# Transparency, Investor Information Acquisition, and Money Market Fund Risk Rebalancing during the 2011-12 Eurozone Crisis*


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**Abstract**

This paper studies investor redemptions and fund manager portfolio rebalancing of prime money market funds (MMFs) during the 2011–2012 Eurozone crisis. We exploit the unique multiple shareclass structure of the MMF industry and the introduction of detailed portfolio holdings disclosure required by 2010 regulatory changes in the MMF industry to shed light on costs and benefits of increased transparency in short-term funding markets identified in the theoretical literature. Consistent with the predictions of models featuring costly (and incomplete) information acquisition, we find that investors with the lowest information acquisition costs are most responsive to cross-sectional heterogeneity in funds' credit risk exposures–suggesting that investors made use of the new information to monitor portfolios–though this monitoring was selective in nature. Following the initial wave of investor redemptions and indicative of a desire to reduce investors' incentives to acquire additional private information, managers catering to investors with the lowest costs of information acquisition disproportionately shift their portfolios away from the riskiest and most information-sensitive securities.



Key words: Money market funds, Eurozone crisis, financial fragility, endogenous information acquisition, transparency in short-term funding markets

JEL: G01, G21, G23


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# 1 Introduction

Transparency in funding markets can have both costs and benefits. In normal times, increased transparency has the potential to reduce risk-sharing opportunities (Hirshleifer (1971)) by reducing investors' and intermediaries' ability to pool idiosyncratic risk across different types of risky collateral. However, transparency also has the potential to reduce the severity of market breakdowns in bad times, when collateral values decline, by reducing informational asymmetries between potential buyers and sellers of assets whose values may have changed (Goldstein and Leitner (2016); Dang et al. (2015)). When investors can choose whether to engage in costly acquisition of private information, financial institutions can design informationally-insensitive (opaque, nearly riskless) securities so as to minimize the need for private information production, which enhances liquidity (Dang et al. (2014), Hanson and Sunderam (2013)).

Money market funds (MMFs) are designed to be highly liquid, relatively safe (information-insensitive) stores of value. However, following substantial worsening of credit market conditions, the value of money market securities can become more informationally sensitive. Formerly homogenous money market funds suddenly become differentiated in their risk exposures, giving an incentive for the most sophisticated investors to acquire additional information about funds' portfolio risk. The desire to return to the more liquid, informationally insensitive state can, in turn, "force" the MMFs with the greatest risk exposures to reduce their holdings of the riskiest assets.

Until recently, and driven by the arguments for the lack of transparency (Holmstrom (2015)), information about MMF portfolio holdings was relatively sparse. Following the severe stress experienced by the MMF industry during the 2008 financial crisis, the SEC enacted a number of reforms intended to make future stress events less likely and/or severe. Motivated by the belief that uncertainty about individual funds' risk exposures likely contributed to run-like behavior during the crisis, one of the provisions of the 2010 amendment to Rule 2A-7 dramatically increased the transparency of information about MMF holdings.[1]

This paper examines investor flow behavior and portfolio risk adjustments in prime MMFs during the 2011–2012 Eurozone crisis, which was arguably the first major macroeconomic event for which MMF in-

[1] The 2010 amendment to rule 2A-7 required MMFs to post complete portfolio information on their websites within 5 days of month-end. Prior to the increased transparency of MMF holdings following the 2010 amendment to rule 2A-7, investors would have had few ways of differentiating between funds that were highly exposed and funds that were less exposed to default risk. In the earlier regime, even if such investors wanted to acquire information about individual funds' risks, it would have been much more costly to acquire such information, potentially creating incentives to run on money market funds more broadly.

vestors had nearly real-time transparency into fund exposures to particular issuers. As such, events in MMFs during the Eurozone crisis offer a rare laboratory for providing empirical evidence allowing us to test the strength of the theoretical tradeoffs associated with increased transparency. We combine (1) granular holdings information; (2) a multi-shareclass structure that allows for within-fund comparisons of flows; and (3) proprietary data on investor characteristics which allow us to more accurately categorize investors according to their level of sophistication. Not only did funds differ significantly in their exposure to European securities, which comprised a large fraction of total holdings and whose risk had substantially increased, they also catered to very different types of investors. Despite the fact that more disaggregate information was technically available for all investors, given its disaggregate nature, only the most sophisticated investors were likely to have utilized it in the process of making their redemption decisions.

Moreover, precisely because MMF securities are designed to informationally insensitive, even highly sophisticated investors are unlikely to have performed comprehensive analysis of the underlying portfolio exposures during the crisis. Models with endogenous information acquisition imply testable predictions about what types of information investors will choose to acquire and how they subsequently act on that information (see, e.g., Kacperczyk et al. (2016), Maćkowiak and Wiederholt (2015) and Sims (2003)). This is particularly relevant if certain types of information are more costly (or valuable) to acquire and some investors have a comparative advantage at acquiring information.

We apply these insights to investors' responses to initial portfolio risk and subsequent portfolio rebalancing by managers following credit market shocks. For example, for two investors in the same fund, but with different levels of sophistication, we would expect the most sophisticated investors to have the highest sensitivity to credit risk changes. If investors choose how much information, if any, to acquire about credit risk, we should expect to see the largest responsiveness to cross-sectional heterogeneity in credit risk among investors with the greatest comparative advantage of processing information. In turn, managers who cater predominantly to highly sophisticated investors have a particularly strong incentive to tilt away from informationally sensitive securities.

Testing these implications requires (i) accurate measures of credit risk commensurate with the information available to investors; and, (ii) good proxies for investors' (heterogeneous) information processing capacity. We combine portfolio holdings detail–the same information which were available to investors in real time–along with a data set of issuer default probabilities in order to calculate a forward-looking, fund-level credit risk measure that moves with market conditions.[2] These detailed holdings data also enable us to study fund managers' portfolio rebalancing decisions throughout the crisis. On the second point, we use a proprietary data set of the types of shareholders in each MMF class which allows us to classify institutional ownership into different categories (corresponding with low/high information acquisition costs) with a higher degree of precision than in previous studies.[3]

Empirically, using cross-sectional flow regressions we find strong evidence in support of the hypothesis that the most sophisticated investors were most responsive to overall credit risk, consistent with sophisticated investors acquiring fund-specific information during the Eurozone crisis. Prime MMFs, especially those serving the most sophisticated investor-types, experienced rapid outflows, amounting to roughly 10% of aggregate assets, from June 8–July 5 of 2011. Within the subset of institutional shareclasses, we find that the most sophisticated investors were more likely to redeem from funds with high credit risk exposures at the onset of the crisis. In contrast, we find no such responsiveness for shareclasses predominately owned by less sophisticated investors, which suggests that this group did not acquire private information about fund-specific credit risk exposures.

During the Eurozone crisis of 2011–2012, a major factor in the behavior of investors was the geographic origin of a particular security. In general, investors moved their money out of MMFs holding Eurozone bank obligations (see, for example, Chernenko and Sunderam, 2014). The crisis emanated from initial concerns about Eurozone bank exposures to a potential Greek default, and the Eurozone crisis was covered widely in the press throughout the second half of 2011 and most of 2012. If the unfolding crisis increased the relative value of private information about individual MMFs' exposures to European default risk, we would expect

[2] Researchers typically estimate the credit risk on a fund using its gross yield, which was available on a daily basis even prior to the 2010 reforms. However, because MMFs price their portfolio holdings at amortized cost, fund yields are somewhat backward-looking in the sense that they do not immediately reflect changes in the credit quality of their portfolios' securities. In other words, if a fund holds a security and that security's credit quality declines, the security's market price should also decline, boosting the security's market yield. But because funds use amortized cost accounting, the rise in the security's yield would not be immediately reflected in the fund's yield. Our analysis suggests that this problem was, at least partly, reduced by the availability of detailed portfolio holdings information following the SEC's 2010 reforms. Our measure, based on a method proposed in Collins and Gallagher (2016), is calculated by joining portfolio securities, maturity-by-maturity and issuer-by-issuer, with annualized default probabilities.

[3] We consider a broad definition of "sophisticated accounts" as those in which natural persons do not represent a beneficial ownership interest. By this definition, we estimate that 26% of self-designated "institutional" share classes of MMFs, in fact, have less than 5% sophisticated ownership, while 16% of institutional classes have at least 95% sophisticated ownership, by dollar value. These results imply the common (but coarse) practice of measuring investor sophistication by means of the fraction of investors within designated "institutional" share classes is imperfect because a large fraction of such money represents retail investments through 401(k) retirement and pooled brokerage omnibus accounts.

investors to focus attention on funds' European credit risk exposures. Accordingly, withdrawals should be particularly sensitive to cross-sectional differences in MMFs' European exposures. This heterogeneity in withdrawal decisions is in contrast to the more uniform withdrawal from money market funds that we would expect from an increase in investor risk aversion. Moreover, such differences should be greater for shareclasses dominated by sophisticated investors that had a larger capacity for collecting and processing information.

Again the empirical evidence is supportive of the selective information acquisition hypothesis. Funds with higher credit risk exposures to European paper saw larger outflows with effects being particularly large for shareclasses with the most sophisticated investors and monotonically increasing in the level of investor sophistication. Whereas, among the most sophisticated institutional investors, we find a large and highly statistically significant relationship between redemptions and initial levels of European credit risk exposure, MMFs' exposures in other regions are not significant predictors of investor redemptions. If anything, we find weak evidence that funds with greater exposure to Asia/Pacific, and, to a lesser extent, the Americas, experienced greater inflows during the Eurozone crisis.

Next, using cross-sectional snapshots of fund portfolios throughout the 15-month crisis, we explore how MMFs altered their portfolio risk allocations over the course of the Eurozone crisis in response to the factors governing investor redemptions at the onset of the crisis. To the extent that MMF managers seek to eliminate the need for investors to acquire private information about portfolio risks, managers of funds catering to the most sophisticated investors, especially those which had the highest exposures at the onset of the crisis, should have the strongest incentive to reduce their exposures to the most informationally sensitive (e.g., European) securities.

We find that managers reallocated risk in a manner consistent with this prediction. Similar to a phenomenon observed by Strahan and Tanyeri (2015) during the 2008 crisis, in the short-run, funds servicing heavy redemptions became temporarily riskier as managers used their liquidity to meet outflows.[4] However, as the Eurozone crisis progressed, funds with a higher level of credit risk at the onset dramatically reduced their credit risk allocation to Europe in favor of credit risk from the Asia/Pacific and, to a lesser extent, the Americas. Again, such reallocations were significantly stronger among funds serving more sophisticated

[4]The disaggregated holdings data indicate that MMF managers reduced European risk exposures by changing portfolio allocations at the time that European securities matured, instead of selling them on the secondary market. Rather, managers met the initial wave of redemptions predominantly by selling securities of U.S. issuers on the secondary market.

investors.

Finally, we conduct an analysis at the issuer-fund level to explore whether managers of high-sophistication funds also changed the composition of their portfolios within regions, so as to reduce the information sensitivity of their holdings. Specifically, we wish to test whether, consistent with our theoretical predictions, the relationship between an individual manager's portfolio exposure to individual issuers and a measure of the issuers' credit risk varies across regions, prior to and during the crisis. To this end we regress various measures of portfolio risk or rebalancing (changes in holdings) on predetermined fund-issuer characteristics and measures of issuer credit risk. Prior to the crisis we find no evidence of a strong within-Europe preference among fund managers. In sharp contrast, during the crisis we find that managers of funds with highly sophisticated investors reduced their exposures to the riskiest European issuers more than their peers, whereas there is no such tendency in the other non-European regions. Such within-region composition changes, which are identifiable with both fund and issuer fixed effects, are hard to reconcile with a simple story of elevated risk aversion during the Eurozone crisis but are fully consistent with managers actively restructuring portfolios so as to be less information-sensitive.

Our paper contributes to a recent literature studying sources of financial fragility in short-term funding markets. Most closely related are several recent papers on the MMF industry during the Eurozone crisis. Similarly, a number of studies examine the behavior of investors in short-term markets during the 2008 crisis.[5] Chernenko and Sunderam, 2014 find that, over the summer of 2011, MMFs holding more Eurozone bank debt experienced greater outflows. Correa et al. (2013) find that, as MMFs reduced lending to European banks, U.S. branches of European banks reduced lending to U.S. entities. Ivashina et al. (2012) make a similar argument, finding that European banks that were more reliant on MMFs experienced larger declines in their outstanding dollar loans.

The main focus of theses papers is quite different from ours, as they study how the lending channel can generate credit supply shocks for firms outside of Europe. Compared with these studies, we exploit MMFs' multi-shareclass structure to study investor monitoring behavior and the implication of investors' endogenous information acquisition for how managers restructure their portfolios following an initial shock

[5] Covitz, Liang, and Suarez (2013) study the asset-backed commercial paper (ABCP) market while McCabe (2010), Kacperczyk and Schnabl (2013), Duygan-Bump et al. (2013), Strahan and Tanyeri (2015) and Schmidt et al. (2016) study investor behavior and flows to MMFs around the Lehman crisis. Goldstein (2013) provides a survey of the empirical literature on bank runs.

to credit risk.[6] In addition to proposing new tests to identify the monitoring mechanism more explicitly (which helps to rule out other explanations for the same aggregate patterns), our focus is on how managers restructure their portfolios, holding total quantity fixed.

The remaining part of the paper proceeds as follows. Section 2 contains a short background on money market funds, the regulatory responses to the MMF crisis of 2008, and provides details of the timeline of the 2011 Eurozone crisis. Section 3 reviews the existing literature and develops the theoretical hypotheses that we test in our empirical analysis. Section 4 introduces our data set which is used to explore the factors that determine fund flows (Section 5) and funds' portfolio risk reallocations (Section 6). Section 7 looks into the issuer-fund relationship by examining changes in funds' risks and their portfolio risks during and after the Eurozone crisis. Section 8 discusses broader implications of our results for financial policy and concludes.

## 2 Money Market Funds and the Eurozone Crisis

This section provides a brief background on the history and regulation of money market funds and the events of the Eurozone crisis.

### 2.1 Institutional background on money market funds

Money market funds are mutual funds that may only invest in short-term high quality money market instruments. With assets totaling \$2.7 trillion at the end of 2014, MMFs are an important investment and cash management vehicle for U.S. corporations and individuals. Moreover, they are a critical provider of short-term financing to corporations, holding 36 percent of commercial paper (CP), 19 percent of repurchase agreements (repos), and 53 percent of U.S. Treasury and agency securities as of March 2013. Although they operate outside of the traditional banking system, MMFs are financial intermediaries that provide investors with a stable asset value (most of the time) and cash on demand.

There are three categories of money market funds: prime, government, and tax-exempt. Prime funds, which managed assets of just under \$1.5 trillion at the end of 2014, are the largest category and the focus of our analysis. These funds invest in a range of money market securities, including CP, bank certificates of

[6] In other words, the primary focus of these earlier studies is on how changes in the total quantity of assets under management (which declined disproportionately for MMFs serving sophisticated investors and with high European credit risk exposures) affect the total amount of lending to issuers in other regions.

deposit (CD), medium-term and floating-rate notes, repos, and Treasury and agency securities.

To provide stability and liquidity to investors, MMFs must adhere to strict portfolio restrictions under SEC Rule 2a-7. One crucial feature of Rule 2a-7 is the use of amortized cost accounting by MMFs, which values portfolio securities at cost plus any amortization of premiums or accumulation of discounts.[7] This provision, along with the ability to round prices to the nearest penny, allows MMFs to maintain, almost always, a constant $1 per share net asset value (NAV). Specifically, MMFs can offer shares at a $1 NAV provided that mark-to-market portfolio values do not deviate by more than 50 bps from $1.[8]

## 2.2 Stress episodes

Prime funds were greatly affected by the financial crisis of 2008 and, therefore, have been considered by some regulators to pose a financial stability concern (e.g., FSOC, 2012). Following Lehman's bankruptcy in September 2008, prime MMFs experienced heavy outflows amounting to about $310 billion (representing 15% of their August 2008 assets). These outflows were especially strong after, for essentially the first time, one fund (the Reserve Primary Fund) "broke the buck", i.e., suspended redemptions and repriced shares to below $1.00.[9] In response, the U.S. Treasury stepped in to guarantee (up to a limit) the investments of shareholders in MMFs. Over the following month, further support was provided by the Federal Reserve, both for MMFs and for CP markets.

The Eurozone crisis drove outflows from MMFs during June and July of 2011. Citing their exposures to Greek debt, on June 15, 2011, Moody's placed several French banks on review for possible downgrade. Additionally, on June 22, 2011, both FDIC Chairman Sheila Bair and Fed Chairman Ben Bernanke, separately, raised concerns about Eurozone risk in MMFs.[10] Consistent with these events, Figure 1 shows that

[7] Beginning in 1977, all mutual funds, including MMFs, were permitted to value securities with 60 days to maturity or less at amortized cost. With the adoption of Rule 2a-7 in 1983, MMFs were allowed to value *all* portfolio securities at amortized cost.

[8] Rule 2a-7 requires a money market fund to periodically compare its NAV (calculated on the basis of amortized cost) with its mark-to-market value. If the fund's mark-to-market value differs from the $1.00 NAV by more than 0.5% ($0.005, or one-half cent, per share), the fund's board must consider promptly what action, if any, it should take, including whether the fund should inject additional of its own funds to "top up" the NAV (provide sponsor support; see, e.g., Kacperczyk and Schnabl (2013)) or discontinue the use of the amortized cost and reprice the securities of the fund below $0.9950 or above $1.0050 per share.

[9] See, e.g., Schmidt et al. (2016) for further details.

[10] According to The Wall Street Journal, Bair "sounded something of an alarm Wednesday when she said money market fund investors who don't want to take the risk of potential losses from the European Union's troubles should 'put their money solely into funds that invest in U.S. Treasury securities"' (Fink, 2011). Similarly, at a press conference following a Fed policy meeting, Bernanke reportedly said that MMFs "do have very substantial exposure to European banks and the so-called core countries – Germany, France, etc.,...that does pose some concern to money market mutual funds..." (Flitter and Leong, 2011). See also Pilon and Hilsenrath (2011), Phillips et al. (2011), and Zeng (2011).

prime MMFs experienced rapid outflows, amounting to roughly 10% of aggregate assets ($113 billion), from June 8–July 5 of 2011 and, at the same time, government MMFs experienced heavy inflows. Relative to the Lehman crisis which saw heavy outflows concentrated in a matter of days, outflows from prime funds were more spread out during the Eurozone crisis.

After this period, however, the influence of the Eurozone crisis on MMF flows becomes less clear. As the summer stretched on, a second potential crisis appeared as Republicans in the U.S. Congress demanded concessions in return for extending the federal debt ceiling. This raised the possibility that the U.S. federal government might default on its debt. MMF Flows were flat in mid-July and remained flat until the debt ceiling deadline approached on August 2. Indeed, in late-July and early-August of 2011, outflows from *both* prime and government MMFs rose sharply, suggesting that these outflows reflected concerns about a technical U.S. Treasury default, rather than contagion from the Eurozone crisis (Gallagher and Collins, 2016). To separate these events, this study focuses on the period from June 8 through July 5 of 2011 when evaluating the factors contributing to rapid outflows from MMFs during the Eurozone crisis.

The Eurozone crisis continued long after flows began to slow from MMFs. Figure 2 shows average 5-year CDS premiums on banks in Europe, the U.S., and the Asia/Pacific. Credit risk tiptoed upward during June and July of 2011 (the same period when MMFs experienced heavy outflows) but did not really accelerate until August of 2011. Credit risk remained high until September of 2012, when the European Central Bank (ECB) announced that it would buy unlimited amounts of the bonds of troubled Eurozone countries, thereby, committing to be be a lender of last resort.

### 2.3 Regulatory responses

In 2010, in an effort to improve the resiliency of MMFs to withstand severe market stresses, the SEC adopted a number of substantial reforms, including amendments to Rule 2a-7 of the Investment Company Act of 1940. The amendments, which went into effect on May 5, 2010, impose several new requirements on money market mutual funds–all of which are intended to limit the potential for runs on money market funds during times of financial market stress. These amendments include both "hard" requirements, such as limits on less-liquid portfolio holdings, as well as "soft" requirements, such as knowing the characteristics of a particular money fund's clients (investors).

Most importantly for our purposes, the amendments to Rule 2a-7 increased both the level of detail and the timeliness required for MMFs' reporting of their fund holdings. Specifically, funds were required to disclose fully disaggregated (security level) holdings information.[11] This information was still provided in a somewhat unstructured format that required far more processing than a simple statistic such as a yield or a credit score.[12] Consequently, the availability of disaggregate holdings information would have been most useful for sophisticated investors with a large capacity for gathering and processing information.

# 3 Hypothesis Development and Related Literature

This section briefly reviews the theoretical literature on the trade-offs for transparency in funding markets and develops a set of hypotheses which we go on to test in the empirical part of the paper.

## 3.1 Costs and Benefits of Transparency in Money Markets

Ever since Hirshleifer (1971), it has been known that increased transparency can reduce risk sharing opportunities. In the banking context, such opportunities can manifest themselves through the ability to buy and sell assets that diversify idiosyncratic risks: e.g., uncertainty about future liquidity needs and/or individual risky project payoffs. Owners of securities written against risky sources of collateral, e.g., depositors, may need to trade before the assets' maturity date. In some cases, private information about future payoffs, if acquired by potential buyers of a security, can create adverse selection problems, potentially making it difficult to trade individual securities (or, at least, not liquidate them without incurring large losses).

Investors whose primary concern is in insuring against their own idiosyncratic liquidity requirements, such as bank depositors and/or MMF clientele, value highly a relatively safe store of value and may not want to devote much attention to monitoring and analyzing risks.[13] As formalized in Gorton and Pennacchi (1990), these types of investors prefer securities whose expected payoffs vary little with changes in aggregate conditions–"informationally insensitive securities". In their framework, investing in informationally

[11] Funds were reuired to report portfolio holdings as of the end of each month to the SEC and on a website available to the public by the fifth day of the following month.

[12] The raw information is not necessarily in a conveniently machine-readable format, and the underlying portfolio information is likely to be most valuable when combined with other, external sources of information.

[13] See Holmstrom (2015) for an excellent discussion of these theoretical tradeoffs, including a detailed discussion of the implications of theoretical insights to the regulatory debate surrounding the MMF industry.

insensitive securities is an optimal strategy for uninformed investors because it minimizes the costs of their potential informational disadvantages in the event that they need to sell these securities at a later date.[14]

MMFs invest in securities which are designed to be informationally insensitive, and the fixed NAV feature further reduces the incentives for acquiring private information about MMF risks. DeMarzo et al. (2005) show that debt is least sensitive to public information and so its value varies less than any other contract with the same initial expected value and satisfying limited liability. Dang, Gorton, and Holmström (2015) take this argument one step further, showing that one can additionally reduce the informational sensitivity by writing over-collateralized debt contracts which use debt as collateral; a nontrivial proportion of MMF holdings are in these types of contracts, such as CP.[15] MMF investors' payoffs resemble these overcollateralized "debt-on-debt" contracts due to the fixed NAV feature, since the value at which investors can redeem their holdings is not sensitive to the value of the underlying assets unless the fund "breaks the buck".[16] Finally, pre-crisis reporting requirements for MMFs reflected a clear desire to limit the degree of information available about portfolio risk.[17]

When production of private information is costly, there can be potential efficiency gains from creating opaque securities. If, conditional on publicly available information, the cost of acquiring private information about a given asset outweighs the expected benefit this information provides, then both buyers and sellers may rationally decide to acquire little to no information. In normal times, private agents do not invest in information that could be used to verify the valuation of ex-ante similar securities and trades are premised on trust. Intermediaries, even if they possess private information, are "secret keepers" (see, e.g., Kaplan (2006) and Dang et al. (2014)), deliberately obfuscating private information about idiosyncratic risks within their portfolios.[18] "Symmetric ignorance" can create liquidity, and investors are, by design, rationally inattentive

[14] See also DeMarzo and Duffie (1999) for a related contribution, albeit in a slightly different context.

[15] Intuitively, lack of informational sensitivity comes from the fact that debt payoffs are flat over a large fraction of the support of the distribution of the value of the underlying collateral, and writing overcollaterized debt contracts on the original debt claims further increases the probability that the terminal payoff is in the flat region.

[16] In our setting, as in Gorton and Pennacchi (1990), collateral is just the portfolio of asset holdings and its value strongly comoves with the portfolio's average default probability. Since CP securities are debt contracts written on portfolios of debt securities and MMF payoffs have debt-like features, there is a sense in which a MMF investment is a debt-on-debt-on-debt security.

[17] To this point, Holmstrom writes: "Money market mutual funds have daily information about their investment positions and the book value of these positions. The book values change constantly as the funds trade their portfolios and investors add and withdraw money from the fund. Yet, the funds do not have to report the daily NAV (Net Asset Value). They only have to file quarterly reports with the SEC and even then the reported value is not the current NAV, but the NAV 30 days ago. It is a purposeful effort to avoid a continuous flow of information into the market."

[18] These tradeoffs are also present in the literature on optimal information disclosure of a regulator following a stress-testing exercise: Goldstein and Leitner (2016) and Bouvard et al. (2015). See also related contributions by Pagano and Volpin (2012) and

to news about the value of MMF portfolios.

These efficiency gains, which are reaped in good times, come at the potential cost of fragility in bad times. If aggregate conditions deterioriate enough, formerly informationally insensitive securities can become sensitive to market conditions. Dang, Gorton, Holmström, and Ordonez write:

> "Everything that adds to liquidity in good times pushes risk into the tail... Panics happen when information-insensitive debt (or banks) turns into information-sensitive debt. A regime shift occurs from a state where no one feels the need to ask detailed questions, to a state where there is enough uncertainty that some of the investors begin to ask questions about the underlying collateral and others get concerned about the possibility... These events are cataclysmic precisely because the liquidity of debt rested on over-collateralisation and trust rather than a precise evaluation of values. Investors are suddenly in the position of equity holders looking for information, but without a market for price discovery."

As in Hanson and Sunderam (2013), investors in markets for near riskless securities are unlikely to have the information processing infrastructure in place which would permit efficient risk reallocation in bad times. It takes time and resources to scale up the capacity to collect and process information; therefore, information acquisition, even by sophisticated investors, is likely selective and incomplete during these periods.

Prior to 2010 it was difficult for investors to acquire private information about the credit risk of individual MMFs. The increased transparency requirements of the May 2010 Amendment to Rule 2A-7 substantially lowered costs for MMF investors to obtain private information throughout the Eurozone crisis, since relatively timely and fully disaggregated portfolio information were available. That said, this multifaceted, multivariate source of information was still quite costly to process, so an investor concerned about the potential credit exposure of an MMF could approach this information from a variety of angles.

Agents' decisions on how much, if any, information to acquire about asset risk is the subject of a literature on rational inattention. Notably, Kacperczyk et al. (2016) study the joint information (attention) and portfolio allocation decisions of investors who, in addition to their standard budget constraints, can choose to acquire signals with endogenous information precision subject to a capacity constraint on their overall ability to process information. In contrast to earlier studies, they emphasize a multivariate framework in which investors can acquire multiple signals, each of which contains different combinations of information about systematic and idiosyncratic risk. In equilibrium, changes in investors' information choices interact with changes in uncertainty about future payoffs. If uncertainty about different MMFs' payoffs is sufficiently

Monnet and Quintin (2014, 2016).

small, investors may rationally decide to acquire no private information. However, if prior uncertainty becomes sufficiently high, sophisticated investors begin to acquire information about money market funds' largely idiosyncratic risks and adjust their holdings accordingly. A similar calculation determines how an investor will choose to acquire information about different potential risk exposures within a single MMF when disaggregated portfolio information is available.[19]

In the next section, we combine insights from the literature discussed above with unique features of the MMF industry in order to develop several novel, testable hypotheses. These hypotheses help to separate endogenous information acquisition from other potential explanations of investor behavior, particularly heterogeneous preferences. Our data from the MMF industry surrounding the European debt crisis–which resembles the transition from an informationally-insensitive to an informationally-sensitive state discussed above–help to inform the role of increased transparency in explaining cross-sectional heterogeneity in investors' initial decisions to withdraw from different MMFs and fund managers' subsequent portfolio rebalancing decisions. These features of the data, we will argue below, uniquely point to the importance of the information frictions discussed above.

## 3.2 Hypothesis Development

In an information-insensitive state, by design investors have little incentive to acquire information about asset payoffs (Holmstrom (2015)). We would therefore expect to see little dispersion in investor flows across funds catering to investors with different degrees of sophistication. In this state, funds with similar yields are viewed as close substitutes such that the expected benefit from distinguishing funds from one another is fairly small. Therefore, many investors may choose rationally not to acquire any additional information about ex-ante default risk and so changes in default risk will not be a major driver of investor flows in the information insensitive state. As emphasized by Dang, Gorton, and Holmström, this feature greatly facilitates liquidity in the money market. This leads to our first hypothesis.

**Hypothesis 1.** *Prior to the Eurozone crisis, i.e., in the information-insensitive regime, the most sophisticated*

[19] In addition to informed investors who can acquire private information, the model of Kacperczyk et al. (2016) contains a group of uninformed investors who make portfolio decisions based only on prices and public signals. While prices in this model partially reveal the (private) information collected by sophisticated investors, in contrast prices for MMFs are fixed (fixed NAV) and so do not carry information about the underlying credit risks unless funds "break the buck". Instead, fund flows play a similar role, albeit with the delay associated with the publication of data on such flows.

*MMF investors did not exhibit stronger responsiveness to changes in credit risk than the less sophisticated investors.*

In contrast, in an information sensitive state it becomes profitable for sophisticated investors to acquire signals about fund-specific risk exposures. Since signals are informative they will differ across funds and, knowing this, investors should act on such signals and pull back more strongly from those funds for which fundamentals are revealed to be weak. This, in turn, leads to a greater reallocation of AUM across funds.[20] Due to the importance of default risk in the information sensitive state, funds are no longer seen as close substitutes and so it becomes important for investors to acquire information about individual funds' specific holdings. This has several testable implications which we next describe.

The 2011 European debt crisis saw sharply elevated default risk levels both relative to the previous period and relative to other regional debt markets. It can therefore be thought of as a much more information sensitive regime relative to the regime that predated the crisis. Our second hypothesis is that investor responses to changes in funds' credit risk should not be uniform across investors but, rather, be related to heterogeneity in proxies for investors' monitoring capacity.

**Hypothesis 2.** *In the informationally sensitive regime, funds that served sophisticated investors with a comparative advantage at monitoring responded more strongly to changes in the funds' credit risk.*

Stated differently, the most sophisticated investors should respond more strongly to cross-sectional differences in credit risk relative to less sophisticated investors. Testing this hypothesis empirically requires that we can separate investors by their degree of sophistication as we would expect more sophisticated investors to have lower monitoring costs.

Our third hypothesis is that, in the presence of non-trivial information acquisition costs, the composition of funds' credit risks should affect investors' redemption decisions. In particular, holding total credit risk constant, investor redemptions should be most responsive to risk exposure measures constructed for securities with the lowest information acquisition costs. Constant media coverage during the European debt crisis meant that systematic and firm-specific information about the credit risk of European debt issuers became

[20] Stated slightly differently, in normal times MMFs are trying their best to act like banks with the objective for the share price to be informationally insensitive. As bad news came out about Europe, investors started to look at fund holdings and withdrew sharply from the funds that were perceived to be riskiest. This lead fund managers to restructure their portfolios so as to make them more "bank-like" again and return to the information-insensitive state.

more readily available both relative to the pre-crisis period and relative to information about debt issued by firms in other locations. We can therefore think of the Eurozone crisis as, both, a disproportionate increase in the risk of Eurozone debt issuers (or the benefits from learning about such risks) and a simultaneous decline in the (relative) cost of acquiring Eurozone-specific information. From this follows our third conjecture:

**Hypothesis 3.** *The most sophisticated investors reacted most strongly to information about funds' exposures to securities with relatively low information acquisition costs and/or high benefits (e.g., securities from Europe) following the start of the European debt crisis.*

Our fourth hypothesis is that, seeking to return to the informationally insensitive state, fund managers' rebalancing decisions take investors' incentives to acquire information into account by reducing exposures to the high-risk, low information cost assets and increasing exposures to assets with higher monitoring costs. The Eurozone crisis offers an ideal experiment for testing this hypothesis as it provides a market scenario in which the initial shock to credit risk was highly geographically concentrated, allowing us to test if risk exposures were reduced in Europe but increased or remained the same for other areas. Holding the change in credit risk constant, managers should more aggressively rebalance away from asset classes for which the benefit of acquiring information about default risk is relatively high (and/or cost is low). As before, this differential responsiveness should be highest for managers catering to investors with the greatest information processing capacity. Finally, if managers' objective is to return to the informationally insensitive regime, then we would expect to see the largest reductions in risk for the funds that were most exposed, since their initial and target risk exposures are likely to differ by the greatest amount.

**Hypothesis 4.** *In the presence of selective investor monitoring, funds' risk exposure should migrate from the most closely monitored to the less closely monitored regions. Moreover, we would expect to find the largest risk reductions for funds with the 1) highest initial exposures and 2) most attentive investors.*

Our final hypothesis contrasts information-driven stories for funds' portfolio rebalancing during the Eurozone crisis with the alternative that investor flows and funds' portfolio decisions were driven by a shock to investors' risk aversion. In particular, if information acquisition is fairly selective in nature, there can be an additional liquidity benefit from reallocating risk away from high toward low information-sensitive securities, while holding total credit risk exposure constant. This mechanism operates both between regions—if news about credit risk of European securities was more prominently featured or the value of the information acquired was perceived to be particularly high—and within regions (if information about the riskiest European issuers was also more readily available and/or valuable). Rebalancing towards less salient, safer, and/or more obscure issuers can help to return the fund to the state of "blissful ignorance" associated with low informational sensitivity. We test this implication at the fund-issuer level.

**Hypothesis 5.** *Following the onset of the Eurozone crisis, funds changed the composition of their European debt exposure with funds catering to the most sophisticated investors rebalancing more aggressively away from the riskiest European issuers.*

# 4 Data and Variables

Our empirical analysis relies on data joined from four sources. Figure 3 depicts information about each of these data sources and the process used to compile it. The union of these data represents, to our knowledge, the most comprehensive and complete empirical database studied to date on MMFs in the academic literature.

Our first data source consists of the complete record of the portfolio holdings of all prime MMFs at each month-end in the 2011–2012 period. The SEC's 2010 Amendments require each MMF, starting in November 2010, to file Form N-MFP each month with the SEC. The SEC releases this data to the public within 60 days of the end of the month. However, by rule, funds must also post their holdings on fund websites within 5 days of month-end, which provided investors with nearly real-time holdings information during the 2011 Eurozone crisis. We obtain this detailed monthly portfolio-level holdings information from SEC's Edgar data site. With respect to each portfolio security, the fund must report the name of the issuer, details about the issue (e.g., the type of security and whether it is collateralized), and the security's maturity.

We categorize the holdings on Form N-MFP by the parent of the issuer. Parent companies are often global firms that may for any number of reasons need dollar funding from MMFs and other financial market participants.[21] Unlike U.S. banks, most large foreign banks do not have significant retail U.S. dollar deposits to fund their global dollar-based operations and thus may seek to borrow dollars elsewhere, such

[21] For example, Honda Auto Receivables Owner Trust, which issues commercial paper in the U.S. to help finance auto loans to U.S. residents, is affiliated with Honda Motor Company Ltd., which we take to be its "parent."

as from MMFs. We assign each parent firm to a particular region of the world based on the parent firm's headquarters. From this data set, we calculate our main credit risk measures (discussed below) as well as measures of fund liquidity and dollar exposures to European banks during the crisis.

To generate our credit risk measure, the "expected loss-to-maturity" (*ELM*) of the fund's portfolio, we need default probabilities that match the remaining maturity of each security in our N-MFP data. We obtain default probabilities from the Risk Management Institute (RMI) of the National University of Singapore. RMI generates forward-looking default probabilities for issuers on a daily basis for maturities of 1, 3, 6, 12, and 24 months ahead.[22] These probabilities are generated using the reduced form forward intensity model of Duan, Sun, and Wang (2012).[23] We hand match firms in the RMI database with the list of parent companies that issue debt to MMFs from our N-MFP data. The expected loss on a security from a given issuer with a given remaining maturity is the relevant default probability times the expected loss given default. Where each security is multiplied by its portfolio weight, *ELM* approximates the annualized expected loss on a fund's portfolio. Appendix A details this calculation and documents the necessary assumptions.

Importantly, for this study, we use this framework to construct a counterfactual measure of credit risk (*CELM*) by applying current default probabilities to past fund portfolio holdings. For example, if we construct our counterfactual portfolios using fund holdings on May 31, 2011, then by comparing *ELM* with *CELM* after May 2011, we can determine whether funds' actual portfolios are more or less risky than their May 2011 portfolios would have been had the fund continued to hold the same securities. This provides an accurate measure of how a portfolio manager's actions altered the risk profile of her fund since May 2011.

Figure 4 shows that *ELM* evolves with market conditions, whereas the most common proxy for fund credit risk, $Yield\,spread$, does not adjust in as timely a fashion. This figure plots monthly asset-weighted averages of three fund credit risk measures (LHS) and, for comparison, the 5-year CDS premium for the iTraxx European senior financial index (RHS). Fund credit risk measures include the expected-loss-to-maturity (*ELM*), the counterfactual *ELM* had funds left their portfolios unchanged after May 31, 2011 (*CELM*), and

[22] RMI covers around 60,400 listed firms (some of which are no longer active) in 106 economies around the world and releases default probabilities for 34,000 firms. In fact, RMI publishes default probabilities for a number of firms which are important for our analysis but for which CDS are simply not traded, notably for Canadian banks.

[23] Covariates include macroeconomic factors (e.g., trailing 1-year returns on the S&P 500), a firm's "distance-to-default" based on Merton (1974), as well as firm-specific capital structure, liquidity, and volatility metrics from 1990 to the present. RMI's default probabilities have a good track record, especially for issuers in developed countries, at maturities of 6 months or less, which is the horizon we are most concerned with in this paper. In particular, Duan, Sun, and Wang (2012) report out-of-sample accuracy ratios that exceed 90% at horizons of 1-3 months. As of RMI's most recent technical report, 1-month accuracy ratios for the U.S., French, and Japanese firms were 0.94, 0.87, and 0.91, respectively (RMI, 2014).

the prime-to-government money market fund yield spread (*Yield spread*). Yield spread is the most commonly used indicator of a prime fund's credit risk. It is simple to calculate, but, as mentioned earlier, the use of amortized cost accounting means that a fund's yield spread can lag behind a fund's "true" credit risk. In Figure 4, average *ELM* and yield spread diverge by as much as 12 bps, and yield spread appears to lag 2–3 months behind *ELM* throughout the crisis. In contrast, *ELM* and, especially, *CELM*, appear to closely track the market's perceived credit risk in European banks as measured by CDS premiums.

So far, we have focused on aggregates or asset-weighted averages; however, the descriptive statistics in Table 1 depict rich heterogeneity in the characteristics of prime MMFs during the Eurozone crisis. Statistics are displayed, both at the class- and fund-level, for key variables. Consistent with Figure 4, we see that some fund managers drastically reduced credit risk during the second half of 2011. For example, by November 2011, ten percent of funds reduced credit risk by 41 bps relative to their counterfactual portfolio. At the other extreme, some fund managers appear to have made little effort to alter their portfolio risks; for example, in the bottom table, $\left[ELM^{11/30/2011} - CELM^{11/30/2011}\right] = 0$ at the 90th percentile. Funds also experienced varying levels of flows. For institutional classes, the 10th and 90th percentile of net flows during the crisis were -19.8% and 7.7%, respectively. Our study exploits this variation across funds during the crisis to better understand the factors motivating investors to redeem and fund managers to adjust exposures.

Third, we use a unique database from the Investment Company Institute (ICI), unavailable to prior studies of money funds (or any other studies of mutual funds), consisting of the proportion of assets, for each MMF share class, held by different categories of investors at the start of 2011.[24] A shortcoming of publicly available data sets, including those that contain information on share class types (such as iMoneyNet), is that so-called "institutional" share classes often are comprised of collective trusts or omnibus accounts sold through brokers, which, as we show, have large numbers of retail investors (also referred to as natural persons). We overcome this problem using a proprietary database compiled by the ICI using information collected from fund transfer agents. We calculate investor sophistication, *SOPH*, as the portion of "truly institutional" investors (i.e., accounts for which natural persons do not represent the beneficial ownership interest) in a given fund or share class.[25]

[24] We use ICI data for two additional purposes. First, we use ICI classifications of share classes as "institutional" or "retail" according to the ICI's reading of fund prospectuses. The ICI also provided the merge key that allowed us to join the RMI/N-MFP data set with ICI and iMoneyNet data based on EDGAR identifiers, CIK codes, and tickers.

[25] In our study, true institutional investors consist of nonfinancial corporations, financial corporations, nonprofit accounts, state/local governments, other intermediated funds (e.g., hedge funds and fund-of-fund mutual funds), and other institutional in-

Prior studies that treat all institutional share classes alike have missed a good deal of the heterogeneity in the underlying investor base. In Figure 5a, we aggregate the assets according to the broad categorizations the ICI allows us to disclose for all prime funds and, separately, for institutional share classes of prime funds. So-called "institutional" share classes are populated by a broad range of investor types, ranging from investment banks to individual investors within their 401(k) plans. Only about half of the money in self-designated prime institutional share classes come from true institutions. A significant fraction originates from natural persons: 25% is held by individuals through retail accounts or through brokers, and another 23% held by trusts and retirement plans for individual investors.[26] Next, Figure 5b illustrates that there is large cross-sectional variation in the share of total "truly institutional" ownership (i.e., $SOPH$) across MMFs. About 42% of share classes have very little or no institutional ownership. On the other hand, 16% of institutional share classes are almost entirely owned by true institutions. Our maintained assumption is that these truly institutional investors are more sophisticated and face lower costs of acquiring information.

Finally, we use a separate data source, iMoneyNet.com, to calculate individual share class and individual fund flows during the Eurozone crisis along with several other explanatory variables. Most notably, from daily iMoneyNet data, we get the the dependent variable for cross-sectional regressions explaining flows ($FLOW$), which is measured as percentage changes in each share class' assets during the crisis. From iMoneyNet, we also measure each class' (log) total net assets ($ASSETS$), historical asset variation ($FLOWSTD$) and gross 7-day annualized yield ($GYIELD$).[27]

## 5 Investor Redemptions and Fund Credit Risk

This section tests the implications for fund flows implied by our discussion of the theoretical literature and development of testable hypotheses (particularly Hypothesis 1, 2 and 3). We explore which fund and investor characteristics contributed to the rapid outflows from prime MMFs that took place early in the Eurozone crisis.

vestors (e.g., international organizations, unions, and cemeteries). A more detailed discussion of the construction of this data set, and its potential biases, is available in Appendix B.

[26] We verify with the ICI that the underlying composition of investor types, at least in aggregate, have not changed substantially through time.

[27] $FLOWSTD$ is calculated as the (log) standard deviation of daily percentage changes in fund assets over the prior 3 months. Gallagher and Collins (2016) argue that this measure captures the historical liquidity needs of a fund's investors.

## 5.1 Motivating evidence

Figure 6 provides preliminary insights into the interaction between investor sophistication and credit risk exposures by showing daily flows aggregated across institutional shareclasses around the announcement on June 15, 2011 that Moody's had downgraded French banks' credit ratings. The figure plots the log percentage change in assets in the days around this announcement for four classes of funds cross-sorted by ELM and investor sophistication, relative to assets under management as of May 31, 2011. Consistent with Hypothesis 1, in the days prior to the announcement, cash flows to all four groups hovered close to zero and were in close alignment. The key comparison is that, conditional on investor sophistication, there was no differential behavior of investors in funds with high and low *ELM* prior to the crisis.

Following the announcement on the downgrade, the behavior of low sophistication investors is similar for both high and low ELM funds, consistent with little to no acquisition of fund-specific information among these investors. In both cases, aggregate flows are moderately negative. In contrast, whereas flows are flat for low ELM funds and highly sophisticated investors, funds with highly sophisticated investors and high ELM experienced notable outflows. For these funds, outflows continued during the two weeks following the downgrade so that, on a cumulative basis, an economically large 12 percent of assets were lost. These patterns are consistent with Hypothesis 2 but do not, of course, control for other investor or fund characteristics that may be relevant. To do so, we next conduct cross-sectional flow regressions at the shareclass level, first using funds' overall credit risk as the primary driver, next using regional credit risk exposures.

## 5.2 Flow regression specification

To more formally test hypothesis 1-3 and evaluate the factors driving flows from MMFs in a regression setting, we model variation in the cross-section at the share class level as follows

$$FLOW_c = \beta_1 RISK_f \times LoSOPH_c + \beta_2 RISK_f \times MidSOPH_c + \beta_3 RISK_f \times HiSOPH_c + \beta_4 SOPH_c + X_c' \gamma + \varepsilon_c \tag{1}$$

For simplicity, share class-level and fund-level variables are denoted by the subscripts "$c$" and "$f$", respectively. The dependent variable, $FLOW_c$, is the percentage change in class assets over the period of heavy outflows, 6/7/2011–7/5/2011. We test a number of portfolio credit risk measures, including a fund's expected-loss-to-maturity ($ELM_f$), its annualized gross yield ($GYIELD_f$), and its counterfactual expected-loss-to-maturity ($CELM$), measured as of 9/31/2011, had the fund continued to hold the same portfolio it held as of 5/31/2011 (just before the Eurozone crisis heated up). We also explore whether the geographical source of credit risk influences flows [e.g., $ELM_f\,(Europe)$]. Class sophistication is measured by the portion of class assets held by sophisticated investors ($SOPH_c$). Observations are binned into low, mid, and high terciles based on the distribution of $SOPH_c$ across institutional share classes.

Regression (1) also includes a number of class-level controls, $X_c'\beta$, such as the logged total net assets of the class and the fund ($ASSETS_c$ and $ASSETS_f$, respectively), the logged historical asset variation ($FLOWSTD_c$), and the share of fund assets not maturing during the period of heavy outflows nor invested in Treasury/Agency securities ($ILLIQUIDITY_f$). Given that there are very few sophisticated investors in retail share classes and that sophisticated investors in retail classes may behave differently than those in institutional classes, we include only classes designated as "institutional" in the fund's prospectus. To ensure our results are relevant to discussions of systemic risk (and, therefore, not driven by large percentage flows from small funds) we use weighted least squares, where observations are weighted by logged class assets ($ASSETS_c$). Since a fund's credit risk is the same for all share classes in the same fund, we cluster standard errors by fund.

### 5.3 Pre-crisis flow regressions

Table 2 reports results used to test Hypothesis 1, i.e., the conjecture that, in the pre-crisis (information-insensitive) state, the most sophisticated investors did not react more strongly to signals of credit risk than less sophisticated investors. The table reports the outcome of estimating Equation (1), in panel form over the 4 months preceding the crisis (February 2011 through May 2011) using monthly flows (measured as month-over-month percentage changes in assets) as the dependent variable. In columns (1)–(6), one-month lagged measures of credit risk (expected-loss-to-maturity and gross yield) are interacted with dummies for low, medium and high levels of investor sophistication. In columns (7)–(9), credit risk is measured as the contribution of European holdings to a fund's expected-loss-to-maturity. Columns also differ in the sets of controls employed.[28]

[28]The sample used in Table 2 consists of the same set of 251 share classes, used in later regressions. However, 25 class-month observations are excluded due to missing daily iMoneyNet data, creating an insufficient number of observations to calculate

Results support Hypothesis 1, suggesting no tendency for more sophisticated investors, compared to less sophisticated investors, to redeem more from riskier funds. Only the coefficients on the interaction between ELM and medium investor sophistication are statistically significant (albeit economically small). Furthermore, statistically significant coefficients are weakly positive, signaling an indifference to, or even an appetite for, risk. Hence, consistent with Chernenko and Sunderam (2014), we find limited evidence of yield chasing behavior in the pre-crisis period. Importantly, tests for differences in the slope coefficients on ELM between high versus low sophistication investors (reported at the bottom of the table) are statistically insignificant; in other words, we find no differential response to credit risk between high and low sophisticated investors. We also find no evidence of a differential response to gross yield ($GYIELD$) and funds' European credit exposures.

### 5.4 Crisis flow regressions

Table 3 investigates drivers of cross-sectional differences in (percentage) flows at the onset of the Eurozone crisis–and, thus, evaluates Hypothesis 2–by reporting regression results following the specification in Equation (1) above. Columns (1) - (3) interact ELM with dummies for low, medium, and high investor sophistication. Consistent with Hypothesis 2, credit risk is markedly more important, both statistically and economically, when the class is owned by a larger portion of sophisticated investors. The magnitude of the effect of ELM on flows goes from being very small and statistically insignificant for the least sophisticated investors ($ELM \times LoSOPHc$, top row) to being highly significant for the most sophisticated group of investors ($ELM \times HiSOPHc$) and the slope coefficients increase monotonically in size from the low to high sophistication group. Moreover, at around -0.6, the coefficient on ELM for the most sophisticated institutional share classes is economically large and different from the corresponding coefficient for the least sophisticated investors (p-value reported in the bottom row). For example, if we assume that a fund with two institutional share classes has the median level of credit risk ($ELM = 16\,bps$), then, according to column (1), the class owned by investors in the highest tercile of sophistication grows its assets by 10.2 percentage points less than the class owned by investors in the lowest sophistication tercile, all else equal

$FLOWSTD_c$. Furthermore, the dependent variable and $FLOWSTD_c$ are both winsorized at the 10th and 90th percentiles to manage some large flows caused by institutions paying taxes out of their MMF shares in March and then adding new cash to MMFs after tax time. Results are qualitatively similar in regressions excluding $FLOWSTD_c$ and in regressions that winsorize at the 1st and 99th percentiles.

(i.e., $-10.2 = 16 \times (-0.624 - 0.013)$).

Our finding that the most sophisticated investors are most responsive to ELM is robust across the three different sets of control variables used in columns (1) - (3). The coefficient on gross yield ($GYIELD$), the risk measure most commonly employed by prior MMF research, is negative but insignificant in the regressions that include ELM. Depending on the specification, the coefficient on $SOPH_c$ is marginally significant. Turning to the other control variables, the size of the assets under management in a particular share class ($ASSETS_c$) and the standard deviation of flows ($FLOWSD_C$) are both significantly negatively associated with flows. Neither fund size, nor our measure of illiquidity have any significant effect on flows.

Columns (4)-(6) in Table 3 replace the ELM - investor sophistication interaction terms with a similar set of interaction terms, except that we use $GYIELD$ as a measure of credit risk. Column (4) shows very similar results to those in column 1: a monotonically increasing effect of risk (yield) on flows as we move from the least sophisticated to the most sophisticated share classes. Again, the effect is statistically insignificant and small for the share class with the least sophisticated investors while conversely it is large and highly significant for the most sophisticated investors. Results in columns (5)-(6) are qualitatively similar, albeit smaller and insignificant, to the interactions in column (4) once ELM is included in the regression. As discussed above, such a result is unsurprising given the somewhat backward-looking nature of $GYIELD$.

Columns (7) through (9) in Table 3 use the counterfactual ELM as of 09/30/2011, $CELM_f^{09/30/2011}$, instead of the actual $ELM$ as a regressor in our cross-sectional model. Recall that $CELM_f$ is constructed by freezing the fund's weights as of 06/07/2011 and then applying the credit risk measures as of the future date. We choose 09/30/2011 because the Eurozone crisis had grown acutely worse by this date. The large and statistically significant coefficients on $CELM$ for the most sophisticated investors show that these investors withdrew money from those funds whose expected loss would have risen by the most during the European crisis. This result does not, of course, imply that the most sophisticated investors necessarily anticipated the unfolding of the crisis. Rather, it suggests that these investors were able to identify funds with the greatest exposure to issuers that were most likely to be adversely affected if, as turned out to be the case, the European crisis continued to escalate.[29]

[29] Interestingly, when we regress class flows on contemporaneous credit risk ($ELM$) and the credit risk in the same fund's portfolio almost 3 months later ($ELM_f^{9/30/2011}$), only contemporaneous credit risk maintains a negative and significant coefficient, meaning that investors redeemed based on their current understanding of credit risk in the fund's portfolio and were largely unable to anticipate how manager portfolio choices would affect that credit risk going forward. Moreover, when the counterfactual mea-

To formally test if the flows of the most sophisticated investors were more sensitive to credit risk than the least sophisticated investors, the bottom row in Table 3 conducts a set of tests of the statistical significance of differences between the slope coefficients for these two groups on the ELM (columns (1) - (3)), yield (columns (4) - (6)) or CELM (columns (7) - (9)) measures. All p-values are less than 10% and the results are particularly strong for the ELM and CELM risk measures, consistent with gross yield being the less informative of the three risk measures.

Taking stock, these results support Hypothesis 2; namely that the most sophisticated investors were most responsive to overall credit risk, suggesting that fund-specific information was acquired during the Eurozone crisis. In the next section, we test whether the information acquired was selective in nature.

### 5.5 Was information acquisition selective? Responsiveness to regional credit risks

We next test Hypothesis 3 by running flow regressions on regional credit risk exposures. Specifically, we now partition the credit risks according to whether they originate from Europe, Asia or the Americas, using the regression

$$Flow_c = \beta_1 ELM_f \times Europe + \beta_2 ELM_f \times AsiaPac + \beta_3 ELM_f \times Americas + \sum_{i=1}^{3} \beta_{3+i} ELM_f(Region) \times Sophi_c + X_c'\gamma + \varepsilon_c, \quad (2)$$

where $Sophi \in \{LoSoph, MidSoph, HiSoph\}$.

Columns (1) and (2) of Table 4 show some evidence that funds with higher credit risk exposure to Europe experienced larger outflows, while conversely funds with higher exposure to Asia saw larger growth in assets, although the latter effect is only statistically significant at the 10% level in the regression with the largest set of control variables (Column 2).[30] We find no significant association between cash flows and the ELM measure for the Americas.

Much stronger effects on flows from regional credit risk exposure can be identified once we interact the regional source of credit risk with the level of investor sophistication, again using dummies for low, medium

sure of future credit risk ($CELM_f^{9/30/2011}$) is included, the estimate on the contemporaneous level of credit risk ($ELM$) weakens dramatically and this effect appears to be driven by sophisticated investors. Even after controlling for contemporaneous credit risk, sophisticated investors were more likely to pull back from funds that would soon become comparatively riskier barring portfolio changes (i.e., the coefficient on $CELM_f^{9/30/2011} \times HighSOPH_c$ is negative and significant).

[30]Given that these regressions always include, at a minimum, three different measures of credit risk, we omit $GYIELD$ from these specifications. However, results are insensitive to this choice.

and high sophistication. For Europe (columns (3) - (5)), consistent with Hypothesis 3 we see a very large and monotonically increasing effect of investor sophistication on outflows with the effect going from being economically small and statistically insignificant for the share classes with the least sophisticated investors to being highly significant and economically large for the most sophisticated investors. Interestingly, when we narrow our definition of European credit risk exposure as exposure to the riskiest five European issuers (as ranked by their credit ratings on 5/31/2011), namely Dexia, Societe Generale, Barclays, Royal Bank of Scotland Group PLC, and KBC Groep NV, we find a particularly large impact of ELM among the most sophisticated investors: The coefficient estimate (Column 5) nearly doubles from -0.569 to -1.021. These are economically large coefficients: compared to a class with zero credit risk from Europe, the median institutional class (i.e., where $ELM_f\,(Europe) = 11.9\,bps$) populated by highly sophisticated investors could expect to grow its assets by 6.7–12.1 percentage points less.[31]

Results are fundamentally different for the two non-European regions. In particular, columns (7) and (8) show that class flows increased for funds with high exposures to Asia that were held by the least sophisticated investors. A similar effect is identified for the funds' exposures to the Americas (column (9)), although the effect appears to be fragile and disappears once we use more control variables (column (10)). Interestingly, the negative effect on flows from exposures to Europe (top line) continues to be important in these regressions. These findings are all consistent with Hypothesis 3 and what we would expect due to a downward shift in the relative cost of acquiring information about the riskiness of European securities.

We conclude from these findings that investors were significantly more reactive to credit risk attributable to funds' European investments. This lends credence to Hypothesis 3, namely that sophisticated investors selectively monitored the credit risks of European firms during the Eurozone crisis.

# 6 Regional Portfolio Risk Reallocations

The flow regressions in Tables 3 and 4 suggest that sophisticated investors acquired information about and predominantly withdrew from funds with above average levels of credit risk. However, investors appear to have selectively monitored risk attributable to investments in Europe compared to other regions. This

[31] Interestingly, when we swap the ELM measure to the counterfactual risk measure as of 09/30/2011, $CELM_f^{09/30/2011}$ reported in column (6), we continue to find that the most sophisticated investors reacted significantly to their funds' European credit risk exposure although the coefficient estimate is somewhat lower than for the ELM measures.

section tests our fourth hypothesis by evaluating whether fund managers responded to these initial outflows by rebalancing their portfolios in the short-, medium-, and long-run, and the extent to which such rebalancing differed for funds which predominantly catered to sophisticated investors.

## 6.1 Reallocation regressions

Our analysis makes use of the following cross-sectional regression at the fund-level:

$$ELM_f^{date} - CELM_f^{date}\,(Region) = \alpha + \beta_1 ELM_f \times LoSOPH_f + \beta_2 ELM_f \times MidSOPH_c + \beta_3 ELM_f \times HiSOPH_c + X_f'\gamma + \varepsilon_f \tag{3}$$

The dependent variable, $ELM_f^{date} - CELM_f^{date}\,(Region)$, is the actual contribution of a region to a fund's credit risk ($ELM_f^{date}$) on a given $date$ minus the counterfactual contribution ($CELM_f^{date}$). By constructing counterfactual portfolios, we can adjust for the credit risk a fund would have had on a given date had the manager elected to do nothing, effectively holding an identical set of securities as those held on May 31, 2011. Thus, the dependent variable is designed to capture a fund manager's efforts since May to actively increase (+) or reduce (-) the contribution of a given region to her fund's credit risk. We take snapshots of this variable at various moments during the Eurozone crisis. Then, we run regressions to test whether managers' portfolio changes are attributable to the same factors (i.e., a fund's European credit exposure, $ELM_f\,(Europe)$, interacted with its investor sophistication, $SOPH_f$) that drove investors to redeem heavily from prime MMFs at the onset of the crisis (6/8/2011–7/5/2011). Our vector of controls $X_f$ includes fund-level versions of the controls considered in the flow regression above in addition to a measure of the size of the shock experienced by each fund during the onset of the crisis, $OUTFLOW_f$.

The specification in Equation 3 can be used to evaluate the short-, medium-, and long-run influences that investor flows had on the fund managers' allocation decisions. Since, in aggregate, MMFs experienced heavy redemptions only at the onset of the Eurozone crisis and since the crisis endured long after redemptions moderated, we can track the responses of fund managers over time. For instance, in the short run, we might expect fund managers to pay little attention to the factors driving outflows from their funds as they simply try to meet redemptions by offloading their most liquid assets.[32]

[32]Looking at the 2008 MMF crisis, Strahan and Tanyeri (2015) find that funds with greater outflows became temporarily riskier

According to Hypothesis 4, we would expect to find negative coefficients $\beta_1$, $\beta_2$, and $\beta_3$ in regions which (1) experienced increases in credit risk and (2) were monitored more closely. Hypothesis 4 also predicts that $|\beta_3| > |\beta_2| > |\beta_1|$, Moreover, to the extent that investors were not monitoring credit risks emanating from other regions, fund managers–especially those catering to the most sophisticated investors–could have an incentive to increase exposures in these less closely monitored regions so that $\beta_1$, $\beta_2$, and $\beta_3$ are expected to be positive outside of Europe.

## 6.2 Shifts in regional risk exposures

To preview our results, Figure 8 plots the asset-weighted average risk response ($\left[ELM^{date} - CELM^{date}\right]$) of prime fund managers in total and by regional contribution. Panels a and b show that by the end of 2011 the average fund in the top tercile of sophisticated ownership (right column) reduced its total credit risk more than the average fund in the bottom tercile (left column). Panel c helps to quantify this difference. It shows the average risk reallocation of funds serving sophisticated investors minus that of funds serving unsophisticated investors normalized by the average $ELM$ of all funds as of May 2011 (16.4 bps). Thus, by the end of 2011, funds serving more sophisticated investors reduced their total risk exposure by 28% more than did funds serving unsophisticated investors (as a percentage of average $ELM$ in May 2011). Risk reductions were entirely met from European investments. However, the average fund in the top tercile of sophisticated ownership was more likely to offset part of the reduction with additional risk from the Asia/Pacific.

Tables 5, 6a, and 6b report the outcome of regressions specified in Equation (3) for the credit risk contribution from issuers based in Europe, Asia/Pacific, and the Americas, respectively. Beginning with Table 5, results in column (1) suggest that, even in the very short run, fund managers with initially high levels of credit risk began to reduce European risk exposures. The point estimates are consistent with Hypothesis 4 though relatively small in magnitude and mostly insignificant, suggesting such efforts were likely impeded by the need to meet redemptions, as is suggested by the positive coefficient on $OUTFLOW$.

By September 2011, funds had begun to more effectively reduce the European contribution to their credit risk. Consistent with Hypothesis 4, the coefficients on $ELM\,(Europe) \times HiSOPH$ are negative and large in scale from September 2011 through December 2012. They also increase in magnitude with investor

as managers fed redemptions with the safest and most liquid assets.

sophistication. According to column (2), funds serving highly sophisticated investors with a two standard deviations higher $ELM\,(Europe)$ (11 bps) at the start of the crisis, reduced the European contribution to their credit risk by 2 bps (about 0.4 of a standard deviation of pre-crisis European $ELM$) more by September. These differences become an order of magnitude larger from November 2011 onwards, a period during which European CDS spreads remained at elevated levels (see Figure 2). Funds with higher credit risks at the onset of the Eurozone crisis, particularly those serving more sophisticated investors, maintained a reduced credit risk allocation to Europe after the Eurozone crisis ended. This effect persists through December 2012, when our sample period ends.

The larger reallocations in later periods are consistent with managers meeting redemptions with safer, more liquid assets while waiting until European securities matured to rid them from their portfolios. Such a result is not surprising since secondary markets for short-term securities, like CDs and CP, are famously thin (Covitz and Downing, 2007) and may be even thinner for non-U.S. issued debt.[33] Tracking CUSIPs on fund holdings over time, we estimate that monthly fund sales account for under 5% of assets, on average, over 2011–2012 (Figure 7). Interestingly, funds sold a larger portion of their U.S. paper than they did paper from Europe or the Asia/Pacific. Differential liquidity across regions might reflect the additional cost of monitoring dollar-denominated debt issued by foreign companies. Furthermore, fund sales of U.S. paper rose during the summer of 2011, while, at the same time, fund sales of European paper slumped and remained low throughout the Eurozone crisis. Falling liquidity and, hence, lower secondary market prices for European paper might explain why just 3% of funds' European CP and CDs were sold into secondary markets during the peak of the Eurozone crisis in November of 2011.

Like their investors, fund managers did not treat all origins of credit risk equally. Results in Table 6a suggest that, after the short-term need to service redemptions dissipated, the same funds that reduced credit risk from Europe appear to have increased credit risk from the Asia/Pacific region. This is evidenced by the positive and significant coefficients on $ELM\,(Europe) \times SOPH$ from September 2011 through September 2012. These coefficients are generally increasing in sophistication and the differences between High and Low $SOPH$ coefficients are borderline significant over the Jan-Sep 2012 period. However, these coefficients are much smaller in magnitude relative to coefficients for the same period in Table 5, which suggests that

[33] For example, Covitz and Downing (2007) write that "CP is an illiquid buy-and-hold instrument" since secondary market offerings of commercial paper account for only about 8% of the total face amount traded, or about 16% of the total transaction volume. Also see Krishnamurthy (2002); Squam Lake (2013); Rosengren (2013).

the reallocation of credit risk out of Europe and into the Asia/Pacific was far less than one-to-one. Similarly, Table 6b shows that funds with initial *ELM* were also more likely to increase the contribution of the Americas to their credit risk over time. This effect declines with investor sophistication, though the differences are insignificant in most cases (especially later in the crisis when most initial holdings have matured).

Fund managers were more reactive to certain origins of risk within Europe than to others. Panel d of Figure 8 plots the average country-specific risk response of prime funds (e.g., the asset-weighted average of $\left[ELM^{date} - CELM^{date}(France)\right]$). By December 2011, the average fund had reduced the contribution of France to its credit risks by 12 basis points relative to its counterfactual portfolio. French investments accounted for the largest portion (30% as of May 2011) of MMFs' European assets. Additionally, on average, French banks were riskier than German banks, for example, which facilitated a larger reduction in French risk exposures. Surprisingly, however, the second largest reduction in risk exposure came from investments in Belgium – which represented just under 2% of MMFs' European assets as of May 2011. This reduction occurred primarily in September–October 2011, around the time of the failure of the Franco-Belgian bank, Dexia. MMFs held $3.9 billion in debt issued by Dexia at the end of May 2011. By October, when Dexia required aid from the French and Belgian governments, MMFs had eliminated their exposure to Dexia. This resulted in a large actual-to-counterfactual change in portfolio risk attributable to Belgium. The remaining risk reductions from Europe came primarily from investments in the UK, Germany, and the Netherlands, with accounted for 22%, 13%, and 11% of MMFs' European assets as of May 2011, respectively. At the other extreme, MMFs added risk from Japan. Indeed, by December 2011, the average fund had offset a third of its French risk reduction with additional risk attributable to Japan.

To summarize, the evidence presented in this section support our fourth hypothesis that fund managers selectively changed their risk exposures and allocations away from (highly informationally-sensitive) European securities towards (less informationally-sensitive) Asia/Pacific and American securities. These reductions were largest among fund managers who specialized in serving clients with the highest information-processing capacity. While these actions could be consistent with a desire to reduce the informational sensitivity of their portfolios, they could also be explained by preference heterogeneity. In particular, following the large increase in global credit risk, the most sophisticated institutional investors may have experienced a larger increase in risk aversion than their less sophisticated counterparts. We address this concern, exploiting the richness of our data, next.

## 7 Issuer-Fund Relationships: Changes in Risks and Portfolio Weights

Here, we test whether managers in high *SOPH* funds differentially changed the composition of their portfolios *within regions* (particularly Europe) in a manner consistent with a desire to reduce the information-sensitivity of their portfolios. Similar to Chernenko and Sunderam (2014), we leverage the granularity of the portfolio information and study fund managers' rebalancing behavior at the fund-issuer level. This analysis enables us to test Hypothesis 5 and helps to distinguish the information-sensitivity mechanism from a simple risk aversion heterogeneity explanation.

Specifically, we run the following regression on all issuer-fund $(i, f)$ relationships, by region:

$$Y_{i,f} \equiv \begin{pmatrix} \text{Portfolio} \\ \text{risk/rebalancing} \\ \text{measure} \end{pmatrix}_{i,f} = \delta_i + \delta_f + \beta_1 \begin{pmatrix} \text{Predetermined} \\ \text{fund} \\ \text{characteristics} \end{pmatrix}_f \times \begin{pmatrix} \text{Issuer} \\ \text{credit} \\ \text{risk} \end{pmatrix}_i + X'_{i,f}\gamma + \varepsilon_{if} \quad (4)$$

The unit of analysis is the issuer-fund level, and our primary interest is in understanding sources of cross-sectional variation in individual fund managers' exposures to the credit risk of different issuers, both prior to and following the onset of the European debt crisis.[34] All of the risk/rebalancing measures considered in this section are constructed such that larger numbers indicate higher portfolio risk. In order to abstract away from modeling high-frequency dynamics and to make the analysis as transparent as possible, we average monthly portfolio risk/rebalancing measures over the crisis period to collapse them to a single fund-issuer cross-section. We choose to average from September 2011 through August 2012, a period throughout which European CDS spreads remained at elevated levels.[35]

We want to test whether the relationship between an individual manager's portfolio exposure to a given issuer and a measure of the issuer's credit risk varies across regions, both prior to and during the crisis.

[34] We exclude from the analysis any issuers that were not held by at least 20 unique funds in May 2011 or at some point during the September 2011-August 2012 period.

[35] The counterfactual credit risk ($CELM_{if}$) is measured as of May 31, 2011. September 2011–August 2012 corresponds to the period of escalated CDS premiums on European financials (see Figure 2). May 31, 2011 is the last date of the portfolio holdings data before investors began to redeem heavily from MMFs in June and July of 2011. The data set used for these regressions includes only those issuer-fund observations that were non-zero in dollar value outstanding during at least one point in the period of interest (May 31, 2011 and/or September 2011–August 2012). Also, to identify the issuer-fixed effects, only issuers that were financed by at least 2 funds at some point during the period of interest are included in the regression sample.

In these regressions, we always include a fund fixed effect; thus the slope coefficients capture sources of heterogeneity in the within-fund composition of credit risk, holding average fund-level risk exposures (or rebalancing) constant. In addition, some specifications also include an issuer fixed effect, which soaks up sources of unobserved heterogeneity in issuer credit risk. Since the key continuous variable of interest in the specifications below, issuer credit risk, is constant for all observations for a given issuer, we cluster our standard errors by issuer.

## 7.1 Baseline (pre-crisis) composition of portfolio risk within regions

Table 7 regresses three different measures of pre-crisis risk exposures on each issuer's 3-month probability of default, measured as of 5/31/2011, $PD_i^{5/11}$, as well as an interaction term between $PD_i^{5/11}$ and our fund-level $HiSOPH_f$ indicator variable. Odd columns include fund fixed effects, and even columns include both fund and issuer fixed effects. As in the previous section, we estimate separate regression specifications for the European, Asia/Pacific, and Americas regions in panels a-c. The primary purpose of these regressions is to understand whether, during the pre-crisis (information-insensitive) period, the composition of within-region credit risk differed across funds catering to investors with different information acquisition costs.

We begin with the results for Europe in panel a. Columns (1) and (2) use the contribution to a fund's total expected loss to maturity from a given issuer, $ELM_{i,f}^{5/11}$, as a dependent variable. We find essentially no cross-sectional relationship between $PD_i^{5/11}$ and $ELM_{i,f}^{5/11}$. The direct coefficients and interaction terms are both economically small and statistically insignificant.[36] More importantly, the interaction term indicates that there is no evidence that the within-region composition of European credit risk differed for $HighSOPH_f$ funds relative to other funds. Note that the inclusion of issuer fixed effects in column (2) leaves the slope coefficient essentially unchanged. Columns (3)-(4) use the spread between issuer $i$'s counterfactual contribution to fund $f$'s credit risk over the crisis and its initial credit risk ($CELM_{i,f}^{crisis} - ELM_{i,f}^{5/11}$) as a second dependent variable. Both direct and interaction terms are small and insignificant. Such a result implies that the changes in funds' counterfactual exposures to individual issuers were essentially orthogonal to issuers' initial levels of credit risk. Finally, columns (5)-(6) use the fraction of total portfolio value allocated to

[36]This relationship obtains despite the fact that, conditional on portfolio weights, $PD_i^{5/11}$ could be mechanically correlated with $ELM_{i,f}^{5/11}$ since the latter is a weighted average of maturity-specific default probabilities. Our finding is consistent with managers limiting their credit risk exposures to the riskiest issuers by altering the maturity structure (or type of collateral) of their positions.

individual issuers, $WEIGHT_{i,f}^{5/11}$, as the dependent variable. Again, we find no evidence of a strong within-Europe preference for fund managers (regardless of investor sophistication) to overweight/underweight issuers with initially high levels of credit risk. Similar results hold for the Americas (panel c).

Panel b of Table 7 shows strong evidence that fund managers' within-Asia/Pacific exposures, measured in terms of $ELM_{i,f}^{5/11}$, were positively correlated with initial issuer default risk. In other words, an above average fraction of total pre-crisis risk exposure emanated from the riskiest Asia/Pacific issuers. The coefficients in column (1) indicates that a 1 standard deviation increase in $PD_i^{5/11}$ is associated with a 1.26 standard deviation increase in $ELM_{i,f}^{5/11}$ for funds in the Low and Mid $SOPH_f$ categories; the corresponding magnitude is 0.86 $HiSOPH_f$ funds. Such a result is consistent with fund managers, especially those catering to less sophisticated investors, reaching for yield within the Asia/Pacific region. However, subsequent increases in $CELM_{i,f}^{crisis} - ELM_{i,f}^{5/11}$ of the Asia/Pacific component of funds' initial portfolios are roughly orthogonal to issuers' initial credit risk.

## 7.2 Crisis risk reallocation regression specification

Next, we study the extent to which funds changed the composition of credit risk following the onset of the Eurozone crisis (i.e., the transition to the information-sensitive state). The goal of these regressions is to determine whether, consistent with Hypothesis 5, funds serving the most sophisticated investors changed the composition of their portfolios so as to limit the risk contribution from the most informationally sensitive securities during the crisis. Our underlying assumption is that securities issued by the riskiest European issuers (mostly financial institutions) were the most informationally sensitive, relative to other European issuers. Therefore, controlling for average credit risk exposure to Europe (through a fund fixed effect) and unobserved issuer characteristics (through an issuer fixed effect), we would expect managers of $HiSOPH_f$ funds to have an extra incentive to reduce exposure to these information-sensitive securities.

Tables 8 and 9 plot the regression coefficients from the following specification:

$$\begin{aligned} Y_{i,f} &= \delta_i + \delta_f + \beta_1 PD_i^{crisis} + \beta_2 PD_i^{crisis} \times HiSOPH_f \\ &+ \beta_3 PD_i^{crisis} \times ELM_f^{5/11} + \beta_4 PD_i^{crisis} \times ELM_f^{5/11} \times HiSOPH_f + X_{i,f}' \gamma + \varepsilon_{if} \end{aligned} \tag{5}$$

Odd columns omit the issuer fixed effect, while even columns include an issuer fixed effect (in which case $\beta_1$ is not identifiable). We also control for several initial portfolio characteristics. Since funds with small (large) initial investments in a given issuer are more likely to experience positive (negative) changes in the dependent variables, we control for the initial portion of fund $f$'s total assets invested in issuer $i$ ($WEIGHT_{i,f}^{5/11}$) as well as the issuer's May 2011 3-month default probablity ($PD_{i,f}^{5/11}$). We allow the slope coefficients on both of these variables to differ for $HighSOPH_f$ funds by including interaction terms.

The main coefficients of interest are $\beta_2, \beta_3$, and $\beta_4$. A negative value of $\beta_2$ in Europe would indicate that, consistent with Hypothesis 5, $HighSOPH_f$ fund managers rebalanced more aggressively away from the riskiest issuers relative to other fund managers. In these specifications, $ELM_f^{5/11}$ is normalized to have mean zero for $HighSOPH_f$ funds. Therefore, the interpretation of $\beta_3$ is as follows: a negative $\beta_3$ indicates that fund managers with above average risk exposures at the onset of the crisis were more likely to reduce their credit risk exposures to the riskiest issuers during the crisis. $\beta_4$ allows this relationship to differ for $HighSOPH_f$ funds. According to Hypothesis 5, managers of funds with highly sophisticated investors, especially those which began the crisis with high credit risk, may have an extra incentive to reduce exposures to the riskiest issuers, in order to minimize the incentives for investors (who may have acquired bad signals about fund initial credit risk) to acquire information in the future. Thus, we expect $\beta_4 < \beta_3 < 0$ for European issuers.

We consider three different measures of portfolio rebalancing behavior. As in section 6, our preferred rebalancing measure is the actual-to-counterfactual spread in issuer $i$'s contribution to fund $f$'s credit risk ($ELM_{i,f} - CELM_{i,f}$). The actual-to-counterfactual spread proxies fund $f$'s efforts during the crisis to alter the profile of its risk (i.e., the outstanding value, maturity, and collaterialization of its security holdings) from issuer $i$ relative to what such risk would have been had the fund maintained its pre-crisis portfolio.

For robustness, we also consider two additional measures. Our second measure ($\triangle ELM_{i,f}$) is the change in issuer $i$'s average contribution to fund $f$'s credit risk minus ELM measured as of May 31, 2011. This alternative dependent variable ensures that earlier results are not driven by a tendency for high sophistication funds, at the onset of the crisis, to hold securities that became comparatively riskier during the crisis (i.e., that difference between $ELM_{if}$ and $CELM_{if}$ is driven purely by changes in $CELM_{if}$). Our final measure is the percentage point change in the portion of fund $f$'s portfolio invested in issuer $i$ ($\triangle WEIGHT_{if}$), which is the difference between average crisis portfolio weights relative to the May 31, 2011 baseline. Note that a reduction in the portfolio credit risk emanating from certain issuers may or may not derive from a lower portfolio weight allocation, since portfolio weights include such securities as Treasury-backed repo, which could have a large portfolio weight but entail little credit risk.

### 7.3 Changes in within-region composition of risk during the crisis

Table 8 reports estimates of Equation 5 for European issuers. In columns (1)-(2), we report the estimates for our preferred rebalancing measure, $ELM_{i,f}^{crisis} - CELM_{i,f}^{crisis}$, omitting the interaction terms. In column (1), both $\beta_1$ and $\beta_2$ are negative, highly statistically significant, and much larger in magnitude relative to the coefficients of $PD_i^{5/11}$ from the pre-crisis regression in Table 7. The point estimates in column (1) suggest that, for $HiSOPH_f$ funds, a 1 standard deviation increase in $PD_i^{crisis}$ is associated with a 0.86 standard deviation reduction in the actual-to-counterfactual ELM spread, consistent with a strong shift in the composition of within-Europe exposure away from the riskiest issuers. While managers of funds with less sophisticated investors also behaved in a similar way, the corresponding slope coefficient (0.35 of a standard deviation) is about 60% smaller. (Recall that there was no relationship between contemporaneous $PD_i^{5/11}$ and $ELM_{i,f}^{5/11}$ in the pre-crisis period.) As turns out to be the case in the majority of our specifications, our estimates of the key coefficient of interest change little when we include a fund fixed effect. In these results, issuer fixed effects primarily impact the slope coefficients on the control variable $WEIGHT_{i,f}^{5/11}$, which is consistently negative.

Columns (3) and (4) include interaction terms between fund initial credit risk and issuer default risk. As is the case in columns (1)-(2), $\beta_1$ and $\beta_2$ remain negative and significant. In column (3), the point estimate of $\beta_1 + \beta_2$, that is responsiveness of $ELM_{i,f}^{crisis} - CELM_{i,f}^{crisis}$ to a one standard deviation increase in $PD_i^{crisis}$ for a $HiSOPH_f$ fund with the average level of $ELM_{i,f}^{5/11}$, is relatively unchanged, though now $\beta_1$ and $\beta_2$ are roughly equal to one another. Thus, in these specifications, the predicted compositional change for $HiSOPH_f$ managers is roughly twice as large relative to other managers. Regardless of the inclusion of issuer fixed effects, both interaction coefficients ($\beta_3$ and $\beta_4$) are economically large and statistically significant, and $\beta_4$ is about three and a half times larger than $\beta_3$. The interpretation of the associated magnitude is as follows: for $HiSOPH_f$ funds, increasing initial $ELM_{i,f}^{5/11}$ by one standard deviation is associated with an additional 0.84 ($\beta_3 + \beta_4$) increase in responsiveness to a one standard deviation change in $PD_i^{crisis}$. In other words, relative to a $HiSOPH_f$ fund with the average initial credit risk, increasing $ELM_{i,f}^{5/11}$ by one standard deviation roughly doubles the responsiveness to issuer credit risk. Again, qualitatively similar results hold for funds with less sophisticated investors, but magnitudes are much smaller.

The regressions in columns (1)-(4) use the actual minus the counterfactual ELM as the dependent variable and so do not show whether the effects from the regressors are driven by movements in the counterfactual ELM. To address this issue, columns (5) and (6) instead use changes to the actual ELM as the dependent variable. In both specifications, $\beta_1$ through $\beta_4$ are negative and statistically significant. Thus, even in absolute terms (and not just relative to their initial portfolio counterfactuals), managers changed the composition of overall European risk exposure by tilting away from the riskiest issuers. Comparing the coefficient estimates across the two different dependent variables in columns (3) - (6), the slope coefficients in columns (5) and (6) are between one third and one quarter the size of the estimates obtained using the own-counterfactual ELM benchmark.

Columns (7) and (8) regress raw changes in portfolio weights on default probabilities. The direct coefficient on $PD_i^{crisis}$, $\beta_1$, is negative and statistically significant, suggesting that all funds disproportionately reduced the fraction of assets under management allocated to the riskiest issuers. Our point estimate of $\beta_2$ has the predicted negative sign, though it is statistically insignificant in both specifications. $\beta_4$ is negative and borderline significant, with a p-value of about 5% in both specifications. The smaller coefficient relative to the other specifications suggest that $HiSOPH_f$ funds achieved additional risk reductions not just by limiting the supply of financing (i.e., $\triangle WEIGHT_{if}$), but also by rolling their investments into shorter-maturing and more collateralized security types.

Table 9 presents the coefficients of interest for issuers based in the Asia/Pacific and Americas–regions that appear to have been associated with less investor monitoring despite the fact that credit risk increased substantially in both regions as well during the period in question (see Figure 2). The table is structured in the same manner as Table 8, but we suppress coefficients on the controls for brevity. Panel a shows regressions for funds' risk exposures to issuers in the Asia-Pacific region. While our estimates of $\beta_1$ and $\beta_2$ are indistiguishable from zero throughout, our estimates of $\beta_3$ and $\beta_4$ are positive and highly significant for the two ELM-based dependent variables (columns (3)-(6)). Such a result indicates that the same funds which were most likely to reduce exposures to the riskiest European issuers (those with high initial $ELM_{i,f}^{5/11}$) were most likely to choose the composition of their portfolio so as to *increase* exposures to the riskiest

Asia/Pacific issuers. As in Table 8, the magnitude of the responsiveness is more than twice as large for managers of $HiSOPH_f$ funds.

Finally, Table 9 panel b studies rebalancing behavior towards American issuers. In general, we find little evidence of a relationship between changes in exposures and individual issuer credit risk. Coefficients in columns (1)-(6) are statistically insignificant and, in all specifications, we find no evidence of differential responses of $HiSOPH_f$ managers to issuer credit risk levels during the crisis period ($\beta_2$ and $\beta_4$ are always small and insignificant).

Taking stock, our results suggest that managers of $HiSOPH_f$ funds disproportionately reduced their exposures to the riskiest European issuers relative to their peers. We find no similar within-region risk reductions in other regions, where, if anything, our estimates suggest that managers of $HiSOPH_f$ funds with the highest initial credit risk exposures actively substituted towards Asian/Pacific issuers with above-average levels of credit risk. These changes occurred during a period in which increases in credit risk were increasing across-the-board. These results, which are hard to reconcile with a simple risk aversion story, are fully consistent with managers with the strongest incentives to reduce the information-sensitivity of their portfolios actively substituting into securities with higher information acquisition costs.

## 8 Discussion

We find evidence that the availability of fully disaggregated portfolio information, which followed from enactment of the 2010 amendments to rule 2A-7, enabled the most sophisticated investors to be more targeted in their withdrawals during the Eurozone crisis. However, like other nearly riskless securities, MMFs are specifically designed so that investors have little to no incentive to carefully monitor portfolio risk-taking. Therefore, even when aggregate conditions change dramatically and portfolio information is available, investors' information acquisition is likely to be selective and incomplete. We find evidence consistent with this in our data, with investors' disproportionately responding to certain types of risk exposures and downplaying others. In turn, managers of funds catering to the most sophisticated investors responded differentially to the change in the credit market landscape during the 2011-2012 Eurozone crisis, rebalancing portfolios away from informationally-sensitive securities more than their peers.

Our result points to the important tradeoffs associated with increased transparency in short-term funding markets, consistent with conclusions from extant theoretical literature on the subject. On one hand, greater transparency naturally facilitates investor monitoring of fund portfolios, which may induce managers to reign-in portfolio risks during the early stages of a crisis.[37] However, increased transparency, especially in conjunction with selective and/or incomplete information acquisition, reduces opportunities for pooling risks. These forces may well have made MMF investors' returns safer, but the associated rapid reduction in credit supply in all likelihood exacerbated the challenges faced by an already-strained European banking sector.[38] Managers' individually rational responses to investors' monitoring behavior can result in a disproportionately strong reduction in credit supply to the most informationally-sensitive securities, holding overall credit risk constant.

When gauging the effects of transparency on events that transpired in the MMF industry during the Eurozone crisis, it should be noted that the aggregate shock to overall credit risk was smaller and unfolded more gradually over time relative to the Lehman episode. Moreover, additional regulatory changes passed in the wake of the 2008 crisis had further strengthened the ability of MMFs to manage investor withdrawals throughout the 2011 crisis. Therefore, strategic complementarities (Schmidt et al. (2016)) are likely to have been less of a concern. Strategic complementarities also interact with transparency requirements, because coordination motives may magnify initially small differences in relative risk exposures across funds by making it easy for investors to disproportionately withdraw from funds perceived to be riskiest during a crisis. However, increased transparency may make broad-based runs on the MMF sector as a whole less likely as portfolio values may be easier to calculate, reducing the scope for first-mover advantages.

Our findings also have implications for the new regulations which take effect in October 2016. In particular, the SEC's 2014 Amendments to Rule 2A-7 will require management companies to segregate investors who are natural persons (i.e., retail) from other, presumably more volatile, types of investors (i.e., institutional) into different portfolios.[39] Funds serving institutional investors will no longer be permitted

[37]Some studies have also shown that more frequent disclosures limit the ability of fund managers to window-dress by making their portfolios look safer on disclosure dates (Morey and O'Neal, 2006; Ortiz et al., 2012). Also, some contend that enhanced disclosure in mutual funds may engender front-running by hedge funds (Aragon et al., 2013; Shive and Yun, 2013) as well as herding, since it enables the imitation of another fund's portfolio (Villatoro, 2009; Verbeek and Wang, 2013).

[38]Related to this tradeoff, Dang et al. (2015) write: "The recent financial crisis has been blamed in part on the complexity and opacity of financial instruments, leading to calls for more transparency. On the contrary, we show that symmetric ignorance creates liquidity in funding markets. Furthermore, we show that the public provision of information that is imperfect can trigger the production of private information and create endogenous adverse selection."

[39]The new rules require a floating net asset value (NAV) for institutional prime and institutional municipal money market funds. Additionally, under the July 2014 rules, non-government money market fund boards can impose liquidity fees and gates (a

to use amortized cost pricing for securities maturing in over 60 days. Instead, institutional prime MMFs will "float" their NAV like other types of mutual funds. In part, the SEC's 2014 reforms were designed to address the fact that institutional classes of MMFs have consistently experienced heavier redemptions than retail share classes during shocks.

Our results suggest that there may exist a positive externality driven by the willingness and ability of sophisticated investors to monitor fund portfolios. Such a benefit is consistent with Hanson and Sunderam (2013), who argue that information-processing capacity of informed investors can act as a public good in markets featuring near riskless securities, and provides a counterpoint to an expanding body of research focusing on negative externalities imposed by sophisticated MMF investors, through their redemption behavior, on their less sophisticated counterparts during a crisis (Coval and Stafford, 2007; McCabe et al., 2012; Schmidt et al., 2016; Kacperczyk and Schnabl, 2013). These externalities, both negative and positive, of pooling investors of different levels of sophistication could have implications for the stability of MMFs going forward since, under the SEC's new 2014 Amendments, "true" institutional investors (i.e., "sophisticated" investors in our study) must be separated from other investor types into different portfolios.

temporary suspension of redemptions) when a fund's weekly liquid assets fall below 30 percent of its total assets (the regulatory minimum). The final rules also include additional diversification, disclosure, and stress testing requirements, as well as updated reporting by MMFs. These rules come with a two-year transition period, requiring full implementation in 2016.

## Table 1: Descriptive Statistics

These are descriptive statistics for key dependent and explanatory variables only. Class-level and fund-level (a.k.a., portfolio-level) variables are denoted by the subscript "$c$" and "$f$", respectively. The final table shows statistics at the fund portfolio level only. Flow variables are measured as a percentage of class or fund assets during the period of rapid redemptions, 6/7/2011–7/5/2011. Credit risk is measured as the expected-loss-to-maturity ($ELM_f$) on the fund's portfolio. Unless otherwise dated, this variable is averaged across days during 6/7–7/5/2011. Measures of a fund portfolio's future credit risk include: $ELM_f^{9/30/2011}$ is the expected-loss-to-maturity on 9/30/2011; $CELM_f^{9/30/2011}$ is the "counterfactual" credit risk, measured as the expected-loss-to-maturity on 9/30/2011 had the fund continued to hold the same portfolio securities it held as of 5/31/2011. *SOPH* is the portion of class or fund assets held by sophisticated investors. $\left[ELM^{date} - CELM^{date}\,(Europe)\right]$ is the actual contribution of Europe to a fund's credit risk on a given date minus the counterfactual contribution had the fund continued to hold the same securities it held as of 5/31/2011 (measured as basis point changes).

| Variable | 10th | 50th | 90th | Mean | Std |
|---|---|---|---|---|---|
| **Retail Classes** | | | | | |
| $FLOW_c$ (%) | -5.3 | 0.0 | 7.1 | 1.3 | 12.6 |
| $ELM_f$ (bps) | 4.3 | 12.6 | 20.1 | 12.6 | 6.0 |
| $ELM_f^{9/30/2011}$ (bps) | 4.9 | 19.7 | 39.3 | 20.4 | 11.6 |
| $CELM_f^{9/30/2011}$ (bps) | 7.5 | 26.9 | 42.2 | 26.5 | 12.1 |
| $ELM_f\,(Europe)$ (bps) | 1.0 | 9.3 | 15.0 | 8.6 | 5.1 |
| $ELM_f\,(Asia/Pac)$ (bps) | 0.1 | 1.5 | 6.1 | 2.4 | 2.7 |
| $ELM_f\,(Americas)$ (bps) | 0.3 | 1.4 | 3.2 | 1.7 | 1.5 |
| $SOPH_c$ (%) | 0.0 | 0.1 | 16.9 | 4.1 | 7.8 |
| $ASSETS_c$ ($ mil) | 8 | 199 | 3,144 | 1,989 | 9,716 |
| **Institutional Classes** | | | | | |
| $FLOW_c$ (%) | -19.8 | -3.5 | 7.7 | -2.9 | 22.9 |
| $ELM_f$ (bps) | 6.2 | 16.0 | 26.0 | 16.1 | 6.5 |
| $ELM_f^{9/30/2011}$ (bps) | 10.8 | 26.7 | 40.5 | 27.2 | 13.1 |
| $CELM_f^{9/30/2011}$ (bps) | 14.1 | 34.4 | 48.1 | 33.5 | 12.4 |
| $ELM_f\,(Europe)$ (bps) | 3.6 | 11.9 | 19.9 | 12.0 | 5.6 |
| $ELM_f\,(Asia/Pac)$ (bps) | 0.2 | 1.9 | 6.2 | 2.9 | 3.0 |
| $ELM_f\,(Americas)$ (bps) | 0.2 | 1.1 | 2.2 | 1.2 | 1.0 |
| $SOPH_c$ (%) | 0.0 | 33.4 | 99.4 | 41.6 | 36.8 |
| $ASSETS_c$ ($ mil) | 25 | 681 | 11,635 | 4,251 | 9,957 |
| **Fund Portfolios** | | | | | |
| $ELM^{11/30/2011}$ (bps) | 4.6 | 20.3 | 36.4 | 20.7 | 12.5 |
| $CELM^{11/30/2011}$ (bps) | 8.1 | 34.5 | 71.0 | 39.3 | 26.9 |
| $\left[ELM^{7/5/2011} - CELM^{7/5/2011}\,(Europe)\right]$ (bps) | -3.1 | -0.5 | 1.0 | -0.8 | 2.0 |
| $\left[ELM^{11/30/2011} - CELM^{11/30/2011}\,(Europe)\right]$ (bps) | -41.1 | -13.3 | 0.0 | -19.6 | 23.3 |
| $\left[ELM^{7/5/2011} - CELM^{7/5/2011}\,(Asia/Pac)\right]$ (bps) | -0.6 | 0.0 | 1.5 | 0.3 | 1.6 |
| $\left[ELM^{11/30/2011} - CELM^{11/30/2011}\,(Asia/Pac)\right]$ (bps) | -1.5 | 0.5 | 4.9 | 1.2 | 3.8 |
| $\left[ELM^{7/5/2011} - CELM^{7/5/2011}\,(Americas)\right]$ (bps) | -0.3 | 0.0 | 0.3 | 0.0 | 0.3 |
| $\left[ELM^{11/30/2011} - CELM^{11/30/2011}\,(Americas)\right]$ (bps) | -2.9 | -0.1 | 2.2 | -0.2 | 2.1 |
| $FLOW$ (%) | -15.2 | -1.0 | 4.9 | -2.7 | 8.9 |
| $OUTFLOW$ (%) | 0.0 | 1.0 | 15.2 | 4.3 | 6.7 |
| $SOPH$ (%) | 0.0 | 8.5 | 76.3 | 23.9 | 30.0 |
| $ASSETS$ ($ mil) | 158 | 1,462 | 20,209 | 8,241 | 18,696 |
| Number of classes | 1.0 | 2.0 | 6.0 | 3.0 | 2.3 |

Table 2: Pre-crisis flow regressions: the influence of credit risk and investor sophistication

These are panel regressions over the 4 months preceding the crisis (February–May 2011). The dependent variable ($FLOW_{c,t}$) is the percentage change in the assets of class, $c$, during month, $t$. Credit risk measures in columns (1)–(6) include the fund's annualized gross yield ($GYIELD_{f,t-1}$) and its expected-loss-to-maturity ($ELM_{f,t-1}$). In columns (7)–(9), credit risk is measured as the contribution of only European holdings to the fund's expected-loss-to-maturity. The other key explanatory variable is the portion of class assets held by sophisticated investors ($SOPH_c$) as of the start of the year. Observations are binned into low, mid, and high terciles based on the distribution of $SOPH_c$ across institutional share classes (e.g., $LoSOPH_c = 1$ when $SOPH_c \leq 13\%$) and interacted. We control for the logged total net assets of the class and the fund ($ASSETS_{c,t-1}$ and $ASSETS_{f,t-1}$, respectively), the logged historical asset variation ($FLOWSTD_{c,t-1}$), and the share of fund assets not maturing during month $t$, nor invested in Treasury/Agency securities ($ILLIQUIDITY_{f,t-1}$). Class-level and fund-level (a.k.a., portfolio-level) variables are denoted by the subscript "$c$" and "$f$", respectively. The sample includes only classes designated as "institutional." All observations are weighted by $ASSETS_{c,t-1}$. All columns include time fixed effects and a constant (not shown for brevity). To manage tax season-related outliers, the $FLOW_{c,t}$ and $FLOWSTD_{c,t-1}$are both winsorized at the 10th and 90th percentiles. In parentheses are t-statistics, calculated using standard errors clustered by fund. Estimates with a p-value below 0.10, 0.05, and 0.01 are marked with a *, **, and ***, respectively.

| Risk measure: | $ELM\,(Overall)$ | | | $GYIELD$ | | | $ELM\,(Europe)$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $RISK_{f,t-1} \times LowSOPH_c$ | 0.030 | 0.039 | 0.046 | -0.015 | -0.055 | -0.057 | -0.007 | -0.002 | 0.020 |
| | (0.826) | (1.019) | (1.184) | (-0.444) | (-1.621) | (-1.642) | (-0.141) | (-0.027) | (0.330) |
| $RISK_{f,t-1} \times MidSOPH_c$ | 0.054*** | 0.060*** | 0.055*** | 0.012 | -0.030 | -0.039 | 0.047 | 0.052 | 0.054 |
| | (5.166) | (5.665) | (4.305) | (0.382) | (-0.911) | (-1.089) | (1.049) | (1.109) | (1.141) |
| $RISK_{f,t-1} \times HighSOPH_c$ | 0.039 | 0.045 | 0.049 | 0.010 | -0.025 | -0.033 | 0.048 | 0.052 | 0.059 |
| | (1.044) | (1.163) | (1.282) | (0.250) | (-0.686) | (-0.866) | (1.227) | (1.298) | (1.433) |
| $SOPH_c$ (%) | 0.007 | 0.007 | 0.005 | 0.002 | -0.002 | -0.002 | 0.001 | 0.001 | -0.000 |
| | (0.634) | (0.652) | (0.474) | (0.111) | (-0.137) | (-0.155) | (0.142) | (0.153) | (-0.015) |
| $GYIELD_{f,t-1}$ | | -0.034 | -0.043 | | | | | -0.012 | -0.023 |
| | | (-1.045) | (-1.246) | | | | | (-0.356) | (-0.680) |
| $ELM_{f,t-1}$ | | | | | 0.056*** | 0.053*** | | | |
| | | | | | (5.512) | (4.207) | | | |
| $ASSETS_{c,t-1}$ | | | 0.322*** | | | 0.314*** | | | 0.320*** |
| | | | (3.105) | | | (3.150) | | | (3.133) |
| $FLOWSTD_{c,t-1}$ | | | 0.009 | | | -0.008 | | | -0.004 |
| | | | (0.052) | | | (-0.045) | | | (-0.021) |
| $ASSETS_{f,t-1}$ | | | -0.136 | | | -0.135 | | | -0.091 |
| | | | (-0.952) | | | (-0.957) | | | (-0.680) |
| $ILLIQUIDITY_{f,t-1}$ | | | -0.012 | | | -0.012 | | | -0.023 |
| | | | (-0.588) | | | (-0.593) | | | (-1.125) |
| N | 979 | 979 | 979 | 979 | 979 | 979 | 979 | 979 | 979 |
| R2 | 0.02 | 0.02 | 0.03 | 0.02 | 0.02 | 0.03 | 0.02 | 0.02 | 0.03 |
| P-value (HML) | 0.888 | 0.927 | 0.966 | 0.544 | 0.443 | 0.514 | 0.389 | 0.414 | 0.541 |

## Table 3: Flow regressions: the influence of credit risk and investor sophistication

These are cross-sectional regressions over the period of rapid outflows from prime MMFs, 6/7–7/5/2011. The dependent variable ($FLOW_c$) is the percentage change in the assets of class $c$ . Credit risk measures in columns (1)–(6) include the annualized gross yield ($GYIELD_f$) and the expected-loss-to-maturity ($ELM_f$) on the fund's portfolio, averaged across days during 6/7–7/5/2011. In columns (7)–(9), credit risk is measured as the counterfactual credit risk of the fund ($CELM$) on 9/31/2011 had the fund held the same portfolio it held as of 5/31/2011. The other key explanatory variable is the portion of class assets held by sophisticated investors ($SOPH_c$) as of the start of the year. Observations are binned into low, mid, and high terciles based on the distribution of $SOPH_c$ across institutional share classes (e.g., $LoSOPH_c = 1$ when $SOPH_c \leq 13\%$) and interacted. We control for the logged total net assets of the class and the fund ($ASSETS_c$ and $ASSETS_f$, respectively), the logged historical asset variation ($FLOWSTD_c$), and the share of fund assets not maturing during the period of interest, nor invested in Treasury/Agency securities ($ILLIQUIDITY_f$). Class-level and fund-level (a.k.a., portfolio-level) variables are denoted by the subscript "$c$" and "$f$", respectively. The sample includes only classes designated as "institutional." All observations are weighted by logged class assets. The constant is not shown for brevity. To manage a handful of outliers, the $FLOW_c$ and $FLOWSTD_c$are both winsorized at the 1st and 99th percentiles. In parentheses are t-statistics, calculated using standard errors clustered by fund. Estimates with a p-value below 0.10, 0.05, and 0.01 are marked with a *, **, and ***, respectively.

| Risk measure: | $ELM\,(Overall)$ | | | $GYIELD$ | | | $Counterfactual\,ELM$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $RISK_f \times LowSOPH_c$ | 0.015 | 0.101 | 0.145 | -0.130 | 0.083 | 0.122 | -0.013 | 0.031 | 0.030 |
| | (0.067) | (0.445) | (0.658) | (-0.493) | (0.319) | (0.512) | (-0.103) | (0.240) | (0.240) |
| $RISK_f \times MidSOPH_c$ | -0.360** | -0.277* | -0.111 | -0.373* | -0.158 | -0.026 | -0.204** | -0.164* | -0.102 |
| | (-2.388) | (-1.734) | (-0.714) | (-1.682) | (-0.701) | (-0.124) | (-2.340) | (-1.844) | (-1.241) |
| $RISK_f \times HighSOPH_c$ | -0.618*** | -0.539*** | -0.409** | -0.568** | -0.394 | -0.258 | -0.338*** | -0.303*** | -0.261*** |
| | (-3.041) | (-2.881) | (-2.425) | (-2.192) | (-1.471) | (-1.073) | (-3.401) | (-3.370) | (-3.373) |
| $SOPH_c$ (%) | 0.087* | 0.088* | 0.107** | 0.093 | 0.109* | 0.115* | 0.097* | 0.099* | 0.118** |
| | (1.726) | (1.723) | (2.127) | (1.469) | (1.753) | (1.876) | (1.916) | (1.927) | (2.363) |
| $GYIELD_f$ | | -0.187 | -0.088 | | | | | -0.171 | -0.031 |
| | | (-0.804) | (-0.439) | | | | | (-0.782) | (-0.169) |
| $ELM_f$ | | | | | -0.252* | -0.142 | | | |
| | | | | | (-1.740) | (-1.047) | | | |
| $ASSETS_c$ | | | -1.840*** | | | -1.859*** | | | -1.826*** |
| | | | (-3.037) | | | (-3.029) | | | (-3.056) |
| $FLOWSTD_c$ | | | -3.058*** | | | -3.112*** | | | -3.082*** |
| | | | (-3.258) | | | (-3.309) | | | (-3.286) |
| $ASSETS_f$ | | | 0.517 | | | 0.612 | | | 0.554 |
| | | | (0.787) | | | (0.948) | | | (0.824) |
| $ILLIQUIDITY_f$ | | | -0.043 | | | -0.051 | | | -0.046 |
| | | | (-0.423) | | | (-0.507) | | | (-0.463) |
| N | 251 | 251 | 251 | 251 | 251 | 251 | 251 | 251 | 251 |
| R2 | 0.05 | 0.06 | 0.13 | 0.04 | 0.05 | 0.12 | 0.06 | 0.06 | 0.14 |
| P-value (HML) | 0.034 | 0.034 | 0.060 | 0.065 | 0.041 | 0.096 | 0.024 | 0.023 | 0.042 |

Table 4: Flow regressions: the influence of regional and future credit risk

These are cross-sectional regressions at the share class level. The dependent variable ($FLOW_c$) is the percentage change in assets during the period of rapid outflows from prime MMFs, 6/7/2011–7/5/2011. Credit risk is measured as the expected-loss-to-maturity ($ELM_f$) on the fund's portfolio, averaged across in days 6/7–7/5/2011. In column (5), $ELM_f$ captures only the contribution of the riskiest 5 European issuers during the Eurozone crisis (Dexia, Societe Generale, Barclays, Royal Bank of Scotland, KBC Groep) to a fund's expected-loss-to-maturity. In column (6), credit risk from Europe is measured using a counterfactual ($CELM$), measured as the contibution to a fund's expected-loss-to-maturity from its Europan holdings on 9/30/2011 had the fund continued to hold the same portfolio securities it held as of 5/31/2011. The other key explanatory variable is the portion of class assets held by sophisticated investors ($SOPH_c$) as of the start of the year. In select regressions, observations are binned into low, mid, and high terciles based on the distribution of $SOPH_c$ across institutional share classes (e.g., $LoSOPH_c = 1$ when $SOPH_c \leq 13\%$). These binary variables are used in interactions. The controls, sample, weights, and winsorizations are the same as those described in Table 3. In parentheses are t-statistics, calculated using standard errors clustered by fund. Estimates with a p-value below 0.10, 0.05, and 0.01 are marked with a *, **, and ***, respectively.

| | | | Europe | | | | Asia/Pacific | | Americas | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| $ELM_f(Europe)$ | -0.443** | -0.304* | | | | | -0.437** | -0.320* | -0.501*** | -0.357** |
| | (-2.46) | (-1.79) | | | | | (-2.45) | (-1.90) | (-2.70) | (-2.06) |
| $ELM_f(AsiaPac)$ | 0.193 | 0.417* | 0.178 | 0.391 | 0.380 | 0.384 | | | 0.173 | 0.364 |
| | (0.75) | (1.67) | (0.66) | (1.53) | (1.52) | (1.49) | | | (0.62) | (1.41) |
| $ELM_f(Americas)$ | 0.539 | 0.515 | 0.400 | 0.364 | 0.662 | 0.358 | 0.618 | 0.515 | | |
| | (0.67) | (0.68) | (0.49) | (0.47) | (0.82) | (0.45) | (0.70) | (0.63) | | |
| $ELM_f(Region) \times LowSOPH_c$ | | | -0.0654 | -0.00120 | 0.0941 | 0.00201 | 0.658** | 0.702*** | 2.257** | 1.239 |
| | | | (-0.19) | (-0.00) | (0.13) | (0.01) | (2.54) | (2.68) | (2.04) | (1.09) |
| $ELM_f(Region) \times MidSOPH_c$ | | | -0.516** | -0.305 | -0.483 | -0.137 | -0.116 | 0.272 | 1.378 | 1.640 |
| | | | (-2.54) | (-1.57) | (-1.07) | (-1.57) | (-0.44) | (0.92) | (0.94) | (1.24) |
| $ELM_f(Region) \times HighSOPH_c$ | | | -0.681*** | -0.551*** | -1.009** | -0.262*** | 0.0965 | 0.221 | -1.491 | -0.917 |
| | | | (-3.30) | (-3.05) | (-2.26) | (-3.02) | (0.13) | (0.33) | (-1.04) | (-0.69) |
| $SOPH_c$ | -0.0110 | 0.0230 | 0.0651 | 0.0938* | 0.0679 | 0.0991** | 0.00310 | 0.0355 | 0.0401 | 0.0541 |
| | (-0.44) | (0.87) | (1.26) | (1.92) | (1.53) | (2.08) | (0.11) | (1.14) | (1.18) | (1.53) |
| $ASSETS_c$ | | -1.953*** | | -1.847*** | -1.896*** | -1.871*** | | -1.927*** | | -1.953*** |
| | | (-3.38) | | (-3.15) | (-3.22) | (-3.19) | | (-3.42) | | (-3.24) |
| $FLOWSTD_c$ | | -3.282*** | | -3.206*** | -3.300*** | -3.255*** | | -3.121*** | | -3.114*** |
| | | (-3.49) | | (-3.33) | (-3.46) | (-3.37) | | (-3.28) | | (-3.22) |
| $ASSETS_f$ | | 0.528 | | 0.389 | 0.182 | 0.393 | | 0.551 | | 0.534 |
| | | (0.83) | | (0.62) | (0.29) | (0.62) | | (0.89) | | (0.86) |
| $ILLIQUIDITY_f$ | | -0.0323 | | -0.0385 | -0.0565 | -0.0473 | | -0.0283 | | -0.0216 |
| | | (-0.31) | | (-0.36) | (-0.52) | (-0.46) | | (-0.26) | | (-0.24) |
| N | 251 | 251 | 251 | 251 | 251 | 251 | 251 | 251 | 251 | 251 |
| R2 | 0.04 | 0.13 | 0.06 | 0.14 | 0.13 | 0.14 | 0.06 | 0.14 | 0.06 | 0.14 |
| P-value (HML) | - | - | 0.141 | 0.174 | 0.232 | 0.133 | 0.485 | 0.509 | 0.048 | 0.235 |
| *ELM* Measure | *ELM* | | *ELM* | *ELM* | *ELM* (Risky5) | *CELM* | *ELM* | | *ELM* | |

Table 5: Portfolio reallocation regressions: Europe

These are cross-sectional regressions at the fund portfolio-level on selected dates. All variables are measured at the fund (a.k.a. portfolio) level. The dependent variable, $\left[ELM^{date} - CELM^{date}\,(Europe)\right]$, is the actual contribution of issuers from Europe to a fund's credit risk on a given date minus the counterfactual contribution had the fund continued to hold the same securities it held as of 5/31/2011 (measured as basis point changes). The first three explanatory variables capture the factors found in Table 3 to motivate investors to redeem from funds. These include a fund's expected-loss-to-maturity, averaged across days in 6/8/2011-7/5/2011, the percentage of portfolio assets held by sophisticated investors ($SOPH$), and the interaction of the two (e.g, $ELM \times high\,SOPH$), where $SOPH$ is binned by tercile. We control for logged fund assets as of 6/7/2011, $ASSETS_f$, since larger funds may have greater credit research capabilities and negotiating power with issuers. In the short- and medium-terms, we also test a direct measure of the size of the shock each fund experienced during the period of rapid outflows from prime MMFs, $OUTFLOW$. When the percentage change in fund in assets from 6/7/2011 through 7/5/2011 is negative, $OUTFLOW$ equals the absolute value of that percentage change; otherwise, $OUTFLOW$ equals zero. We also control for the fund-level logged flow standard deviation ($FLOWSTDEV_f$) 1 minus the portion of fund assets that are maturing or highly liquid during the shock (6/1/2011–7/5/2011), $ILLIQUIDITY$, since more liquid funds may respond differently to outflows. The constant is not shown for brevity. Robust standard errors are shown in parentheses. Estimates with a p-value below 0.10, 0.05, and 0.01 are marked with a *, **, and ***, respectively.

| | July 2011 | Sep 2011 | Nov 2011 | Jan 2012 | Mar 2012 | Jun 2012 | Sep 2012 | Dec 2012 |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $ELM \times LowSOPH_f$ | -0.049 | -0.155 | -1.007*** | -0.820*** | -0.644*** | -0.848*** | -0.283*** | -0.430*** |
| | (0.034) | (0.108) | (0.260) | (0.165) | (0.128) | (0.189) | (0.064) | (0.110) |
| $ELM \times MidSOPH_f$ | -0.075** | -0.181 | -1.218*** | -1.126*** | -0.845*** | -1.273*** | -0.388*** | -0.676*** |
| | (0.035) | (0.126) | (0.317) | (0.233) | (0.182) | (0.261) | (0.071) | (0.154) |
| $ELM \times HighSOPH_f$ | -0.105 | -0.337** | -2.399*** | -1.810*** | -1.370*** | -2.193*** | -0.555*** | -1.276*** |
| | (0.072) | (0.161) | (0.707) | (0.524) | (0.390) | (0.543) | (0.123) | (0.384) |
| $SOPH_f$ | 0 | 0.008 | 0.157 | 0.087 | 0.063 | 0.089 | 0.018 | 0.071 |
| | (0.010) | (0.034) | (0.101) | (0.072) | (0.053) | (0.075) | (0.019) | (0.050) |
| $ASSETS_f$ | 0.192** | 0.187 | 2.114** | 0.995* | 0.948** | 1.145** | 0.283* | 0.899*** |
| | (0.086) | (0.288) | (0.815) | (0.549) | (0.421) | (0.555) | (0.154) | (0.344) |
| $FLOWSTD_f$ | -0.039 | 0.538 | -1.812 | 0.142 | 0.392 | 0.396 | 0.319 | 0.032 |
| | (0.159) | (0.618) | (1.660) | (0.851) | (0.639) | (0.888) | (0.276) | (0.552) |
| $OUTFLOW_f$ | 0.053* | 0.121 | 0.213 | 0.021 | -0.016 | 0.21 | 0.035 | 0.137 |
| | (0.030) | (0.084) | (0.289) | (0.202) | (0.178) | (0.208) | (0.059) | (0.120) |
| $ILLIQUIDITY_f$ | -0.015 | 0.079** | 0.035 | 0.031 | 0.019 | 0.095 | 0.033 | 0.026 |
| | (0.020) | (0.038) | (0.129) | (0.091) | (0.072) | (0.101) | (0.025) | (0.067) |
| N | 188 | 188 | 188 | 179 | 178 | 176 | 175 | 172 |
| R2 | 0.090 | 0.090 | 0.180 | 0.280 | 0.280 | 0.350 | 0.380 | 0.280 |
| P Value (HML) | 0.383 | 0.278 | 0.046 | 0.051 | 0.051 | 0.01 | 0.034 | 0.023 |

Table 6: Portfolio reallocation regressions: Asia/Pacific and Americas

These are cross-sectional regressions at the fund portfolio-level on selected dates. All variables are measured at the fund (a.k.a. portfolio) level. The dependent variable, $\left[ELM^{date} - CELM^{date}\left(Region\right)\right]$, is the actual contribution of issuers from the Asia/Pacific region to a fund's credit risk on a given date minus the counterfactual contribution had the fund continued to hold the same securities it held as of 5/31/2011 (measured as basis point changes). We report the coefficients on interactions between a fund's expected-loss-to-maturity, averaged across days in 6/8/2011-7/5/2011 and three terciles of the percentage of portfolio assets held by sophisticated investors ($SOPH$). Each regression also includes the same controls as in Table 5, which are not reported for brevity. Robust standard errors are shown in parentheses. Estimates with a p-value below 0.10, 0.05, and 0.01 are marked with a *, **, and ***, respectively.

(a) Asia/Pacific

| | July 2011 | Sep 2011 | Nov 2011 | Jan 2012 | Mar 2012 | Jun 2012 | Sep 2012 | Dec 2012 |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $ELM \times LowSOPH_f$ | -0.042 | 0.011 | 0.021 | 0.089** | 0.149*** | 0.066 | -0.008 | -0.037 |
| | (0.040) | (0.066) | (0.075) | (0.043) | (0.038) | (0.041) | (0.050) | (0.028) |
| $ELM \times MidSOPH_f$ | -0.024 | 0.070 | 0.110 | 0.172*** | 0.168*** | 0.117** | 0.037 | -0.017 |
| | (0.027) | (0.071) | (0.074) | (0.051) | (0.040) | (0.045) | (0.064) | (0.027) |
| $ELM \times HighSOPH_f$ | -0.063 | 0.166 | 0.201 | 0.272*** | 0.303*** | 0.206*** | 0.198* | 0.001 |
| | (0.061) | (0.158) | (0.175) | (0.093) | (0.077) | (0.059) | (0.105) | (0.037) |
| N | 188 | 188 | 188 | 179 | 178 | 176 | 175 | 172 |
| R2 | 0.07 | 0.10 | 0.10 | 0.21 | 0.17 | 0.16 | 0.15 | 0.12 |
| P Value (HML) | 0.745 | 0.230 | 0.278 | 0.072 | 0.056 | 0.040 | 0.055 | 0.417 |

(b) Americas

| | July 2011 | Sep 2011 | Nov 2011 | Jan 2012 | Mar 2012 | Jun 2012 | Sep 2012 | Dec 2012 |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $ELM \times LowSOPH_f$ | 0.013*** | 0.005 | 0.104*** | 0.067*** | 0.052*** | 0.070** | 0.144*** | 0.142*** |
| | (0.003) | (0.019) | (0.029) | (0.023) | (0.017) | (0.029) | (0.042) | (0.035) |
| $ELM \times MidSOPH_f$ | 0.011*** | -0.010 | 0.086*** | 0.071*** | 0.060*** | 0.057** | 0.158*** | 0.162*** |
| | (0.003) | (0.021) | (0.033) | (0.025) | (0.019) | (0.029) | (0.046) | (0.040) |
| $ELM \times HighSOPH_f$ | 0.007 | -0.072** | -0.005 | 0.026 | 0.045 | 0.022 | 0.177* | 0.204** |
| | (0.005) | (0.034) | (0.064) | (0.039) | (0.032) | (0.044) | (0.092) | (0.095) |
| N | 188 | 188 | 188 | 179 | 178 | 176 | 175 | 172 |
| R2 | 0.13 | 0.05 | 0.11 | 0.15 | 0.15 | 0.10 | 0.17 | 0.18 |
| P Value (HML) | 0.241 | 0.029 | 0.083 | 0.307 | 0.834 | 0.315 | 0.719 | 0.508 |

Table 7: Fund-issuer level portfolio regressions - Credit risk of pre-crisis portfolios

These are cross-sectional regressions across issuer-fund relationships for the subset of widely-held issuers in each region. The first dependent variable is the expected loss to maturity of fund $f$ from issuer $i$ as of May 31, 2011, $ELM_{i,f}^{5/11}$. The second dependent variable spread between issuer $i$'s counterfactual contribution to fund $f$'s credit risk over the crisis and its initial credit risk ($CELM_{if}^{crisis} - ELM_{if}^{5/11}$). $CELM_{if}^{crisis}$ is generated by averaging values of $CELM_{ift}$ from September 2011–August 2012, which corresponds to the period of high CDS premiums on European financials. $CELM_{ift}$ is the counterfactual risk contribution of the issuer on time $t$ had the fund continued to hold the same securities it held as of May 31, 2011. The third dependent variable is the portion of fund $f$'s portfolio assets allocated to issuer $i$ ($WEIGHT_{if}^{5/11}$). Explanatory variables are the issuer's 3-month probability of default $PD_i^{5/11}$, measured as of May 2011, and an interaction between $PD_i^{5/11}$and an indicator variable for whether a fund is in the top tercile of investor sophistication ($HighSOPH_f$). All continuous variables are normalized by their cross-sectional standard deviations. Rows below the coefficients indicate whether regressions include issuer- and /or fund-fixed effects. Standard errors are clustered by issuer and are shown in parentheses. Estimates with a p-value below 0.10, 0.05, and 0.01 are marked with a *, **, and ***, respectively.

(a) Europe

| | $ELM_{i,f}^{5/11}$ | | $CELM_{i,f}^{crisis} - ELM_{i,f}^{5/11}$ | | $WEIGHT_{i,f}^{5/11}$ | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $PD_i^{5/11}$ | 0.035 | | 0.044 | | -0.005 | |
| | (0.090) | | (0.081) | | (0.054) | |
| $PD_i^{5/11} \times HighSOPH_f$ | 0.025 | 0.025 | 0.063 | 0.063 | 0.003 | 0.003 |
| | (0.055) | (0.056) | (0.105) | (0.105) | (0.027) | (0.028) |
| N | 12,173 | 12,173 | 12,173 | 12,173 | 12,173 | 12,173 |
| R2 | 0.06 | 0.44 | 0.03 | 0.17 | 0.05 | 0.33 |

(b) Asia/Pacific

| | $ELM_{i,f}^{5/11}$ | | $CELM_{i,f}^{crisis} - ELM_{i,f}^{5/11}$ | | $WEIGHT_{i,f}^{5/11}$ | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $PD_i^{5/11}$ | 1.264*** | | -0.042 | | 0.060 | |
| | (0.176) | | (0.031) | | (0.070) | |
| $PD_i^{5/11} \times HighSOPH_f$ | -0.398*** | -0.398*** | 0.005 | 0.005 | -0.041* | -0.041* |
| | (0.046) | (0.046) | (0.005) | (0.005) | (0.021) | (0.021) |
| N | 3,885 | 3,885 | 3,885 | 3,885 | 3,885 | 3,885 |
| R2 | 0.19 | 0.25 | 0.03 | 0.44 | 0.12 | 0.31 |

(c) Americas

| | $ELM_{i,f}^{5/11}$ | | $CELM_{i,f}^{crisis} - ELM_{i,f}^{5/11}$ | | $WEIGHT_{i,f}^{5/11}$ | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $PD_i^{5/11}$ | 0.009 | | 0.002 | | -0.058 | |
| | (0.014) | | (0.012) | | (0.048) | |
| $PD_i^{5/11} \times HighSOPH_f$ | -0.002 | -0.002 | -0.001 | -0.001 | 0.023* | 0.023* |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.013) | (0.013) |
| Fund FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Issuer FE | No | Yes | No | Yes | No | Yes |
| N | 27,195 | 27,195 | 27,195 | 27,195 | 27,195 | 27,195 |
| R2 | 0.01 | 0.22 | 0.01 | 0.32 | 0.01 | 0.18 |

## Table 8: Fund-issuer level portfolio reallocation regressions: Europe

These are cross-sectional regressions across issuer-fund relationships for the subset of widely-held European issuers. The first dependent variable is the spread between issuer $i$'s actual minus counterfactual contribution to fund $f$'s credit risk ($ELM - CELM_{if}$). This variable is generated by averaging values of $(ELM_{ift} - CELM_{ift})$ over the Eurozone crisis (September 2011–August 2012, which corresponds to the period of high CDS premiums on European financials). $CELM_{ift}$ is the counterfactual risk contribution of the issuer on time $t$ had the fund continued to hold the same securities it held as of May 31, 2011 (the last observation before investors began to redeem heavily from MMFs). The other two dependent variables are the change in issuer $i$'s contribution to fund $f$'s credit risk ($\triangle ELM_{if}$) and the change in the portion of fund $f$'s portfolio assets allocated to issuer $i$ ($\triangle WEIGHT_{if}$). Changes are measured by averaging values over the Eurozone crisis and then subtracting the corresponding value as of May 31, 2011. Explanatory variables include interactions of an indicator variable for when a fund is in the top tercile of investor sophistication ($highSOPH_f$), the fund's total initial credit risk ($ELM_f^{5/2011}$), and the issuer's 3-month probability of default, measured as of May 31, 2011 ($PD_i^{5/11}$) and averaged over the crisis ($PD_i^{crisis}$). Since funds with small initial investments in a given issuer are more likely to experience positive changes in the dependent variables, we control for the initial proportion of fund $f$'s total assets invested in issuer $i$ ($WEIGHT_{i,f}^{5/2011}$). All continuous variables are standardized. Rows below the coefficients indicate whether regressions include issuer- and /or fund-fixed effects. The constant is not shown for brevity. Standard errors are clustered by issuer and are shown in parentheses. Estimates with a p-value below 0.10, 0.05, and 0.01 are marked with a *, **, and ***, respectively.

| Dependent variable: | $ELM_{if}^{crisis} - CELM_{if}^{crisis}$ | | | | $ELM_{if}^{crisis} - ELM_{if}^{5/11}$ | | $WEIGHT_{if}^{crisis} - WEIGHT_{if}^{5/11}$ | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $PD_i^{crisis}$ | -0.348*** | | -0.432*** | | -0.131*** | | -0.029*** | |
| | (0.015) | | (0.020) | | (0.012) | | (0.010) | |
| $PD_i^{crisis} \times HighSOPH_f$ | -0.510*** | -0.510*** | -0.412*** | -0.412*** | -0.123*** | -0.120*** | -0.015 | -0.012 |
| | (0.020) | (0.018) | (0.021) | (0.020) | (0.023) | (0.023) | (0.015) | (0.015) |
| $PD_i^{crisis} \times ELM_f^{5/11}$ | | | -0.180*** | -0.179*** | -0.049*** | -0.046*** | -0.008 | -0.006 |
| | | | (0.009) | (0.009) | (0.012) | (0.016) | (0.006) | (0.009) |
| $PD_i^{crisis} \times ELM_f^{5/11} \times HighSOPH_f$ | | | -0.657*** | -0.657*** | -0.210*** | -0.207*** | -0.035** | -0.032* |
| | | | (0.027) | (0.025) | (0.016) | (0.015) | (0.017) | (0.017) |
| $PD_i^{5/11}$ | 0.005 | | 0.005 | | -0.004 | | -0.004 | |
| | (0.007) | | (0.006) | | (0.010) | | (0.012) | |
| $PD_i^{5/11} \times HighSOPH_f$ | 0.014 | 0.014 | 0.015 | 0.015 | 0.003 | 0.002 | -0.002 | -0.003 |
| | (0.022) | (0.023) | (0.020) | (0.021) | (0.013) | (0.015) | (0.013) | (0.014) |
| $WEIGHT_{if}^{5/11}$ | -0.331*** | -0.363*** | -0.325*** | -0.353** | -0.186* | -0.301*** | -0.671*** | -0.768*** |
| | (0.118) | (0.133) | (0.118) | (0.133) | (0.094) | (0.082) | (0.084) | (0.068) |
| $WEIGHT_{if}^{5/11} \times HighSOPH_f$ | -0.054 | -0.047 | -0.029 | -0.021 | 0.180** | 0.185** | 0.008 | 0.016 |
| | (0.129) | (0.127) | (0.115) | (0.111) | (0.087) | (0.080) | (0.056) | (0.057) |
| Fund FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Issuer FE | No | Yes | No | Yes | No | Yes | No | Yes |
| N | 12,173 | 12,173 | 12,173 | 12,173 | 12,173 | 12,173 | 12,173 | 12,173 |
| R2 | 0.20 | 0.23 | 0.25 | 0.28 | 0.08 | 0.20 | 0.44 | 0.53 |

Table 9: Fund-issuer level portfolio reallocation regressions: Asia/Pacific and Americas

These are cross-sectional regressions across issuer-fund relationships for the subset of widely-held Asia/Pacific and Americas issuers. Specifications and variable definitions are identical to those in Table 8 above, though coefficients on some of the controls are suppressed for brevity. Rows below the coefficients indicate whether regressions include issuer- and /or fund-fixed effects. The constant is not shown for brevity. Standard errors are clustered by issuer and are shown in parentheses. Estimates with a p-value below 0.10, 0.05, and 0.01 are marked with a *, **, and ***, respectively.

(a) Asia/Pacific

| Dependent variable: | $ELM_{if}^{crisis} - CELM_{if}^{crisis}$ | | | | $ELM_{if}^{crisis} - ELM_{if}^{5/11}$ | | $WEIGHT_{if}^{crisis} - WEIGHT_{if}^{5/11}$ | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $PD_i^{crisis}$ | 0.030 | | 0.076 | | 2.899 | | -0.165 | |
| | (0.303) | | (0.318) | | (2.179) | | (0.612) | |
| $PD_i^{crisis} \times HighSOPH_f$ | 0.072 | 0.079 | 0.002 | 0.004 | -0.204 | -0.191 | -0.124 | -0.124 |
| | (0.287) | (0.293) | (0.284) | (0.289) | (1.035) | (1.050) | (0.412) | (0.450) |
| $PD_i^{crisis} \times ELM_f^{5/11}$ | | | 0.126*** | 0.137** | 0.436** | 0.474** | 0.145* | 0.180* |
| | | | (0.042) | (0.049) | (0.163) | (0.169) | (0.074) | (0.086) |
| $PD_i^{crisis} \times ELM_f^{5/11} \times HighSOPH_f$ | | | 0.205*** | 0.206*** | 0.679** | 0.681** | -0.024 | -0.020 |
| | | | (0.058) | (0.056) | (0.260) | (0.253) | (0.069) | (0.064) |
| N | 3,885 | 3,885 | 3,885 | 3,885 | 3,885 | 3,885 | 3,885 | 3,885 |
| R2 | 0.20 | 0.26 | 0.22 | 0.28 | 0.22 | 0.34 | 0.22 | 0.36 |

(b) Americas

| Dependent variable: | $ELM_{if}^{crisis} - CELM_{if}^{crisis}$ | | | | $ELM_{if}^{crisis} - ELM_{if}^{5/11}$ | | $WEIGHT_{if}^{crisis} - WEIGHT_{if}^{5/11}$ | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $PD_i^{crisis}$ | 0.018 | | 0.029 | | 0.917 | | 0.313 | |
| | (0.074) | | (0.076) | | (0.640) | | (0.218) | |
| $PD_i^{crisis} \times HighSOPH_f$ | 0.016 | 0.017 | 0.005 | 0.006 | -0.052 | -0.046 | 0.144 | 0.164 |
| | (0.028) | (0.029) | (0.027) | (0.027) | (0.044) | (0.039) | (0.195) | (0.219) |
| $PD_i^{crisis} \times ELM_f^{5/11}$ | | | 0.023 | 0.023 | 0.080 | 0.080 | 0.064* | 0.064* |
| | | | (0.017) | (0.017) | (0.063) | (0.062) | (0.038) | (0.036) |
| $PD_i^{crisis} \times ELM_f^{5/11} \times HighSOPH_f$ | | | -0.000 | -0.001 | -0.027 | -0.028 | 0.061 | 0.056 |
| | | | (0.017) | (0.017) | (0.022) | (0.023) | (0.052) | (0.048) |
| Fund FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Issuer FE | No | Yes | No | Yes | No | Yes | No | Yes |
| N | 27,195 | 27,195 | 27,195 | 27,195 | 27,195 | 27,195 | 27,195 | 27,195 |
| R2 | 0.07 | 0.15 | 0.07 | 0.15 | 0.10 | 0.43 | 0.27 | 0.38 |

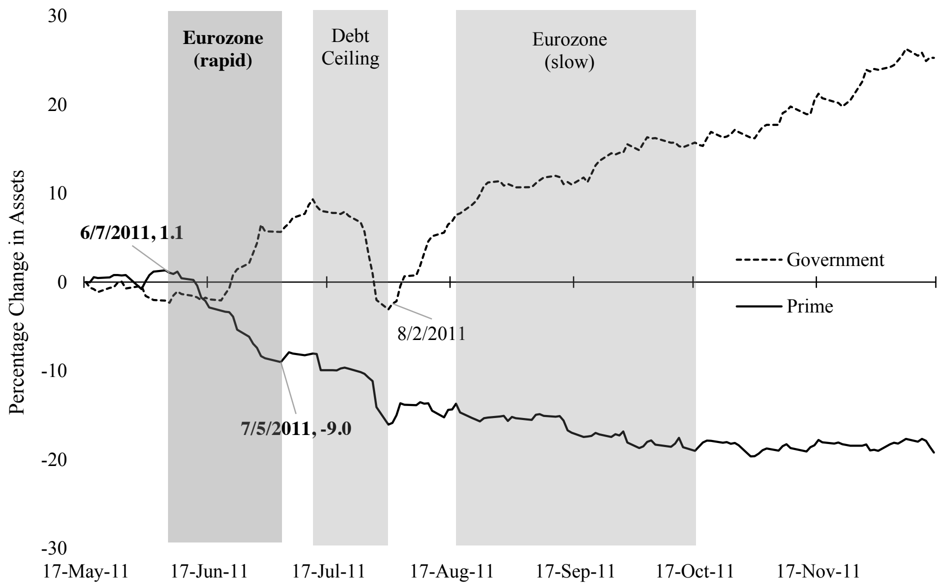



Figure 1: Aggregate MMF institutional share class flows

This figure shows the change in aggregate institutional share class assets of MMFs from May 17–December 16 of 2011. Changes in assets are normalized by asset values on May 17, 2011. The graph shows flows split by investment objective (i.e., prime versus government-only MMFs).

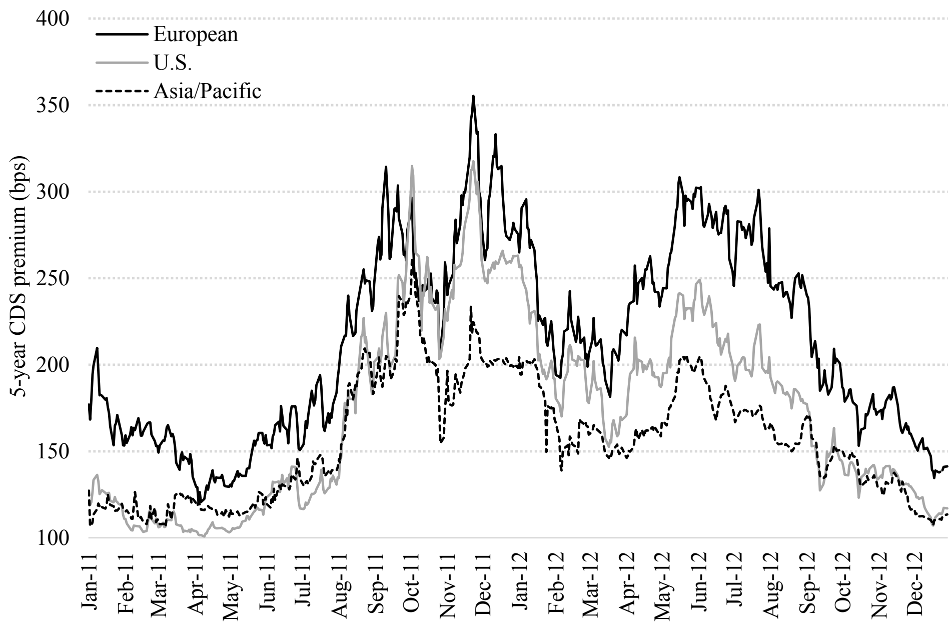



Figure 2: 5-Year CDS premiums for banks by region, 2011

The CDS premium for European financials is the iTraxx senior financial index for Europe. The CDS premiums for large Asia/Pacific and U.S. banks is the average of 5-year CDS premiums for (Sumitomo Bank and Mizuho Bank, National Australia Bank, Westpac, and ANZ) and (Bank of America, JPMorgan Chase, Citi, Wells Fargo, and Goldman Sachs), respectively. Canadian banks are excluded because their CDS is thinly traded.

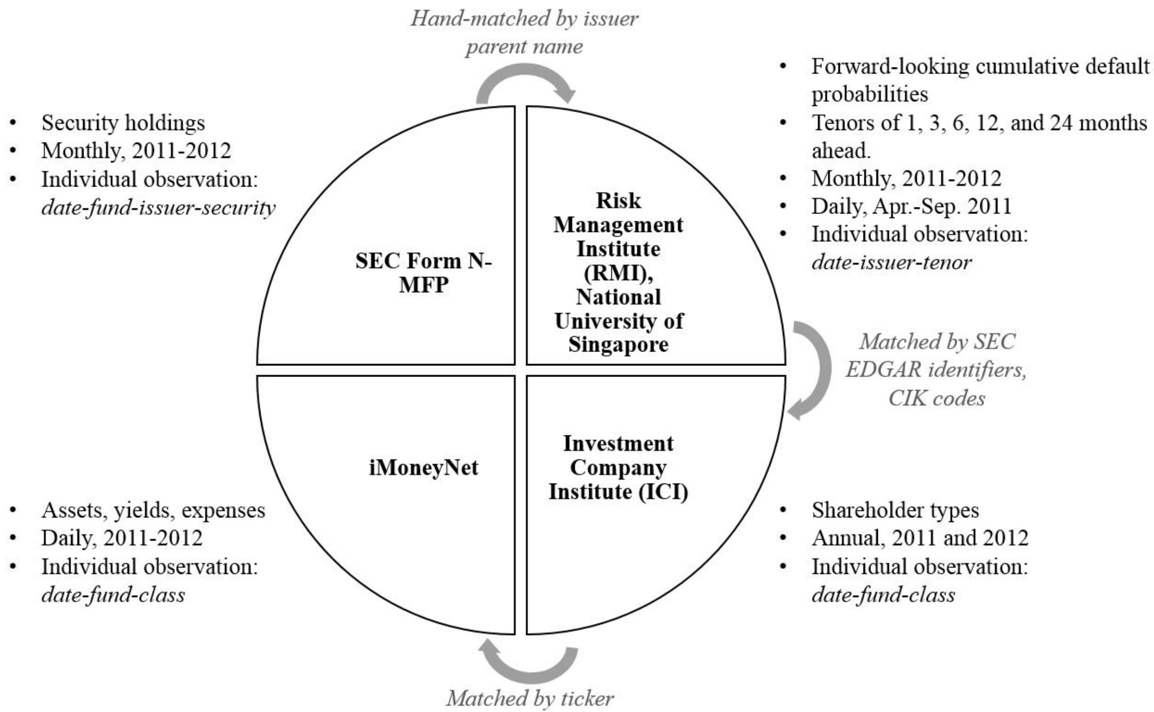



Figure 3: Data aggregation process

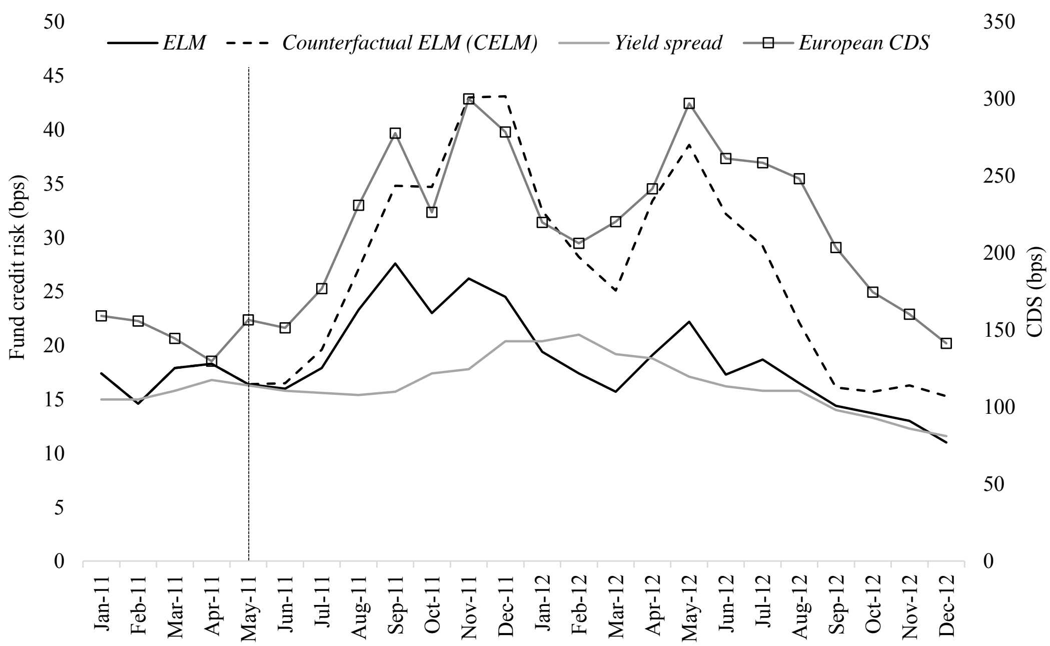


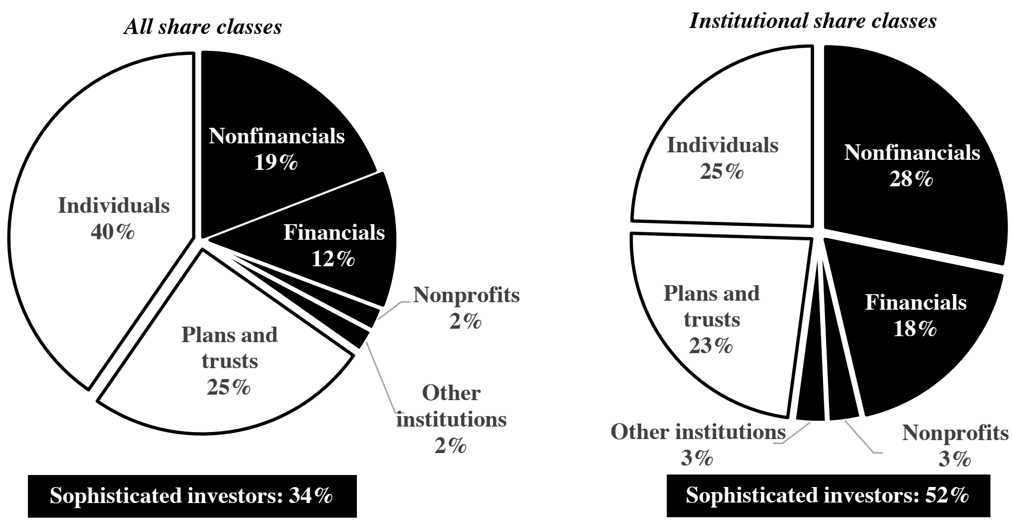

Figure 4: Credit risk measures over time

This figure shows the asset-weighted average credit risk in prime MMFs (LHS) and the CDS premium for the iTraxx senior financial index for Europe (RHS). The credit risk in prime MMFs as of month-end is measured in 3 ways: the annualized expected-loss-to-maturity (*ELM*), the counterfactual annualized *ELM* had prime funds continued to hold their end-May portfolio allocations (*CELM*), and the annualized gross yield on each prime MMF minus the yield on the average government MMF (*Yield spread*).

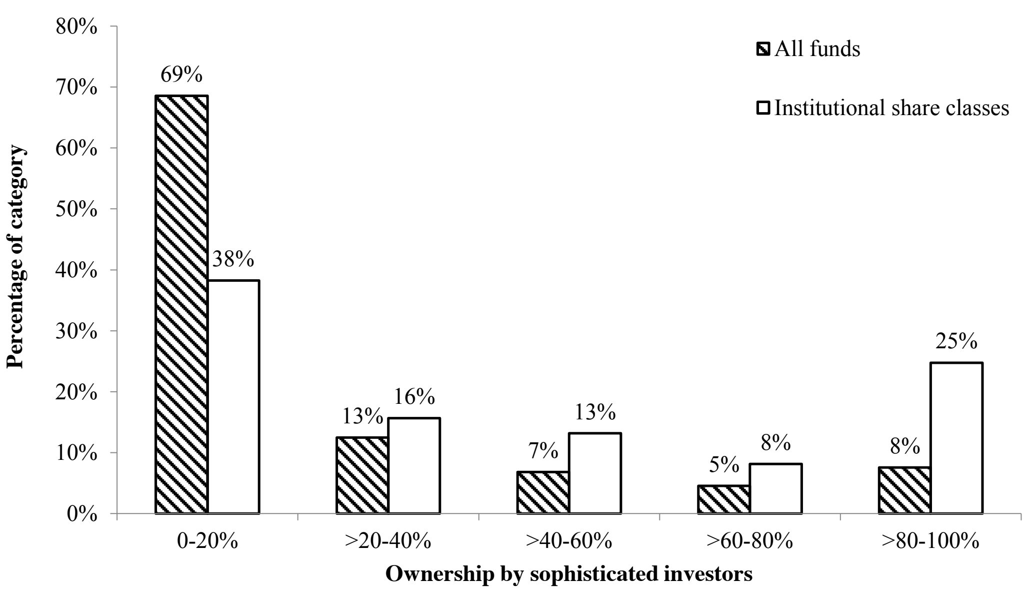
Figure 5: Prime MMF shareholder-types

This figure shows the portion of aggregate assets of prime MMFs owned by different types of investors and the distribution of investor sophistication (*SOPH*) across prime MMFs. "Other institutions" includes other intermediated funds (e.g., hedge funds and fund-of-fund mutual funds) , state/local governments, and other types of institutions (e.g., international organizations, unions, and cemeteries). "Individuals" includes about equal proportions of individual-directed retail accounts and pooled brokerage omnibus accounts. "Plans and trusts" are primarily fiduciary accounts (e.g., estates and inheritance trusts) and retirement plans (e.g., 401(k) and defined benefit pension plans) along with a small amounts from College 529 Savings Plans.

(a) The portion of aggregate assets of prime MMFs owned by different types of investors




(b) The distribution of investor sophistication (*SOPH*) across prime MMFs



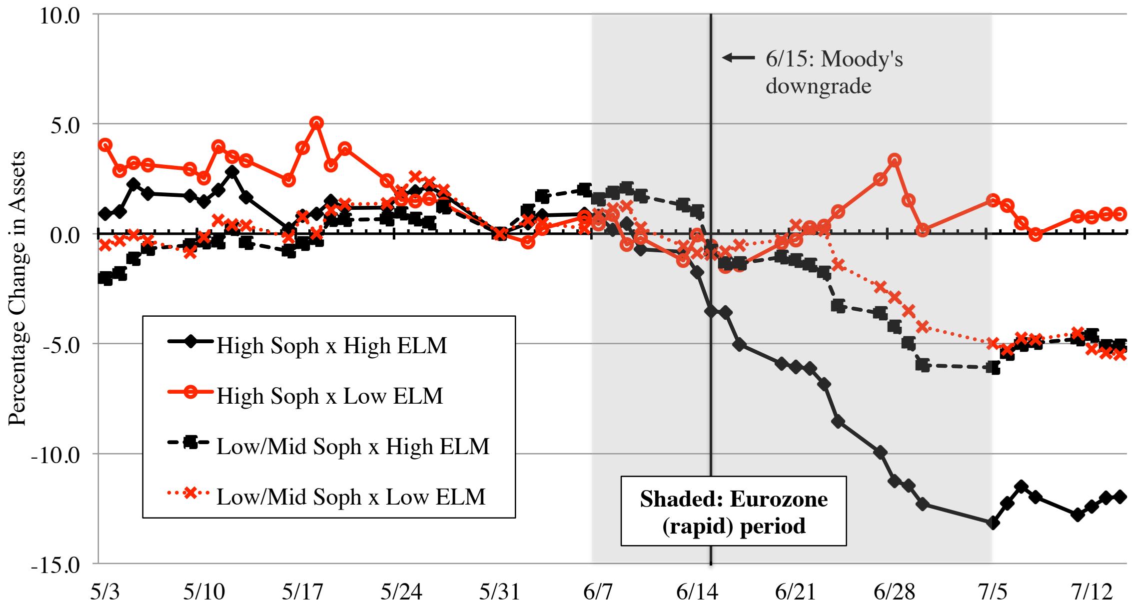



Figure 6: Aggregate prime institutional flows by investor sophistication and credit risk

This figure shows the percentage change in prime institutional share class assets of MMFs from May 1 through July 14 of 2011. Changes in assets are normalized by asset values on May 31, 2011. We sort institutional shareclasses into terciles based on the concentration of sophisticated investors. Solid lines plot flows (percentage changes in assets under management) for shareclasses in the top tercile, while dashed/dotted lines correspond with institutional shareclasses in the mid and bottom terciles. We also sort funds into two bins based on our measure of credit risk (*ELM*). Black and red lines correspond with funds in the High and Low *ELM* bins, respectively.

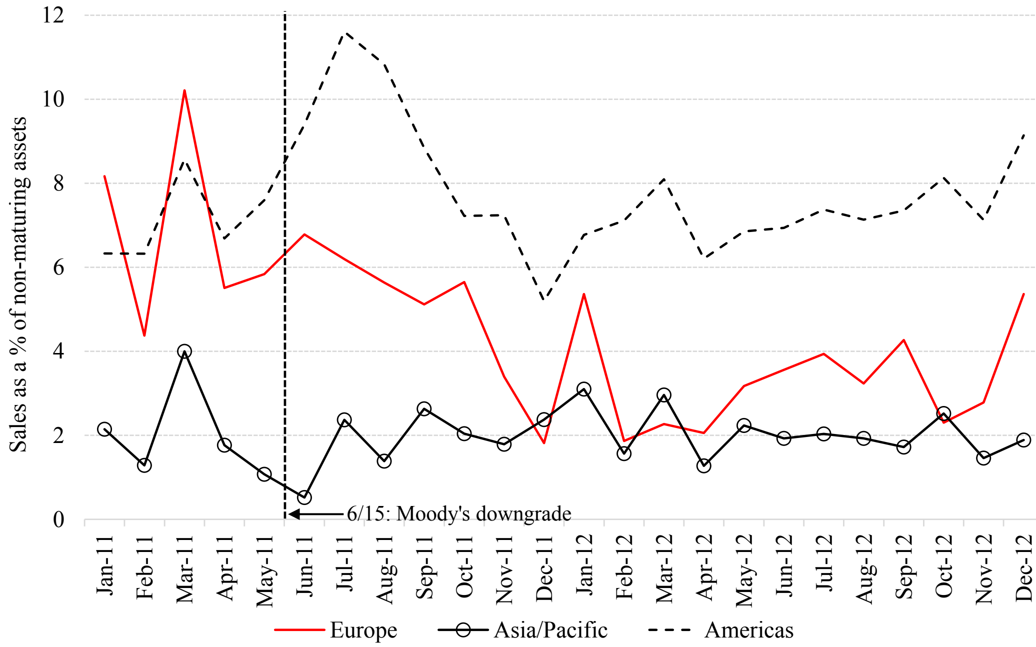



Figure 7: Fund Sales of CP and CDs into Secondary Markets

This figure shows the estimated portion of total prime MMF assets in CP and CDs that were sold during a given month, by region of the issuer. These statistics are estimated by tracking CUSIPs held by individual funds over time. For example, if on its January 31 SEC filing a hypothetical fund reports holding a CD with CUSIP "96121H6Q2" that matures on March 5, then that same CUSIP should be reported on the fund's February 28 filing (at its amortized cost value). If that CUSIP is missing from the February 28 filing, we can assume the fund sold the CD on the secondary market during February. We study only CDs and CP with at least one month to maturity because these security types are riskier and not part of a fund's liquidity during the month of interest; therefore, a fund may wish to eliminate these holdings during a credit event. Also, while nearly 100% of CP and almost 80% of CDs listed on SEC Form N-MFP have CUSIPs, only 10% of repos have CUSIPs. Overall, about a quarter of all prime MMF assets (and a third of their European assets) are missing CUSIP identifiers. Therefore, these statistics should be regarded as rough estimates of funds' use of secondary markets to eliminate CP and CDs.

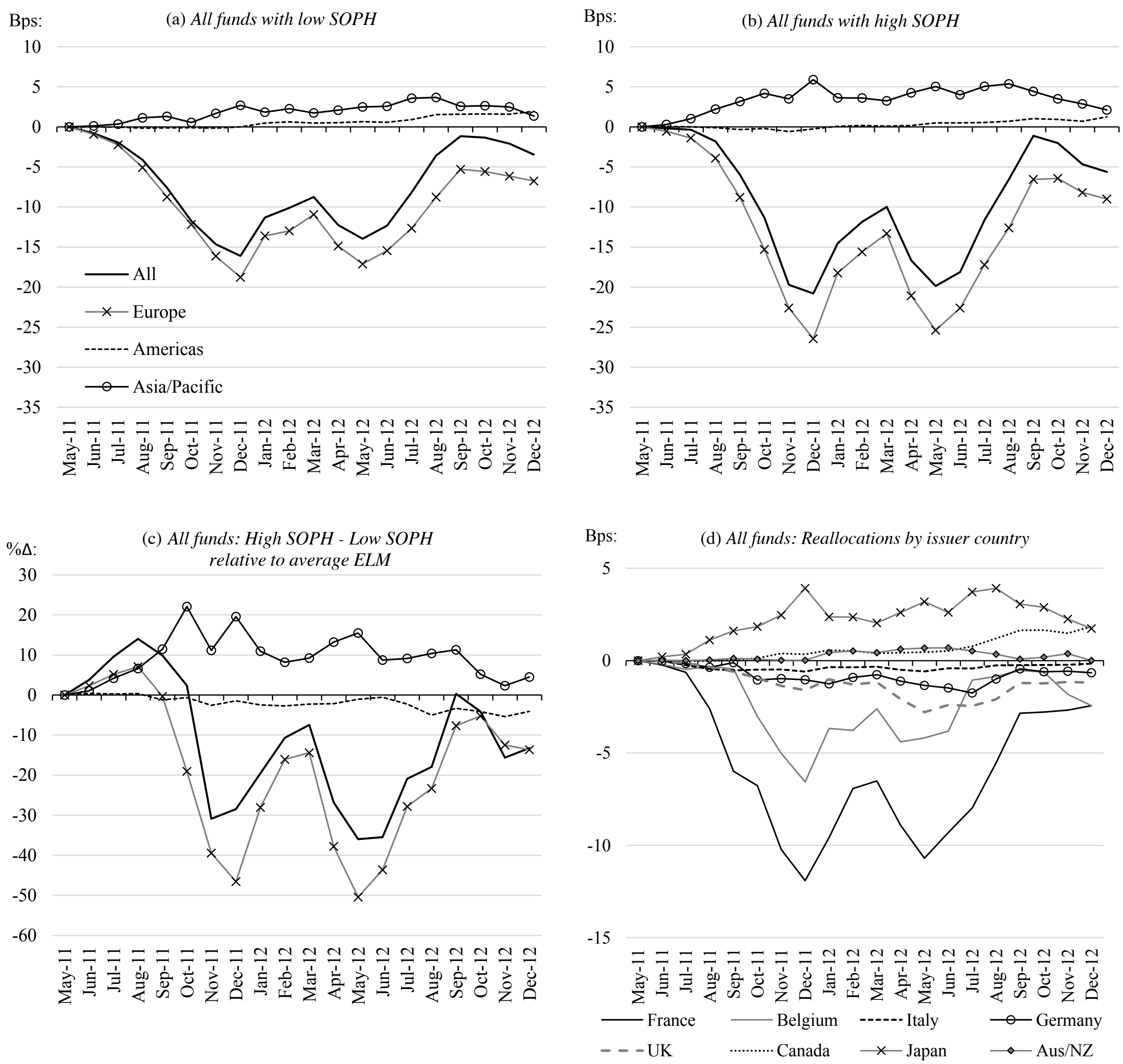



Figure 8: Country credit risk reallocations, $\left[ELM^{date} - CELM^{date}\left(Country\right)\right]$

This figure shows the asset-weighted average $\left[ELM^{date} - CELM^{date}\left(Region\right)\right]$ across each group of prime MMFs. This is calculated as the actual contribution of a given region to a fund's credit risk (*ELM*) on a given *date* minus the counterfactual contribution had the fund continued to hold the same securities it held as of May 31, 2011 (measured as basis point changes). Panel a (top left) includes only those funds with ownership by sophisticated investors (*SOPH*) in the bottom tercile, while Panel b (top right) includes only those funds with *SOPH* in the top tercile. The lines in Panel c (bottom left) are calculated as the average risk reallocation for all high *SOPH* funds minus the average risk reallocation for all low *SOPH* funds within the fund sample. We normalize these differences by the average fund *ELM* as of May 31, 2011 (17.5bps). Panel d (bottom right) shows the asset-weighted average $\left[ELM^{date} - CELM^{date}\left(Country\right)\right]$ across all prime MMFs. This is calculated as the actual contribution of a given country to a fund's credit risk (*ELM*) on a given *date* minus the counterfactual contribution had the fund continued to hold the same securities it held as of May 31, 2011 (measured as basis point changes). Omitted countries, such as the U.S., have an average risk response that is consistently very close to zero.

# A Construction of the Expected-Loss-to-Maturity ($ELM$) Credit Risk Measure

To evaluate the risk preferences of funds and their investors during the Eurozone crisis we need a measure of credit risks in MMF portfolios. This is necessary because MMFs price their portfolio holdings at amortized cost, such that fund yields (and yield spreads) do not immediately reflect changes in the credit quality of their portfolios' securities. Furthermore, current market yields on MMFs' outstanding portfolio securities are frequently unavailable since secondary markets for short-term securities, like CDs and CP, are notoriously thin (Covitz and Downing, 2007). Thus, to study credit risk in MMFs, we must use a measure that evolves with market conditions.

This appendix describes the approach used in this paper – which is based on a method proposed in Collins and Gallagher (2016) – to estimate the credit risk of prime money market funds. For exposition, we introduce the following notation:

| | | |
|---|---|---|
| $I$ | = | total number of issuers in a fund's portfolio |
| $J$ | = | total number of securities in a fund's portfolio |
| $T_j$ | = | remaining days to maturity for security $j$ |
| $w_{ij}$ | = | proportion of a fund's assets invested in security $j$ issued by issuer $i$ |
| $R_i$ | = | recovery rate on an issuer $i$'s securities in the event of a default |
| $p_i(T_j)$ | = | cumulative probability up to time $T_j$ that issuer $i$ defaults; i.e., $P(D_i < T_j)$ |
| $\widetilde{p}_i(T_j)$ | = | $1-[1-p_i(T_j)]^{360/T_j}$, the annualized counterpart of $p_i(T_j)$ |

Define expected loss-to-maturity ($ELM$) for a given fund at a given moment in time to be:

$$ELM = \sum_{i=1}^{I}\sum_{j=1}^{J} w_{ij}(1-R_i)\widetilde{p}_i(T_j) \tag{6}$$

To make Equation (6) operational, we use default probabilities provided by RMI, which are described in Section 4.1. By hand, we match the month-end portfolio holdings of prime MMFs issuer-by-issuer and maturity-by-maturity with default probabilities obtained from RMI. Given the RMI default probabilities, the annualized expected loss on each security $j$ issued by issuer $i$ is simply $(1-R_i)\widetilde{p}_i(T_j)$.[40] In other words,

[40]To make Equation (6) operational, we linearly interpolate default probabilities for every day between the maturities that RMI

the expected loss on a security from a given issuer with a given remaining maturity is the relevant default probability times the expected loss given default. *ELM* approximates the annualized expected loss on a fund's portfolio, where each security is multiplied by its portfolio weight, $w_{ij}$. Thus, from expected losses on individual portfolio securities, we can calculate the expected losses on individual prime MMFs, as in Equation (6), and on prime MMFs as a group (i.e., asset-weighted average *ELM*). We can also sum the contribution to a fund's total credit risk of securities issued by companies headquartered in a given region (e.g., $ELM\,(Europe) = \sum_{i=1}^{I} \sum_{j=1}^{J} w_{ij}(1-R_i)\widetilde{p}_i(T_j)$, where $i \in Europe$).

To calculate *ELM* we also need recovery rates, $R_i$, for each issuer. Consistent with market practice (and with Collins and Gallagher, 2016), we use a recovery rate of .40 for all private sector issuers except Japanese banks. For Japanese banks, we follow market convention and use a recovery rate of .35. Prior research suggests that the added complexity of randomizing recovery rates may not offer much additional insight. Tarashev and Zhu (2008) indicate, based on data collected from Markit for 136 entities, that the recovery rate market participants expect varies in a narrow range around 40 percent for daily data from late 2003 to early 2005. Consequently, we simply fix our recovery rates at either .35 or .4 depending on the parent company. If our chosen recovery rates reasonably approximate market views, a fund's *ELM* should be a close, leading indicator of its gross yield spread, which is indeed the case.

We are able to match default probabilities from RMI with the list of parent firms collected from the N-MFP reports for over 90% of the assets of prime MMFs (excluding, from the denominator, assets issued by the U.S. government). Here we explain our strategy for handling the 10% of assets that could not be matched to an RMI default probability and the assumptions we make about the appropriate recovery rates and default probabilities to assign to certain security types.

- The fixed income securities MMFs hold sometimes have credit enhancements, such as a guarantee, letter of credit, or other provision that guarantees return of principal and interest. Although such enhancements reduce the risk of holding a security, we do not take them into account except in cases where the guarantee is provided by the U.S. government or other sovereign nation, in which cases we set $R_i = 1$.
- One exception to the above rule is when the security is a Variable Rate Demand Note (VRDN) issued by a company that is not in the RMI database. For example, if Akron Hardware issues a VRDN

provides. Because some of the securities held by prime funds mature within 1 to 7 days (e.g., overnight repurchase agreements), we also need estimates of default probabilities for maturities of less than 1 month. We solve this problem by ruling out the possibility of instantaneous default (i.e., $\widetilde{p}_i(T_j = 0) = 0$), allowing us to linearly interpolate between that value and $\widetilde{p}_i(T_j) = 30/360$. Through this process we obtain $p_i(T_j)$ for any intervening maturity.

with a demand feature provided by Bank of America, we would apply Bank of America's probability of default before maturity (with the maturity set to the next put date). About 3% of fund assets are matched to default probabilities following this method.

- MMFs sometimes hold asset-backed securities. All else equal, asset-backed commercial paper (ABCP) have less credit risk than securities that are not asset-backed. For example, recovery rates on asset-backed securities that defaulted during the 2007-2008 crisis are generally reported to have been much higher (in the range of 80 percent or more) compared with a recovery rate of about 40 percent on unsecured Lehman Brothers debt. Thus, for ABCP, we set $R_i = 0.80$.

- Repurchase agreements (repo) are more than fully collateralized by securities that a fund's repo counterparty (the borrower) must place with a third-party custodian. All else equal, this makes repo less risky than other senior unsecured debt. Thus, we we set $R_i = 0.80$ for repo unless the repo is fully collateralized by Treasury and agency securities, in which case we treat repo as having the default risk of the U.S. government (i.e., $R_i = 1$).

- About 5% of fund holdings are issued by municipalities (for which RMI does not calculate default probabilities). These are most often in the form of VRDNs, which typically have 1-day or 7-day demand features. These securities are generally considered to be of high credit quality since the fund can tender the securities to the demand feature provider (usually a financial institution). Rather than omit these securities from our analysis, we calculate the municipal-to-government money market fund spread on each day and assume the expected loss on a municipal security on a given day equals this spread.

- To calculate an expected loss for the remaining 2% of assets that we cannot match with default probabilities, we use the average default probability of the security's closest peer group. Peer groups are comprised of securities with a similar maturity that are issued by other companies within the same sector and region.

- RMI does not publish default probabilities for sovereigns. Consequently, we simply assume that the default probabilities for U.S. Treasury and agency securities are zero at all maturities.

As a final note, Collins and Gallagher (2016) explain why the above simplifying assumptions cannot be avoided by using the yield and/or CUSIP detail available for each security on Form N-MFP to infer a fund's credit risk. The yields on individual securities are usually reported as of the date of purchase, not the date of filing. Thus, an aggregate credit risk measure based on reported security-level yields would lag behind the current market. This issue cannot generally be overcome by using the CUSIPs listed on Form N-MFP and linking those with current market yields from an outside data provider. The majority of prime MMF assets are CP and CDs, for which in many cases price quotes are not readily available from data services such as Bloomberg. Even if secondary markets were deeper, 24% of prime MMF assets do not have a CUSIPs reported on Form N-MFP as of May 2011. Even more troublesome, funds often enter their own internal

CUSIPs on the Form, introducing matching error. Therefore, current market yields are unavailable for the majority of holdings. *ELM* overcomes these deficiencies.

# B Investor Sophistication Measure (*SOPH*)

Our study separates truly institutional investors (those who act as an investment agent for a principal that is not a natural person) from truly retail investors (including those that invest through a large 401(k) plan or through an omnibus brokerage account). To achieve this, we segregate high-level investor types by whether they are predominantly institutional or retail in origin. For example, we have fund ownership by financial corporations, nonfinancial corporations, retirement plans, retail broker-directed accounts, and retail self-directed accounts. Operationally, if we determine that most investors within a given category likely have social security numbers, then we label these shareholdings as being truly retail (i.e., "unsophisticated"), a classification which closely approximates the regulatory distinction between institutional and retail accounts in the SEC's 2014 amendments. Otherwise, they are labeled as truly institutional (i.e., "sophisticated").[41] Throughout our analysis, we measure investor sophistication, *SOPH*, as the portion of truly institutional investors in a given fund or share class.

The mutual fund industry and its transfer agents use what are called social codes to categorize shareholder types. These social codes classify different types of investor accounts, such as 529 college savings plans and defined benefit retirement accounts. Different transfer agents have different classification schemes, thus, the data coming to the ICI from the transfer agents is modified in order to fit a unified classification system. The final data set tells us that the high-level category of fiduciary accounts consists of subcategories such as estates and inheritance trusts. Although we only know aggregate share class assets in the higher-level categories (e.g., retirement plans), knowledge of the underlying subcategories (e.g., 401(k) accounts) helps to guide our process of separating high-level shareholder types into either truly institutional or retail. In the end, we chose to classify shares held by these investor types as being truly institutional in nature: nonfinancial companies, financial companies, nonprofits, state and local governments, other funds, and other institutions. Within these six categories, the vast majority of assets come from financial and nonfinancial

[41] In our study, true institutional investors consist of nonfinancial corporations, financial corporations, nonprofit accounts, state/local governments, other intermediated funds, and other institutional investors. "Other institutional investors" are generally international organizations, unions, and cemeteries. The "other intermediated funds" category typically accounts for less than 1% of prime MMF assets. We classify these accounts as institutional because an unknown share comes from hedge funds.

companies, which are clearly truly institutional. Our retail categories include: retirement plans, 529 plans, fiduciary accounts, brokers dealer/omnibus accounts, and individual investor accounts. While these categorizations may not be perfect, conversations with industry experts lead us to believe that this approach, given the limitations of the categorizations, produces the lowest asset misclassification.

Since this is survey data, it has the potential for measurement error. As of 2011, the survey captures 95% of prime MMF dollar assets and 81% of share classes, by number, excluding estimates. Since transfer agents often charge funds to return information on the types of shareholders in their funds, in any given year, a fund may choose not to acquire the data. When a fund does not respond to the survey at the end of a particular year, the ICI estimates its responses by interpolating between prior and future responses or, until a future response is available, using the prior response. In the rare instances when a fund has never reported, the ICI estimates the assets belonging to each shareholder-type in each share class of the fund based on responses from the funds' peer group. Once these estimates are incorporated, 100% of dollar assets and numbers of share classes are represented.

Our study uses the full data set, including estimates. We do this for two reasons. First, after omitting estimates, we find that investor make-up changes very little over time, meaning the ICIs estimates are likely to be fairly accurate. Second, since it is mostly small funds' responses that must occasionally be estimated, omitting the estimates could result in a selection bias if small funds behave differently than large funds. Our main results are robust to excluding these estimates, however. Furthermore, we believe this to be the best data set in existence on MMF shareholders.

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