)		(2.34)		(0.33)		(2.07)
$\#funds_{it-1}$		-0.224***		-0.344***		-0.240***		-0.363***
		(-5.39)		(-3.70)		(-5.57)		(-3.76)
$Similarity_{it-1} * Crisis_t$					-0.687***	-0.808***	-0.629**	-0.717**
					(-3.43)	(-3.60)	(-2.46)	(-2.53)
$HHI_{it-1} * Crisis_t$						13.489**		6.693
						(2.09)		(0.87)
$\#funds_{it-1} * Crisis_t$						0.073*		0.045
						(1.85)		(0.96)
Issuer, time FE, security controls	Y	Y	Y	Y	Y	Y	Y	Y
Issuer*year, time FE, security controls	N	N	Y	Y	N	N	Y	Y
R^2	6.80	7.62	14.92	15.86	7.19	8.11	15.13	16.10
Adjusted R^2	0.62	1.45	0.97	2.01	1.02	1.90	1.18	2.21
Observations	4,536	4,536	4,479	4,479	4,536	4,536	4,479	4,479
Issuers	237	237	231	231	237	237	231	231
Issuers*Year	-	-	586	586	-	-	586	586
Months	43	43	43	43	43	43	43	43

Panel B: Funding liquidity risk and issuer's average fund similarity - sample splits

	All issuers	Bank issuers		
$\Delta Outstanding_{it}$	(1)	(2)	(3)	(4)
$Similarity_{it-1}$	0.015	0.106	<0.001	0.065
	(0.11)	(0.55)	(0.00)	(0.29)
$Similarity_{it-1} * Bank_i$	-0.029			
	(-0.13)			
$Similarity_{it-1} * Bank_i * Crisis_t$		-0.449		-0.612*
		(-1.10)		(-1.77)
$Similarity_{it-1} * EUbank_i$			0.136	-0.222
			(0.35)	(-0.53)
$Similarity_{it-1} * EUbank_i * Crisis_t$				-0.255***
				(-3.85)
Issuer, time FE, issuer and security controls	Y	Y	Y	Y
R^2	7.62	6.27	6.19	7.69
Adjusted R^2	1.43	0.14	0.05	1.58
Observations	4,536	2,979	2,979	2,979
Issuers	237	135	135	135
Months	43	43	43	43

Table 7: **Issuer funding liquidity risk and average issuer similarity: fund flows from similar vs. non-similar investors**

This table shows the effect of average fund similarity of an issuer on the issuer's access to funding from similar and non-similar investors. An investor is labelled "similar" when her similarity is above the median similarity of funds in a given month. Δ*Outstanding* is the percentage change in total funding to issuer i between time $t-1$ and time t. The table reports regression results separately for funding flows (Δ*Outstanding*) from "Similar" (Columns (1)-(2)) versus "Non-similar" investors (Columns (3)-(4)). $Similarity_{it}$ is the average similarity of the funds investing in issuer i at time t. *Crisis*: 2011-06 - 2011-12. *NoCrisis=1-Crisis*. Security controls include the weighted average maturity and weighted average yield of funding contracts between issuer i and all funds investing in issuer i at time $t-1$. T-statistics based on standard errors clustered at the issuer level in parentheses.

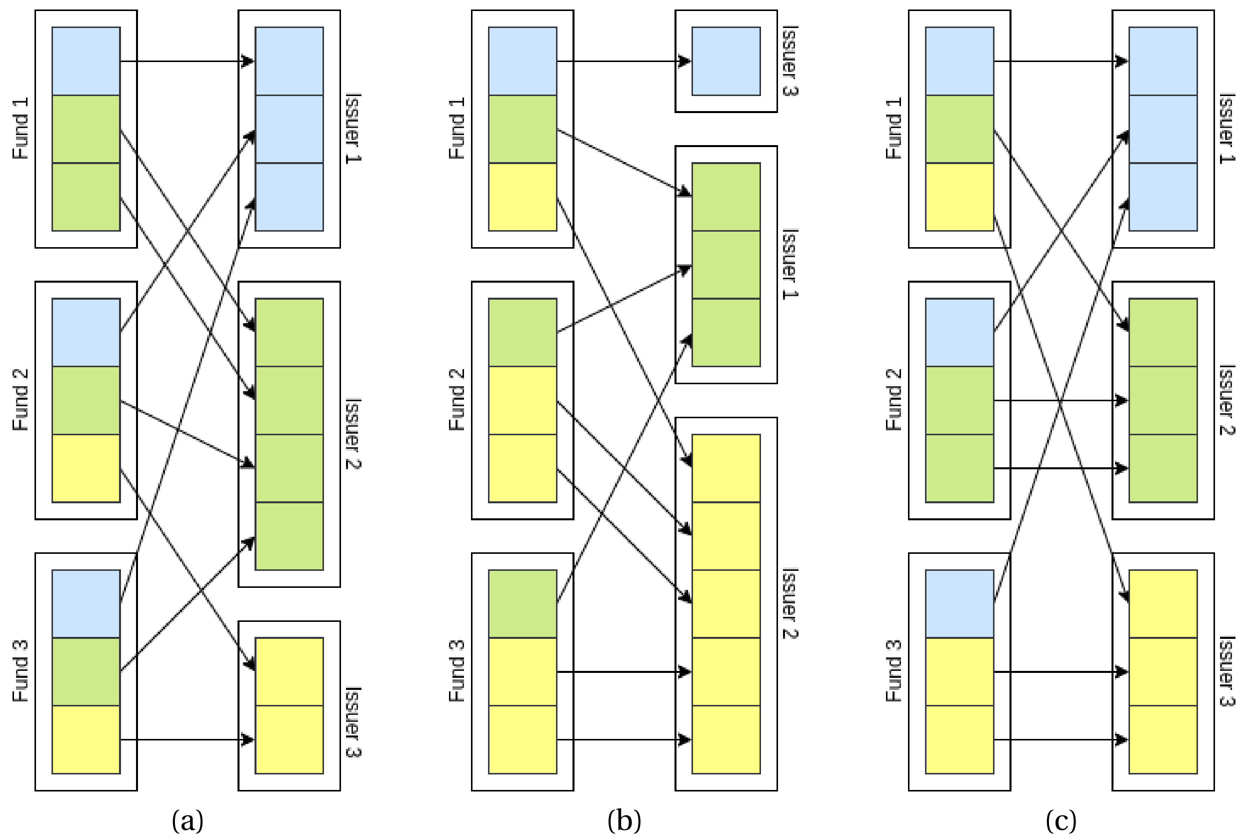
	$\Delta Outstanding_{it}$			
	Similar		Non-similar	
	(1)	(2)	(3)	(4)
$Similarity_{it-1} * NoCrisis_t$	-0.512**	-0.796***	0.684**	0.674
	(-2.24)	(-2.77)	(2.53)	(2.54)
$HHI_{it-1} * NoCrisis_t$		0.787		4.015
		(0.15)		(0.44)
$\#funds_{it-1} * NoCrisis_t$		-0.231***		-0.130**
		(-4.93)		(-2.36)
$Similarity_{it-1} * Crisis_t$	-1.267***	-1.964***	-0.082	-0.019
	(-3.54)	(-3.87)	(-0.24)	(-0.05)
$HHI_{it-1} * Crisis_t$		21.842**		21.029*
		(2.49)		(1.74)
$\#funds_{it-1} * Crisis_t$		-0.138***		-0.091
		(-2.65)		(-1.18)
Issuer, time FE, security controls	Y	Y	Y	Y
R^2	8.76	9.63	7.18	7.43
Adjusted R^2	1.32	2.15	0.17	0.27
Observations	3,490	3,490	2,494	2,494
Issuers	218	218	129	129
Months	43	43	43	43

D Online Appendix

This Online Appendix provides supplementary information for *Similar Investors.* (Georg et al., 2020). In Section D.1, we provide additional examples to illustrate our similarity measure. Section D.2 presents additional robustness checks and additional analyses, complemented by additional Tables in Section D.3.

D.1 Additional Examples

Figure 5: Portfolio Composition in Examples 3, 4 & 5



(a), (b), (c): Investments of funds f_1, f_2, f_3 (left column) in security issuers i_1, i_2, i_3 (right column) corresponding to Examples 3, 4, and 5, respectively. Different colors denote different security issuers. Each arrow represents an investment of 1 by a fund in a security issuer.

Compared to examples 1 and 2 in the paper, we now consider examples with only funds of the same size to show that our results are robust to controlling for fund size. In example 3, we consider two exact funds that are fully diversified and one different fund that is concentrated. In example 4, we consider the reverse case where the two exact funds are concentrated and a different fund is fully diversified. Finally in example 5, all funds are different but two funds are concentrated and one fund is fully diversified.

Example 3. In our third example, there are three funds of equal size and three issuers. As in example 1, we have two funds (funds f_2 and f_3) that invest one unit in each issuer. As a result, the two funds are fully diversified and hold the exact same portfolios. Fund f_1, in contrast, invests one unit in issuer i_1 and two units in issuer i_2. As a result, fund f_1 is different compared to funds f_2 and f_3 because fund f_1 is concentrated in issuer i_2 and has no exposure to issuer i_3.

- Funds' investment in three security issuers is given as:

$$\begin{array}{ccccc} & & i_1 & i_2 & i_3 \\ f_1 & = & 1 & 2 & 0 \\ f_2 & = & 1 & 1 & 1 \\ f_3 & = & 1 & 1 & 1 \end{array}$$

  This implies the weighted average fund distances:

$$\begin{aligned} \text{Wgt.Avg.Distance}_{f_1} &= (0.471, 0.471, 0.471) \\ \text{Wgt.Avg.Distance}_{f_2} &= (0.236, 0.314, 0.0) \\ \text{Wgt.Avg.Distance}_{f_3} &= (0.236, 0.314, 0.0) \end{aligned}$$

  where the i-th column corresponds to security issuer i.

- And results in the average similarity measures:

$$\begin{aligned} S_{f_1} &= (66.67, 66.67, 66.67) \\ S_{f_2} &= (83.33, 77.78, 100.0) \\ S_{f_3} &= (83.33, 77.78, 100.0) \end{aligned}$$

Example 4. We again consider three funds of same size, and three issuers. We now have the alternative case where the two same funds (f_2 and f_3) are concentrated, while the fund that is different (f_1) is fully diversified.

- Funds' investment in three security issuers is given as:

$$\begin{array}{cccccc} & & i_1 & i_2 & i_3 \\ f_1 & = & 1 & 1 & 1 \\ f_2 & = & 1 & 2 & 0 \\ f_3 & = & 1 & 2 & 0 \end{array}$$

  This implies the weighted average fund distances:

$$\begin{aligned} \text{Wgt.Avg.Distance}_{f_1} &= (0.471, 0.471, \emptyset) \\ \text{Wgt.Avg.Distance}_{f_2} &= (0.236, 0.157, 0.471) \\ \text{Wgt.Avg.Distance}_{f_3} &= (0.236, 0.157, 0.471) \end{aligned}$$

  where the i-th column corresponds to security issuer i.

- And results in the average similarity measures:

$$\begin{aligned} S_{f_1} &= (66.67, 66.67, \emptyset) \\ S_{f_2} &= (83.33, 88.89, 66.67) \\ S_{f_3} &= (83.33, 88.89, 66.67) \end{aligned}$$

Comparing the similarity of funds in issuer i_1 in examples 3 and 4, we find that for this issuer receiving the same amount and composition of funding, the similarity of its funds does not change whether the funds are concentrated or diversified. This is similar to the cases in examples 1 and 2, with the difference that funds now have the same size.

Example 5. In this example with three funds of same size and three issuers, the two concentrated funds (f_2 and f_3) are different and the diversified fund (f_1) is also different from the two concentrated funds.

- Funds' investment in three security issuers is given as:

$$\begin{array}{cccc} & i_1 & i_2 & i_3 \\ f_1 = & 1 & 1 & 1 \\ f_2 = & 1 & 0 & 2 \\ f_3 = & 1 & 2 & 0 \end{array}$$

This implies the weighted average fund distances:

$$\begin{aligned} \text{Wgt.Avg.Distance}_{f_1} &= (0.471, 0.471, 0.471) \\ \text{Wgt.Avg.Distance}_{f_2} &= (0.707, 0.786, 0.471) \\ \text{Wgt.Avg.Distance}_{f_3} &= (0.707, 0.471, 0.786) \end{aligned}$$

where the i-th column corresponds to security issuer i.

- And results in the average similarity measures:

$$\begin{aligned} S_{f_1} &= (66.67, 66.67, 66.67) \\ S_{f_2} &= (50.00, 44.44, 66.67) \\ S_{f_3} &= (50.00, 66.67, 44.44) \end{aligned}$$

For issuer i_1, we observe that the differentiation between funds f_2 and f_3 lowers the similarity of the two funds, but has no effect on the similarity of fund f_1. According to our first hypothesis (H1), funds f_2 and f_3 are now less likely to withdraw funding from issuer i_1. On average, the similarity of funds investing is issuer i_1 is lower, which strengthen the funding structure of issuer i_1 according to our second hypothesis (H2).

D.2 Robustness and Additional Analyses

In this section, we further address additional concerns about (i) the comparison between our novel similarity measure and other measures of similarity previously employed in the literature, (ii) the effect of fund similarity on secured funding, and (iii) censoring and truncation of our dependent variable Δ*Outstanding*. We show evidence that our $Similarity_{fi,t}$ measure outperforms other, more "conventional" measures of similarity in predicting future fund flows to an issuer in Table SI-2 in the Appendix. Following the literature on asset commonality (Cai et al., 2018b), we compute the similarity of a fund to all other funds in our sample (all U.S. MMFs). This means that, instead of averaging fund similarity over funds investing in a particular issuer, we do so across all other funds. We use both an unweighted and weighted average with weights given by the fund size. We find that the unweighted average fund similarity to all funds is not significant in explaining both the outflow probability and the percentage fund flows to an issuer. We find similar results for the weighted average fund similarity to all funds in Columns (3) and (6), and show that only $Similarity_{fi,t}$ significantly predicts fund flows to an issuer in Columns (1) and (4) for the same sample.

We repeat our benchmark regressions for *Outflow* and Δ*Outstanding* separately for the four different types of security contracts (certificates of deposit, financial commercial paper, government agency repos, Treasury repos) in Table SI-3 in the Appendix. The table shows that some issuers are able to substitute the loss of funding from unsecured contracts with funding contracts that are secured with collateral. Indeed, it is plausible that investor similarity and exposure to joint liquidation costs is less of a concern for secured funding. Issuers who have the eligible collateral and access to secured funding markets can substitute the loss of funding from similar investors in unsecured markets with repurchase agreements.

Finally, we study the censorship and truncation biases in the regressions on fund flows in Table SI-4 in the Appendix. Our dependent variable Δ*Outstanding* is right- and left-censored since fund flows can only take values in the [-100%,100%] range. The constraint requiring observations to lie in a specific range might induce a censorship bias when the "true" value of the constrained observations is not known. In addition, our dependent variable Δ*Outstanding* is truncated because, given the definition of the variable, we left out all the observations for which funds have a zero exposure to an issuer at time t or $t-1$. Such truncation can introduce a sample selection bias (truncation bias) when parameters are estimated by OLS. To study censorship and truncation biases, we estimate the γ parameter using a truncated regression and a censored regression (Tobit model) in order to adjust for the misspecified distribution of the error term in the OLS regression. We compare the estimated parameters with the OLS parameter in Table SI-4, where all regressions include security controls but no fixed effects.[19] For all regression models, the estimates obtained for the γ parameter are negative and significant at the 1% level, implying that the biases will not qualitatively affect the interpretation of our results.

[19]Fixed effects are left out in the non-linear regression models to avoid a potential incidental parameter problem (Greene, 2002).

D.3 Additional Tables

Table SI-1: **Descriptive statistics: all securities**

This table provides descriptive statistics describing U.S. MMFs, unsecured investments and repurchase agreements. Panel A reports descriptive moments of variables at the issuer level. Panel B reports descriptive moments at the security level (at the issuer-fund pair level) for the same variables on the sample of issuers who have access to U.S. MMFs via at least three funds. Panel C reports average variables at the issuer level describing funds received by issuers via U.S. MMFs on different sample splits. Panels A and C: Amount is the total principal amount invested by U.S. MMFs in an issuer. $\Delta Outstanding_{it}$ is the percentage change in the amount invested by U.S. MMFs in an issuer. Yield and maturity are, respectively, the weighted average yield and maturity of an issuer, where weights are given by the relative volume of the fund investment in the issuer. $Similarity_{it}$ is the average similarity of the funds investing in an issuer. Panel B: Amount is the principal amount invested by one fund in an issuer via one security type. $\Delta Outstanding_{fit}$ is the percentage change the amount invested by one fund in an issuer. Yield and maturity are, respectively, the yield and maturity of the security. $Similarity_{fit}$ is the similarity of a fund investing in an issuer to the other funds investing in the same issuer. Crisis: 2011-06 - 2011-12. GIIPS: Greece, Ireland, Italy, Portugal and Spain.

Panel A: Descriptive statistics at the issuer level (all securities)

	Obs.	Mean	Std. Dev.	Min.	Max.
Amount (1'000 USD)	5,839	7,897	14,456	0.00	281,874
Unsecured (%)	5,838	85.24	31.18	0.00	100.00
$\Delta Outstanding_{it}$ (pct change)	4,951	0.06	28.90	-99.23	99.85
Yield (bps)	5,839	0.24	0.16	0.00	6.00
Maturity (days)	5,839	52.54	63.28	0.00	395.00
$Similarity_{it}$ (%)	5,669	85.99	10.95	28.64	100.00
# Funds per issuer	5,839	29.19	39.76	0.00	189.00
HHI	5,838	0.45	0.39	0.02	1.00
Issuers	308				
of which, fin. institutions	213				
of which, banks	161				
of which, EU banks	40				
of which, GIIPS banks	4				

Panel B: Descriptive statistics at the fund-issuer level (all securities)

	Obs	Mean	Std. Dev.	Min	Max
Amount (1'000 USD)	200,907	229	486	0.00	10,461
$\Delta Outstanding_{fit}$ (pct. change)	156,856	-0.25	31.57	-99.99	100.00
Yield (bps)	188,737	0.25	0.15	0.00	6.00
Maturity (days)	200,884	38.35	44.00	0.63	391.00
$Similarity_{fit}$ (%)	196,159	87.34	7.54	27.18	100.00
Fund size	200,907	7,383	12,950	0.19	86,434
# Issuers per fund	200,907	23.32	10.98	1.00	55.00
Fund HHI	200,907	9.85	9.70	2.80	100.00
Fund*issuer*security	14,564				
Funds	331				
Issuers	148				

Panel C: Descriptive statistics at the issuer level (all securities) - sample splits.

	Amount	% unsec.	ΔOut_{it}	Yield	Maturity	Sim_{it}	#Funds	HHI	Obs.	Issuers
Before crisis	8,525	84.45	0.23	0.31	43.13	85.48	31.62	0.40	530	132
Crisis	8,290	84.07	-1.81	0.26	34.26	84.74	31.33	0.41	814	171
After crisis	7,752	85.55	0.37	0.23	56.96	86.29	28.52	0.47	4,495	278
Not a bank	2,401	93.04	-0.82	0.21	50.17	87.12	9.31	0.62	2,201	147
Bank	11,223	80.52	0.52	0.26	53.98	85.30	41.22	0.35	3,638	161
Non-EU bank	10,542	82.23	0.69	0.27	59.99	86.05	41.21	0.38	2,831	133
EU bank	14,588	72.36	-0.08	0.21	32.45	82.35	43.73	0.25	744	24
GIIPS bank	2,086	100.00	-0.82	0.35	38.26	86.14	12.00	0.44	63	4

Note: ΔOut_{it} is $\Delta Outstanding_{it}$; Sim_{it} is $Similarity_{it}$

Table SI-2: **Fund rollover decision and fund similarity: other measures of fund similarity**

This table shows the effect of different measures of fund similarity on funds' decision to roll over funding to an issuer. *Outflow* is an indicator variable equal to one if a fund f was investing in issuer i at time $t-1$ and invests less in issuer i at time t, and equal to zero otherwise. Δ*Outstanding*: the percentage change in the security exposure of fund f to issuer i between time $t-1$ and time t. $Similarity_{fit}$ is the similarity of fund f to the other funds investing in issuer i at time t. Average Similarity to All Funds is the unweighted average similarity between fund f and all other funds in the sample. Weighted Average Similarity to All Funds is the weighted average similarity between fund f and all other funds in the sample, with weights given by fund size. The reported regression results control for the level of funding demand (issuer*month fixed effects), fund characteristics, fund fixed effects, and month fixed effects. Security controls and fixed effects include the weighted average maturity and the weighted average yield of funding contracts between issuer i and fund f at time $t-1$, as well as fixed effects for the type of security. T-statistics based on standard errors clustered at the fund*month, issuer and month level.

	$Outflow_{fit}$			$\Delta Outstanding_{fit}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Similarity_{fit-1}$	0.004***			-0.500***		
	(4.37)			(-7.25)		
Average Similarity to All Funds		4.46×10^{-4}			-0.083	
		(-0.47)			(-1.61)	
Weighted Average Similarity to All Funds			$-4,.65\times10^{-4}$			-0.075
			(-0.55)			(-1.51)
Issuer*month FE	Y	Y	Y	Y	Y	Y
Fund, month FE	Y	Y	Y	Y	Y	Y
Security controls, FE	Y	Y	Y	Y	Y	Y
R^2	22.01	21.98	21.98	9.22	9.11	9.11
Adjusted R^2	19.77	19.73	19.73	6.14	6.03	6.03
Observations	136844	136844	136844	112949	112949	112949
Issuers*month	3575	3575	3575	3449	3449	3449
Funds	210	210	210	204	204	204
Months	43	43	43	43	43	43

Table SI-3: **Fund rollover decision and fund similarity: security types**

This table shows the effect of fund similarity on funds' decision to roll over funding to an issuer for different types of securities, controlling for the level of funding demand (issuer*month fixed effects). $Similarity_{fit}$ is the similarity of fund f to the other funds investing in issuer i at time t. *CD* are certificates of deposit, *Fin. CP* are financial commercial paper, *Gvt Repo* are government agency repurchase agreements, *Trsy Repo* are Treasury repurchase agreements. Security controls include the weighted average maturity and weighted average yield of funding contracts between issuer i and fund f at time $t-1$. T-statistics based on standard errors clustered at the fund*month, issuer and month level.

	$Outflow_{fit}$				$\Delta Outstanding_{fit}$			
	CD	Fin. CP	Gvt Repo	Trsy Repo	CD	Fin. CP	Gvt Repo	Trsy Repo
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similarity_{fit-1}$	0.005***	0.004***	-0.002**	-0.004**	-0.599***	-0.483***	0.080	0.292*
	(3.36)	(4.12)	(-2.24)	(-2.51)	(-7.78)	(-5.27)	(0.76)	(1.84)
Issuer*month FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund controls, fund, month FE	Y	Y	Y	Y	Y	Y	Y	Y
Security controls, FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	21.968	29.33	17.30	17.20	10.42	14.78	12.12	13.00
Adjusted R^2	19.51	25.25	12.63	11.56	7.21	8.85	5.02	4.33
Observations	76,121	61,252	25,104	20,152	64,604	48,807	16,859	13,175
Issuers*month	2,092	3,094	1,043	965	2,001	2,931	978	898
Funds	199	200	252	273	192	196	235	250
Months	43	43	43	43	43	43	43	43

Table SI-4: **Fund rollover decision and fund similarity: truncated and censored regressions**
This table reports the regression results from truncated and censored models. T-statistics based on robust standard errors in parentheses.

	$\Delta Outstanding_{fit}$					
	OLS		Truncated]-1,1[		Censored [-1,1]	
	(1)	(2)	(3)	(4)	(5)	(6)
$Similarity_{fit-1}$	-0.157***	-0.180***	-0.063***	-0.076***	-0.123***	-0.145***
	(-6.02)	(-6.96)	(-3.84)	(-4.63)	(-5.77)	(-6.80)
Security controls	Y	N	Y	N	Y	N
R^2/Log-likelihood	1.23	0.04	-544,866	-545,405	-590,060	-590,915
Observations	120,891	120,891	113,723	113,723	120,891	120,891

Table SI-5: **Issuer funding liquidity risk and share of funding from similar investors**

This table shows the effect of average fund similarity of an issuer on the issuer's access to funding. Δ*Outstanding* is the percentage change in total funding to issuer i between time $t-1$ and time t. $Similar\,share_{it}$ is the share of funding from similar investors, where investors are considered "similar" if their similarity measure is above the similarity of all U.S. MMFs in month t. Panel A reports regression results controlling for issuer and month fixed effects in Columns (1)-(4), issuer*year and month fixed effects in Columns (5)-(8). Panel B reports regression results on different sample splits, controlling for the issuer's number of funds and HHI in addition to issuer and month fixed effects. *Crisis*: 2011-06 - 2011-12. *Bank* is a dummy variable equal to one if the issuer is a bank, and zero otherwise. Regressions of Columns (2)-(4) are based on a restricted sample where issuers are banks only. *EUbank* is a dummy variable equal to one if the issuer bank is located in the European Union, and zero otherwise. Security controls include the weighted average maturity and weighted average yield of funding contracts between issuer i and all funds investing in issuer i at time $t-1$. T-statistics based on standard errors clustered at the issuer level in parentheses.

Panel A: Funding liquidity risk and share of funding from similar investors

$\Delta Outstanding_{it}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Similar\,share_{it-1}$	0.038	0.025	0.034	0.010	0.060**	0.048**	0.055*	0.033
	(1.64)	(1.04)	(1.13)	(0.35)	(2.53)	(1.99)	(1.73)	(1.06)
HHI_{it-1}		2.966		13.473**		1.057		12.395**
		(0.86)		(2.23)		(0.30)		(2.01)
$\#funds_{it-1}$		-0.223***		-0.344***		-0.235***		-0.362***
		(-5.34)		(-3.68)		(-5.50)		(-3.70)
$Similar\,share_{it-1} * Crisis_t$					-0.125***	-0.138***	-0.111**	-0.117**
					(-2.91)	(-3.09)	(-2.10)	(-2.15)
$HHI_{it-1} * Crisis_t$						10.092		3.714
						(1.63)		(0.51)
$\#funds_{it-1} * Crisis_t$						0.072*		0.049
						(1.82)		(1.03)
Issuer, time FE, security controls	Y	Y	Y	Y	Y	Y	Y	Y
Issuer*year, time FE, security controls	N	N	Y	Y	N	N	Y	Y
R^2	6.86	7.66	14.94	15.86	7.18	8.02	15.11	16.04
Adjusted R^2	0.69	1.49	0.99	2.01	1.01	1.80	1.16	2.14
Observations	4,536	4,536	4,479	4,479	4,536	4,536	4,479	4,479
Issuers	237	237	231	231	237	237	231	231
Issuers*Year	-	-	586	586	-	-	586	586
Months	43	43	43	43	43	43	43	43

Panel B: Funding liquidity risk and share of funding from similar investors - sample splits

$\Delta Outstanding_{it}$	All issuers	Bank issuers		
	(1)	(2)	(3)	(4)
$Similar\,share_{it-1}$	0.037	0.025	-0.025	-0.023
	(1.00)	(0.84)	(-0.83)	(-0.71)
$Similar\,share_{it-1} * Bank_i$	-0.025			
	(-0.52)			
$Similar\,share_{it-1} * Bank_i * Crisis_t$		-0.060		-0.010
		(-0.90)		(-0.15)
$Similar\,share_{it-1} * EUbank_i$			0.114*	0.129*
			(1.69)	(1.92)
$Similar\,share_{it-1} * EUbank_i * Crisis_t$				-0.230***
				(-3.04)
Issuer, time FE, issuer and security controls	Y	Y	Y	Y
R^2	7.67	6.26	6.38	7.31
Adjusted R^2	1.47	0.12	0.25	1.17
Observations	4,536	2,979	2,979	2,979
Issuers	237	135	135	135
Months	43	43	43	43