By Force of Flow: Investor Behavior and Money Market Fund Risk Allocations During the Eurozone Crisis*

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Abstract

This paper studies fund flows and risk allocation decisions among prime money market funds (MMFs) during the 2011–2012 eurozone crisis. We exploit much more granular measures of fund credit risk and investor sophistication than previously employed in the literature. Empirically, we find that funds with greater credit risks experienced larger outflows during the eurozone crisis. This effect was substantially magnified among funds held by the most sophisticated investors. A key finding in our study is that these sophisticated investors were quicker to redeem when credit risk was attributable to European investments, relative to the same level of credit risk attributable to other regions. In turn, we find that managers of riskier funds serving sophisticated investors more aggressively reduced their European risk exposure, while often adding risk exposure to other regions. Taken together, our results suggest that sophisticated investors closely monitor money fund portfolios and increase redemptions when funds are on a riskier trajectory; in addition, fund managers appear to endogenize this threat by reallocating portfolio risks in a way that addresses redemptions. Our paper provides a unique perspective on this mechanism, as we study a period when, for the first time, investors had nearly real-time portfolio information on their money fund investments.

Key words: Money market mutual funds, eurozone crisis, monitoring, sophistication, credit risk, portfolio choice, strategic complementarities
JEL: G01, G21, G23

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1 Introduction

An important question in financial policy is whether enhanced portfolio disclosure has a positive or negative effect on systemic risk. 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. And, unsophisticated investors could unwittingly benefit from the discipline imposed on fund managers by their sophisticated counterparts. Furthermore, 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). On the other hand, if fund investors have perfect information about the securities in fund portfolios, runs might be triggered earlier during a credit event, possibly increasing the frequency and duration of negative feedback loops. 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). We add a new perspective to this debate by examining investor flow behavior and portfolio risk adjustments in prime money market mutual funds (MMFs) during the 2011–2012 eurozone crisis.

For several reasons, we believe that events in MMFs during the eurozone crisis offer a rare laboratory for researchers interested in the interaction between portfolio disclosure, "run-like" behavior of investors, and manager portfolio choice during major credit shocks. Notably, perhaps more than any other large intermediated asset pool, MMFs serve investors that are both highly risk-averse and heterogeneous in their sophistication levels. We demonstrate this latter fact using a proprietary dataset of the types of shareholders in each MMF class. For example, 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.[1] Such a large heterogeneity across MMFs is not captured in prior research, and, therefore, misses some important factors in studying the mechanisms of investor runs and fund manager portfolio choice.[2] Furthermore, under a set of

[1]By contrast the vast majority (over 95%) of long-term mutual fund assets are held by households only (i.e., retail investors). See Figure 2.2 on page 30 in https://www.ici.org/pdf/2015_factbook.pdf.

[2]Notably, 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.

reforms to Rule 2a-7 (the key rule that governs MMFs) enacted by the Security and Exchange Commission's (SEC) in 2010 (the "2010 Amendments"), MMFs are required to post detailed portfolio holdings information on fund websites at month-end. Thus, the eurozone crisis is arguably the first major macroeconomic event for which MMF investors had nearly real-time transparency into fund exposures to particular issuers.

Portfolio transparency is particularly relevant to researchers and investors seeking to differentiate money funds based on portfolio credit risks. Researchers typically estimate the credit risk on a fund using its gross yield. 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.[3] We exploit portfolio holdings detail along with a dataset of issuer default probabilities in order to calculate a forward-looking, fund-level credit risk measure that moves with market conditions.[4] For example, if a fund holds a Wells Fargo certificate of deposit (CD) that has a remaining maturity of 1 month, that CD is matched with Wells Fargo's annualized 1-month cumulative default probability. This default probability is multiplied by the presumed default loss rate on Wells Fargo to generate an annualized expected loss on the security. Aggregating (on an asset-weighted basis) across all of a fund's holdings provides a forward-looking estimate of the "expected loss-to-maturity" (*ELM*) of the fund's portfolio.

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). We explore the extent to which, within regions, these movements reflected rigorous credit risk monitoring on the part of fund investors–rather than a broad withdrawal from all eurozone bank obligations–and whether funds reallocated their portfolio risks in response to these changes in credit risk. Crucially, we exploit the interaction between investor sophistication and credit risk, thus informing narratives of whether investor monitoring can lead to safer fund portfolios. Consistent with the mechanism in Cipriani et al. (2013), who argue that MMF managers can aggregate the private information of their investors, we study whether managers serving the best informed

[3]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. Instead, only if that security matures and the fund rolls over its holding of that security, would the fund's yield then rise to reflect the increased credit risk. A delay in the updating of yields is obviously problematic for investors wishing to assess portfolio risk during a credit shock. 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.

[4]This 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.

investors reallocated more aggresively away from the riskiest European issuers. At every turn, our analysis is facilitated by data that permits greater accuracy, compared to prior studies, in measuring the effects of investor type (sophistication) and risk exposure (*ELM*) on fund flows and portfolio adjustments.

With a two-part empirical identification strategy, we first identify the fund and investor characteristics contributing to a period of rapid outflows from prime MMFs that took place early-on in the eurozone crisis. In particular, 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. However, the eurozone crisis continued for 14 months after flows from MMFs slowed. This unique feature of the eurozone crisis sets the stage for the second-part of our identification strategy. Using cross-sectional snapshots of fund portfolios throughout the 15-month crisis, in the second-part of our study, we explore how MMFs altered their portfolio risk allocations over the course of the eurozone crisis in response to the profile of their investors, notably their level of sophistication, and the characteristics of their risk exposures.

Empirically, we find that credit risk is an important driver of MMF flows. Whereas, a fund's yield does not correlate significantly with subsequent fund flows during the eurozone crisis after controlling for other charcteristics, the *ELM* measure is a significant predictor of fund flows, particularly for funds populated by a larger fraction of sophisticated investors. MMFs with a greater contribution from Europe to their total credit risk were particularly exposed to outflows during the eurozone crisis. In fact, investors reacted significantly more to the same level of credit risk when it came from European holdings compared to holdings from other geographical origins. Evidence suggests that this result is not driven purely by the weight of European bank investments in a fund's portfolio, but is conditional upon the amount of credit risk associated with those investments (i.e. the contribution to a fund's *ELM* from its European bank investments) – implying a careful level of credit analysis on the part of sophisticated investors. Interestingly, using a counterfactual version of *ELM*, which measures the credit risk of funds in the future assuming funds held identical securities to those held at the onset of the crisis (i.e., we "freeze" their holdings), we find that sophisticated investors withdrew their investments particularly aggressively from funds with the largest ex-post risk exposures. In other words, at the onset of the eurozone crisis, investors redeemed more from funds that would have become riskier had managers not adjusted portfolio weights. This finding invites a crucial question: did investors overreact, such that they underestimated the ability of fund managers to adapt to the ongoing eurozone crisis, or did the actions of investors push managers to make portfolio changes?

Anticipated risks appear to have Granger-caused funds to reduce their risk exposures in order to preempt additional future withdrawals. 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. However, in the medium-to-long-run managers reallocated risk in a way that closely conformed with investor preferences. These reallocations signal that fund managers not only observed the factors driving cross-sectional variation in outflows across funds but also translated these factors into a set of portfolio instructions. These portfolio instructions differed by the sophistication of a fund's shareholders. In particular, 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. As expected, such reallocations were significantly stronger among funds serving more sophisticated investors – suggesting that investors, indeed, pushed fund managers to make larger portfolio changes. These adjusted risk preferences persist for at least 3 months after the eurozone crisis was, at least temporarily, resolved.

Generally speaking, our results suggest that sophisticated investors utilize enhanced MMF portfolio disclosure information to an extent not fully documented by prior research. During the early stages of a crisis, sophisticated investors form opinions about the credit risks associated with individual fund holdings and redeem when research signals a fund is on a perilous trajectory. Managers observe the cross-sectional behavior of investors across funds and reallocate risk in a way designed to lessen outflows. Thus, to a certain extent, sophisticated investors act as credit analysts for the funds, which also implies that they act as de facto credit analysts for less sophisticated investors that share a claim on the same portfolio of assets. 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 extant 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., 2015). 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 Amendment rules, "true" institutional investors (i.e., "sophisticated" investors in our study) must be separated from other investor types into different portfolios.

2 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. To provide stability and liquidity to investors, MMFs must adhere to the strict portfolio restrictions under Securities and Exchange Commission (SEC) Rule 2a-7.

There are three categories of money market funds. First, with assets of just under \$1.5 trillion at the end of 2014, "prime" funds are the largest category. These funds invest in a range of money market securities, including CP, bank certificates of deposit (CD), medium-term and floating-rate notes, repos, and Treasury and agency securities. 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). Second, "tax-exempt" funds, the smallest of the three categories, invest in tax-exempt securities issued by state and local governments. Third, "government" funds typically invest only in Treasury or agency securities or repos backed by Treasuries and agencies. This paper focuses on "prime" MMFs.

Unlike other mutual funds, MMFs must comply with SEC Rule 2a-7. One crucial feature of Rule 2a-7 is the use of amortized cost accounting by MMFs. Under the amortized cost pricing method, portfolio securities generally are valued at cost plus any amortization of premiums or accumulation of discounts. Beginning in 1977, all mutual funds, including MMFs, were permitted to value securities with a remaining maturity of 60 days or less at amortized cost. With the adoption of Rule 2a-7 in 1983, MMFs explicitly were allowed to use amortized cost pricing to value *all* of the securities in their portfolios. This provision, along with the ability to round their prices to the nearest penny, allows MMFs to maintain, almost always, a constant \$1 per share net asset value (NAV).[5] Specifically, MMFs can offer shares at a stable NAV provided that the mark-to-market portfolio values do not deviate by more than 50 bps from the stable NAV.

Following Lehman's bankruptcy in September 2008, prime MMFs experienced heavy outflows. About \$310 billion (representing 15% of their August 2008 assets) flowed out of prime MMFs. These outflows were especially strong on September 17 and 18 after AIG's near collapse and Reserve Primary Fund's suspension of redemptions and repricing of their shares to below \$1.00 (i.e., the Reserve Primary Fund "broke the buck"). A flight-to-quality was underway: for every dollar that left these prime MMFs, 61 cents flowed into government MMFs (ICI, 2013). At the same time, market participants feared that CP buyers might disappear, thus, spreading the crisis to the industrial and commercial banking sectors. Concerns mounted as investors and regulators recognized that MMFs were having difficulty selling assets into frozen markets in order to meet redemptions. 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. In 2010, in an effort to improve the resiliency of MMFs to withstand severe market stresses, the SEC adopted a number of substantial reforms. After 2010, many regulators called for further reforms of MMFs, citing heavy outflows from MMFs during the eurozone crisis of 2011 as evidence that MMFs remain a financial stability concern.

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.[6] Consistent with these events, prime MMFs experienced rapid outflows, amounting to roughly 10% of aggregate assets (\$113 billion), from June 8–July 5 of 2011 and government MMFs experienced heavy inflows (Figure 1). After this period, however, the influence of

[5]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 discontinue the use of the amortized cost and reprice the securities of the fund below \$0.9950 or above \$1.0050 per share.

[6]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). Also, see for example Pilon and Hilsenrath (2011), Phillips et al. (2011), Zeng (2011), and WSJ (2011).

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 euro-zone countries, thereby, committing to be be a lender of last resort.

Of great interest is whether the SEC's 2010 reforms have been effective at reducing the potential for MMF runs, partly because the SEC, citing events during the 2011 eurozone crisis, recently enacted additional requirements in an attempt to further reduce the potential for runs. In particular, the SEC's 2014 Amendments to Rule 2A-7 (which will be effective in 2016) 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.[7] Funds serving institutional investors will no longer be permitted 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, these SEC's 2014 reforms were designed to address the fact that institutional classes of MMFs have consistently experienced heavier redemptions than retail shareclasses during shocks. From this observation, it has been widely assumed that "institutional" investors are more likely to run from MMFs during

[7]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 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.

a stress event (e.g.,Kacperczyk and Schnabl, 2013; Scharfstein, 2012). This has been attributed to a variety of factors. Some regulators and academics (e.g., FSOC, 2012; IOSCO, 2012; McCabe, 2010) contend that these investors may have a greater understanding of the negative externalities that their actions pose on other investors and may, therefore, seek to redeem first. In other words, institutions may be more likely to recognize and respond to strategic complementarities. According to this view, sophisticated investors seek to exit a fund at a price that could potentially exploit other investors who do not redeem as quickly should liquidity dry up. Also, institutional shareholders may have greater capital at risk and may better monitor their funds' portfolio holdings (Schapiro, 2012). We exploit unprecedentedly detailed data, described in Section 4.2, about the types of shareholders in individual classes of MMFs to study monotoring behavior.

3 Related Literature

A number of prior studies examine the run-like behavior by investors in short-term markets during the 2008 crisis. These studies generally support the view that runs were not indiscriminate panics, but tended to occur during periods with deteriorating credit quality.[8] For example, Covitz, Liang, and Suarez (2013) study asset-backed commercial paper (ABCP) markets (not MMFs) and find that the weakest issuers had the most difficult time turning over their paper. Similarly, Kacperczyk and Schnabl (2013) observe that MMFs with higher gross yield spreads (over Treasury securities) had larger outflows during the September 2008 crisis. Duygan-Bump et al. (2013) reveal that funds with greater holdings of ABCP had larger outflows during the 2008 crisis. McCabe (2010) observes larger outflows in funds with greater portfolio risks (especially those holding Lehman debt), a history of volatile asset fluctuations, and a smaller likelihood that the sponsors would purchase or guarantee defaulted securities.

The fundamental risks of an investment and its investors' strategic considerations are not independent from one another. Schmidt et al. (2015) concentrate on the interactions between these two factors when examining flows from MMFs during the 2008 crisis. They develop a static coordination game with strategic complementarities (i.e., self-fulfilling expectations that other sophisticated investors will run) and information asymmetries. From this model they derive a set of predictions on the relationship between investor sophistication and fund flows during a negative shock, which can empirically identify strategic complemen-

[8]For classic models of bank runs, see Diamond and Dybvig, 1983 and Jacklin and Bhattacharya, 1988. For a survey of related empirical literature on bank runs from prior to the financial crisis, see Goldstein (2013).

tarities.[9] Schmidt et al. (2015) show empirical evidence that is consistent with strategic complementarities playing an important role in investor actions during the 2008 crisis. However, they observe a negative but insignificant relationship between a fund's portfolio risk (as measured by its gross yield) and subsequent outflows after controlling for investor characteristics, arguing that, within the context of the Lehman episode, cross-sectional heterogeneity in strategic complementarities across funds was likely to have been an order of magnitude larger relative to observable heterogeneity in portfolio risks.[10]

Strahan and Tanyeri (2015) study MMF portfolio managers' responses to investor redemptions during the 2008 crisis. They discover that funds that came under more liquidity stress during the crisis (i.e., that experienced heavy outflows relative to liquidity) became temporarily riskier as they were forced to sell safe and liquid assets to meet redemptions. In the long-term, however, higher-risk funds that were "burned" during the crisis responded by lowering their share of "risky" portfolio securities. Strahan and Tanyeri (2015) interpret their results as evidence that the Treasury's temporary guarantee of MMF assets did not induce moral hazard.

Using an exclusive dataset of individual funds' credit risks joined with their investor profiles, we measure the extent to which investors monitored and altered the portfolio choice of fund managers during the eurozone crisis of 2011. Although our study is most similar in design to those of Schmidt et al. (2015) and Strahan and Tanyeri (2015), it is novel in several respects. Most importantly, the availability of portfolio holdings detail, made possible by the SEC's 2010 reforms, allows us to conduct a much richer analysis of fund portfolio risks than was possible during the 2008 crisis. Furthermore, this nearly real-time transparency was available to investors at the time of the 2011 eurozone crisis. Furthermore, due to data limitations, Strahan and Tanyeri (2015) measure changes in fund manager portfolio risk allocations rather coarsely – as the change in fund assets invested in CP and bank-issued securities – a measure which cannot capture the extent to which some CP programs and certain banks were much less risky than others during the 2008 crisis. Our study of the 2011 eurozone crisis is able to discern when similar security-types carry different levels of

[9]They predict that: (1) sophisticated investors react more strongly to weak portfolio fundamentals than unsophisticated investor outflows; (2) outflows are weakly increasing in the fraction of sophisticated investors (within the same fund); (3) the larger the fraction of sophisticated investors with claims on the same portfolio (and, thus, the stronger the strategic complementarities), the greater the outflows.

[10]In other words, while a common, adverse shock to credit quality was a key trigger for run-like behavior, differences in strategic complementarities across funds had more explanatory power to explain the speed and magnitude of investor redemption behavior across funds. The authors also suggest that this insignificant relationship may be due, in part, to imprecision in their proxy for fund portfolio credit risk, given its backward-looking nature.

credit risk. Finally, to measure the influence of investor sophistication on flows, all other studies on MMFs use proxies, such as a fund's expense ratio or whether it is categorized as an "institutional" share class. As discussed in Section 4.2, we apply a proprietary dataset from the ICI of shareholder types. Finally, our study occurs after the SEC's 2010 reforms, permitting some discussion around how the reforms may have influenced run incentives and manager behavior.

Ours is not the first study to explore the portfolio choices of MMF managers during the eurozone crisis; however; other studies focus on the financing outcomes of borrowers rather the revealed preferences of portfolio managers. For example, Chernenko and Sunderam, 2014 find that, over the summer of 2011, MMFs holding more eurozone bank debt experienced greater outflows. They argue that these outfolows triggered "collateral damage", a reduction in the supply of credit available to firms outside of Europe. 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.

Unlike these studies, we analyze why MMF portfolios diverge in their allocation of credit risk across different regions as the crisis evolves. To understand this distinction, it may be helpful to provide an example. According to 5-year CDS premiums as of September 30, 2011, market participants considered debt issued by Bank of America (BOA) to be much riskier than debt issued by the French bank, BNP Paribas (BNP), with CDS of 422 bps versus 256 bps, respectively. Imagine that a fund manager holds equal portions of debt issued by these two banks, alone, in her portfolio. Hit with heavy outflows, she cuts the supply of financing offered to BOA by 10% and to BNP by 40%. Our study is interested in the fact that, in the end, BOA would now constitute a larger portion of the fund's portfolio than before the outflows. This, in turn, signals the fund manager's preference for debt issued by BOA over debt issued by BNP, despite the fact that BOA is considerably riskier and, as a result, the asset-weighted CDS premium on the fund's portfolio is now higher than it was before the reallocation (note that our ELM measure tracks CDS spreads). A fund manager who makes such a portfolio choice may be acting purely on her own volition or, alternatively, she may be responding to the demands of investors who have expressed an aversion to debt issued by French banks. We exploit predetermined variation in investor sophistication (and, in turn, monitoring costs) to try and isolate the component that is due to investor preferences.

While European issuers experienced a broad increase in credit risk during the period of interest, Figure 2 demonstrates that this increase was not at all limited to Europe. Our data allow us to see whether investors' actions (and fund managers' responses) were particularly sensitive to European credit risk, relative to similar increases in risks emanating from other regions. Given the salience of the European debt crisis, the evidence we present below is consistent with investors selectively monitoring the credit quality of their MMFs' portfolios, focusing primarily on exposures to European issuers. Our data enable us to test whether this revealed preference of investors was reflected in the future portfolio adjustments of their fund managers.

4 Data and Variables

The comprehensive data available on money market funds enables an examination of the factors motivating both fund investors and fund managers to pull back from short-term markets during the eurozone crisis of 2011. Our two-part empirical analysis uses two datsets. The first dataset captures the characteristics of individual share classes of prime MMFs, including their flows, portfolio risks, and investor profiles, during the period of rapid aggregate redemptions shown in Figure 1 above. The second dataset involves periodic cross-sectional snapshots of each fund's regional risk allocations joined with the characteristics of individual prime funds. This section describes the sources of the data used to construct these two datasets. Then, it details the calculation of our unique measures of investor sophistication and portfolio credit risk.

4.1 Data Sources

Our primary 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 2010 Amendments to Rule 2a-7 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, providing investors with nearly real-time holdings information during the 2011 eurozone crisis. We obtain this detailed monthly portfolio-level holdings information from SECs Edgar data site. With respect to each portfolio security, the fund must report the name of the issuer, details about the issue (such as 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. 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." Parent companies are often global firms that may for any number of reasons need dollar funding from MMFs and other financial market participants. 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 as from MMFs. We assign each parent firm to a particular region of the world based on the parent firm's headquarters. For example, BNP Paribas SA is headquartered in France and thus assigned a region of "Europe." Similarly, JPMorgan Chase & Co, although having worldwide operations, is assigned a region of "U.S." From this dataset, we calculate our main credit risk measures (discussed below) as well as measures of fund liquidity, $LIQUIDITY$, and fund exposures to European banks, $EXPOSURE_f(Europe\,bank)$, during the crisis.[11]

To generate our credit risk measures, described in more detail at the end of this section, 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. These probabilities are generated using the reduced form forward intensity model of Duan, Sun, and Wang (2012), published in the Journal of Econometrics. 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. 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.[12] We hand match firms in the RMI database with the list of parent companies that issue debt to MMFs from our N-MFP data.

We use a separate data source, iMoneyNet.com, to calculate individual share class and individual fund

[11] $LIQUIDITY$ is the percentage of fund assets as of 5/31/2011 maturing before the end of the shock (6/1/2011–7/5/2011) plus any investments in Treasury securities or U.S. Agency securities maturing in under 60 days. $EXPOSURE_f(Europe\,bank)$ is the percentage of fund assets invested in European banks.

[12] 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) reports out-of-sample accuracy ratios 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).

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 class' assets from 6/7/2011–7/5/2011. From iMoneyNet, we also measure each class' (log) total net assets ($ASSETS$), historical liquidity needs of its investors ($FLOWSTD$)[13], both measured as of 6/7/2011, and gross 7-day annualized yield ($GYIELD$) averaged over 6/7/2011–7/5/2011.

Finally, we obtained four essential elements from the Investment Company Institute (ICI). Most notably, we use a unique database from the 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. The information is gathered from fund transfer agents. A more detailed discussion of the construction of this dataset, and its potential biases, is available in Appendix B. Using this database we calculate our measure of investor sophistication ($SOPH$), described in the next subsection. Second, we obtain the estimated number of accounts in each share class of MMFs from ICI data. Since classes serving larger average balance investors may experience larger asset swings, we divide each class' assets by its estimated number of accounts to produce the control variable *BALANCESIZE*.[14] Third, we use ICI classifications of share classes as "institutional" or "retail" according to the ICI's reading of fund prospectuses. Finally, the ICI provided the merge key that allowed us to join the RMI/N-MFP dataset with ICI and iMoneyNet data based on EDGAR identifiers, CIK codes, and tickers.

The union of datasets from these four sources (SEC Form N-MFP, RMI, iMoneyNet, and the ICI) represents, to our knowledge, the most comprehensive and complete empirical database studied to date on MMFs in the academic literature. We believe that these data allow a uniquely rigourous analysis of fund investor and fund manager behavior during a credit shock.

[13] $FLOWSTD$ is calculated as the (log) standard deviation of daily percentage changes in fund assets over the prior 3 months. McCabe (2010) uses a similar measure to assess the level of "redemption risk" a fund faced during the 2008 crisis.

[14] One weakness of this variable is that ICI data does not look through to the underlying accounts in pooled brokerage omnibus accounts. Thus, we overestimate *BALANCESIZE* when the class is largely held by brokerage omnibus clients. To address this concern, we ensure our key flow regression results are qualitatively robust to omitting this control variable and/or replacing it with logged total net assets, $ASSETS$. We do not include both variables since we find that $ASSETS$ is highly correlated with *BALANCESIZE*, $\rho = 0.73$, and is more collinear with portfolio credit risk.

4.2 Investor Sophistication Measure (*SOPH*)

A shortcoming of publicly available datasets, 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 from the ICI, which contains information on fund ownership of each share class by investors belonging to different categories at the start of 2011. For example, we have fund ownership by financial corporations, nonfinancial corporations, retirement plans, retail broker-directed accounts, and retail self-directed accounts.

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. 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"). 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 investors (e.g., international organizations, unions, and cemeteries).[15] We assume that truly institutional investors (i.e., accounts for which natural persons do not represent the beneficial ownership interest) are more sophisticated cash managers. Throughout our analysis, we measure investor sophistication, *SOPH*, as the portion of truly institutional investors in a given fund or share class.

As we now show, prior studies that treat all institutional share classes alike have missed a good deal of the heterogeneity in the true character of the underlying investors. In Figure 3, we aggregate the assets according to the broad categorizations the ICI allows us to disclose for all prime funds (Figure 3a) and, separately, for institutional share classes of prime funds (Figure 3b). So-called "institutional" share classes are

[15] The "other intermediated funds" category typically accounts for less than 1% of prime MMF assets. We classify these accounts as institutional primarily because a portion may come from hedge funds. However, the remaining assets in these shareclasses could be a mix of retail and institutional investors. We have no way of separating assets in these two types of accounts.

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, as 25% is held by individuals through retail accounts or through their brokers. Further significant proportions are held by trusts and retirement plans for individual investors. We verify with the ICI that the underlying composition of investor types, at least in aggregate, have not changed substantially through time.

Next, in Figure 4, we observe a large cross-sectional variation in the share of true institutional investors (i.e., $SOPH$) in the capital structure of MMFs. This variation allows us to analyze how investor sophistication relates to outflows during the eurozone crisis. About 42% of share classes have very little or no institutional ownership (Figure 4a). On the other hand, 16% of institutional share classes are almost entirely owned by true institutions (Figure 4b). We would expect flows to be more variable in such money fund classes. Indeed, Figure 1b confirms that, among institutional share classes of prime MMFs, aggregate outflows (as a percentage of assets) during the crisis were heavily concentrated in classes with higher levels of $SOPH$. Classes in the mid and high terciles of investor sophistication experienced outflows of 10.3% and 13.0% relative to their total assets on May 17, 2011, respectively. It seems that for many institutional share classes, retail shareholders currently represent a significant buffer against potential run-like investor behavior of highly sophisticated cash managers.

4.3 Credit Risk Measure: Expected-Loss-to-Maturity (ELM)

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.

One option is to use CDS premiums to measure the credit risk in MMF portfolios. Numerous recent studies have sought to assess the credit risk, capital adequacy, or systemic risk associated with bank portfolios using CDS premiums (e.g., Segoviano and Goodhart, 2009; Avesani, Pascual, and Li, 2006; Huang, Zhou, and Zhu, 2009). Money market funds pose a unique problem, though, in that the bulk of their assets are very short-term, typically maturing in 3 months or less, while CDS premiums are not generally quoted at maturities of less than 6 months. Furthermore, market participants indicate that CDS are often thinly traded at 6- and 12-month horizons. Collins and Gallagher (2016) offer a way to circumvent these problems.

This subsection describes the approach used in this paper – which is taken from 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:

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

To make Equation (1) operational, we use default probabilities provided by the Risk Management Institute (RMI), which is 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.[16] Given the RMI default probabilities, the annualized expected loss on each security j issued by issuer i is simply $(1-R_i)\widetilde{p}_i(T_j)$. In other words, 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

[16]In measuring a fund's credit risk, we use the final legal maturity date (e.g., 271 days) as reported to the SEC in form N-MFP. The final legal maturity includes any "demand feature" a security may have, which allows a fund to demand its return of capital within a prespecified number of days. This is in contrast to the security's maturity date, which a fund may use to determine its weighted average maturity (*WAM*). Consider, for example, a floating rate note that matures in 271 days but has a yield that resets weekly. Consistent with the security's weekly interest rate reset, the fund may use a maturity of 7 days in calculating its *WAM*. But the fund must use the final legal maturity date of 271 days in calculating the fund's weighted average life (*WAL*).

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 (1), 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 $i \in Europe$).

Importantly, for this study, we use this setup 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 portfolio manager actions altered the risk profile of the fund since May 2011.

To make Equation (1) operational, we linearly interpolate default probabilities for every day between the maturities that RMI 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., for any random variable x whose support is in the range $[0, \infty)$, if x has a continuous cumulative probability distribution, then $P[x \leq 0] = 0$. This condition implies that $\widetilde{p}_i(T_j = 0) = 0$, 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.

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.

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). Appendix A details our strategy for handling the 10% of assets that could not be matched to an RMI default probability. Appendix A also explains the assumptions we make about the appropriate recovery rates and default probabilities to assign to certain security-types, such as those that are fully-collateralized or issued by the U.S. government.

Figure 5 shows that *ELM* evolves with market conditions, whereas the most common proxy for fund credit risk, *Yield spread*, does not. 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 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 weakens the value of this metric. Consequently, a fund's yield spread lags behind, and is less variable than a fund's true credit risk. Consistent with this expectation, 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. Most importantly, *ELM* and, especially, *CELM*, appear to closely track the market's perceived credit risk in European banks as measured by CDS premiums. In sum, Figure 5 demonstrates the value in using the expected-loss-to-maturity to measure a fund's credit risk during a crisis period.

Until now, 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 5, 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 44 bps/yr relative to their counterfactual portfolio (i.e., in the bottom table $\left[ELM^{11/30/2011} - CELM^{11/30/2011}\right] = -44.1$ at the 10th percentile). At the other extreme, some fund managers appear to have made little effort to alter their portfolio risks (i.e., in the bottom table $\left[ELM^{11/30/2011} - CELM^{11/30/2011}\right] = -1.0$ at the 90th percentile). Funds also experienced varying levels of flows during the onset of the crisis. For institutional classes, the 10th and 90th percentile of net flows during the crisis were -15.2% and 4.9%, respectively. Our study exploits this variation across funds during the crisis to better understand the factors motivating investors to redeem, and, in turn, the response of fund managers.

5 Factors determining fund flows

This study undertakes a two-part empirical identification strategy. First, we identify the fund and investor characteristics contributing to a period of rapid outflows from prime MMFs that took place early in the eurozone crisis. Second, using the characteristics identified, we turn to the response of fund managers over the remainder of the eurozone crisis. In particular, we measure the extent to which fund managers altered their portfolios according to the factors driving redemptions from their funds. This section describes the first part of the identification strategy and the results.

5.1 Empirical Strategy

We begin by evaluating the extent to which investors in MMFs responded to portfolio credit risks. A number of prior studies identify significant links between runs on short-term investments and tail risk in those investments during crises (e.g., Covitz et al., 2013; Kacperczyk and Schnabl, 2013; Duygan-Bump et al., 2013; Strahan and Tanyeri, 2015). Other studies find the links to be less evident (e.g., Schmidt et al., 2015; Chernenko and Sunderam, 2014). As argued in Section 4.3, variation in the statistical importance of credit risk across studies may be attributable to imprecise proxies for fund risk, which, in turn, is attributable to the use of amortized cost accounting in calculating yields, as well as to the lower frequency and more limited availability of portfolio holdings data before 2010. Our measure, the expected-loss-to-maturity on the fund portfolio, mitigates this measurement error.

It has been widely noted that outflows are heavier among institutional share classes of MMFs during crises (Schmidt et al., 2015), which has been interpreted as evidence that sophisticated investors engage more actively in portfolio monitoring than do unsophisticated investors. However, as discussed in Section 4.2, this paper identifies a large amount of heterogeneity in the shareholders of self-identified "institutional" share classes of MMFs, ranging from individuals within retirement plans to sophisticated financial institutions. Using a new measure of the types of investors in each share class, we can more precisely explore the links between investor sophistication and responses to credit risk.

To evaluate the factors driving outflows from MMFs, we model variation in the cross-section at the share class level as follows:

$$FLOW_c = \alpha + \beta_1 \times CREDIT\,RISK_f + \beta_2 SOPH_c + \beta_3 CREDIT\,RISK_f \times SOPH_c + \beta_4 CONTROLS + \varepsilon_c \tag{2}$$

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 annualized gross yield ($GYIELD_f$) and expected-loss-to-maturity (ELM_f) along with two measures of a fund's future credit risk ($ELM_f^{9/30/2011}$) and its counterfactual counterpart ($CELM_f^{9/30/2011}$). 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 ($SOPH_c$). In select regressions, observations are binned into low, mid, and high investor sophistication terciles based on the distribution of $SOPH_c$ across institutional share classes (e.g., $Low\,SOPH_c$). These binary variables are used in interactions. Since not all sophisticated investors are likely to have the same liquidity needs, we control for the logged average balance size ($BALANCESIZE_c$) and the logged historical asset variation ($FLOWSTD_c$) of the share class. And, since sophisticated investors in retail share classes may behave differently than those in institutional classes, we also include a dummy variable to control for whether the class is identified as "institutional" ($INST_c$) in the fund's prospectus. To address systemic risk concerns, in some specifications, we use weighted least squares, where observations are weighted by class assets ($ASSETS_c$). Since some key variables, such as a fund's credit risk, are measured at the portfolio-level, we cluster standard errors by fund.

We also explore a related hypothesis that outflows from prime MMFs during credit shocks, like the eurozone crisis, are motivated by or, at least, exacerbated by first-mover incentives. As Goldstein (2013) notes, interactions between strategic behavior and fundamentals complicates empirical identification of strategic complementarities. In their study of the 2008 crisis, Schmidt et al. (2015) offer an empirical method to identify strategic complementarities in MMFs during a credit event. They note that, if MMF investors engage in a coordination game with strategic complementarities, then, "among share classes with similar levels of investor sophistication, outflows following a negative shock to fundamentals should be larger when the share class is a claim on a fund with a higher fraction of sophisticated investors." In other words, we should observe more (less) outflows at the class-level when investors believe that their portfolio is owned by a larger (smaller) portion of sophisticated investors (i.e., investors who may to try to front-run others' redemptions during a credit shock). Following the method of Schmidt et al. (2015), we add to Equation (2) a measure of the portion of portfolio assets owned by sophisticated investors ($SOPH_f$). If sophisticated investors responded to first-mover incentives during the eurozone crisis, the estimates on $SOPH_f$ should be negative and monotonically decreasing in the sophistication-level of the class.

As a robustness check, since investors may not be able to easily determine the sophistication-level of other investors with a claim on the same fund, we try two alternative measures of sophistication at the portfolio-level. Similar to Schmidt et al. (2015), we measure portfolio-level sophistication as the portion of fund assets held in institutional classes with expense ratios in the bottom 50th ($ER_f < 23$ bps) and 25th ($ER_f < 18$ bps) percentiles. Since all investors can easily access information on expense ratios and class-types from fund prospectuses and data providers like Crane Data and iMoneyNet, this method should sidestep information asymmetries among individual investors.

5.2 Empirical Results

Results indicate an advanced ability by the the most sophisticated investors to evaluate and respond to credit risk in fund portfolios. We investigate the cross-sectional differences in (percentage) flows during the June 7, 2011-July 5, 2011 period of the eurozone crisis. Table 2 shows regression results following the specification in Equation (2) above. Columns (1) and (2) indicate that investors respond differently to different measures of a fund's credit risk. The coefficient on gross yield ($GYIELD$), the measure most commonly employed by prior MMF research, is negative but insignificant. Even after controlling for gross yield, ELM is statistically significant, but only moderate in magnitude. Coefficients suggest that share classes with a one standard deviation (6.7 bps) higher level of ELM grow their assets by 1.1-1.4 percentage points less during the period of rapid outflows from prime MMFs (6/7/2011–7/5/2011). Indeed, across all classes, the median class by ELM ($ELM = 15.4\, bps$) could expect to lose only about 3 percent of its assets due to its level of credit risk alone. However, columns (3)–(6) show that credit risk is markedly more important, both statistically and economically, when the class is owned by a larger portion of sophisticated investors. For example, a class in the highest tercile of investor sophistication, gathers flows of 3.3 percentage points less than the mean share class when its portfolio ELM is one standard deviation higher (-0.490x6.7). Put differently, within the high sophistication tercile, the median class by ELM ($ELM = 18.6\, bps$) could expect to lose 10% of its assets (-0.539×0.186) more than the average share class due to its credit risk alone. As expected, we find the strongest evidence of monitoring among the population of investors which are likely to have a comparative advantage at doing so.

If one is interested in the question of whether large-scale redemptions from MMFs could have systemic implications for financial markets: it is the total dollar flows (relative to the size of the economy) that matters. As such, in columns (5)–(7), regression results are weighted by share class assets. In these specifications, the monotonically decreasing relationship along investor sophistication terciles between net flows (as a percentage of assets) and credit risk holds. However, the R-squared rises dramatically to 46% for the full sample (column 5), and to 29% for institutional share classes only (column 6). This suggests that, although these variables may explain only about 8% of the variation in net flows across classes (column 3), they explain a substantial portion of the movement in aggregate investor dollars from prime MMFs during the eurozone crisis.

Perhaps surprisingly, the estimates in Table 3, indicate that sophisticated investors are able to anticipate the trajectory of credit risk in their fund's current portfolio up to 3 months in advance. Or, under a slightly weaker interpretation, these investors were correctly able to identify issuers who would experience the largest increase in credit risk were the European crisis to continue to escalate, as ultimately proved to be the case. In column (1), we regress class flows on contemporaneous credit risk (*ELM*) and the credit risk in the same fund's portfolio almost 3 months later ($ELM_f^{9/30/2011}$) – when the eurozone crisis grew acutely worse. Only contemporaneous credit risk obtains 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. While investors had difficulty anticipating the actions of fund managers, they were able to predict how a fund's current portfolio would perform in the near future. The estimate on the counterfactual measure of credit risk ($CELM_f^{9/30/2011}$) in Column (2) indicates that, even after controlling for contemporaneous credit risk, investors were more likely to pull back from funds that would soon become comparatively riskier barring portfolio changes. Columns (3) and (4) show that this effect is driven by sophisticated investors. Although not shown, we note that these findings hold when $CELM_f^{date}$ is calculated as of July and August of 2011. However, the effect dissipates after September 2011, even among the most sophisticated investors – perhaps, indicating a limit on how deep into the crisis sophisticated investors could forecast.

Investors were significantly more reactive to credit risk emanating from funds' European investments compared to other regions' investments. In Table 4, we regress class flows on the regional contributions to a fund's total credit risk. Columns (1) and (2) imply that, compared to a class with zero credit risk from Europe, the median class (i.e., where $ELM_f\,(Europe) = 11.4$) could expect to grow its assets 3.9-4.6 percentage points less. It is possible that this result is being driven, not by the credit risk of fund investments in Europe *per se*, but instead by the fund's aggregate exposure to European banks. In other words, it is conceivable that investors, who may have limited portfolio monitoring capacities, merely sum together a fund holdings of securities issued by European banks rather than consider the precise credit risk associated with each security type, maturity, and issuer (as we do in this study through our *ELM* measure). Columns (3) and (4) challenge this possibility. When we control for the portion of fund assets invested in European banks, $EXPOSURE_f\,(Europe\,bank)$, in column (3), the coefficient on $ELM_f\,(Europe)$ is statistically insignificant but remains negative and of similar magnitude despite the collinarity introduced. In column (4), when we restrict the sample to only those institutional classes in the highest tercile of investor sophistication, the statistical and economic significance of $ELM_f\,(Europe)$ grows substantially – indicating that sophisticated investors use more advanced measures of credit risk than those based purely on exposures.[17]

The remaining columns in Table 4 reveal that, within institutional classes, aversion to credit risk from European investments is a function of investor sophistication. From column (5) we may conclude that sophisticated investors largely disregarded the contribution of Asia/Pacific investments to a fund's credit risk. Oddly, the least sophisticated tercile of investors appear to have actually gravitated toward funds with higher $ELM_f\,(Asia/Pac)$, perhaps due to yield incentives. This may signal that less sophisticated investors were more likely to ignore the potential for contagion from Europe to the global financial system. Column (6) suggests that the most sophisticated investors were somewhat more averse to risk from the Americas, but not significantly so. In contrast, based on column (7), it appears that sophisticated investors had a strong aversion to credit risk derived from funds' European investments. Finally, the results in column (8),

[17]Using a fund's net yield as a rough measure of its overall credit risk, Chernenko and Sunderam (2014) write that their results suggest "that investors were not withdrawing from funds that generally invest in riskier assets, only from those with large exposures to Eurozone banks." We would disagree slightly with this interpretation. Our results reveal a negative and significant affect on flows from a fund's overall credit risk when measured by *ELM*. While we concede that this result is driven by the European contribution to a fund's *ELM*, we also find that the weight of European bank obligations in a fund's portfolio, which is similar to "$Fund\,euro\,share$" in Chernenko and Sunderam (2014), has no independent affect on its flows (Table 4, columns 3 and 4). Thus, we conclude that investors were indeed withdrawing from large exposures to riskier assets, but only when those assets were issued by European banks. In other words, it is the European contribution to a fund's credit risk that matters to investors, rather than purely the European bank portfolio weight. Consistent with our interpretation, Chernenko and Sunderam (2014) also find that investors responded more to a fund's non-repo (i.e., uncollateralized and, therefore, likely "riskier") eurozone bank holdings.

generated from asset-weighted least squares, suggest that the interaction of $ELM_f\,(Europe)$ and investor sophistication explains a substantial portion of the dollar outflows from prime MMFs during the crisis (*R-squared=0.32*).

If investors react more strongly to the same expected loss when it is attributable to European investments, perhaps, they also react more strongly when it is attributable to certain countries within Europe. In results not shown, we test this possibility by rerunning the specifications in columns (1), (2), (4), of Table 4, only now we replace $ELM_f\,(Europe)$ with the risk contribution of each country in Europe [e.g., $ELM_f\,(France)$]. Coefficients on these country risk variables are generally negative but insignificant, indicating that investors were significantly more averse to credit risk from the entire continent of Europe but not to that from particular European countries. Thus, it appears that investors were concerned about Eurozone default risk per se as opposed to default of, say, French banks (note, for example, that MMFs had already eliminated direct exposure to Greek issuers prior to May 2011). While this finding may appear surprising given the concentration of default risks among certain countries, a possible explanation of this result is that the country risk variables do not account for within-country variations in banks' Eurozone risk exposure, which would tend to dilute the power of the test.

Finally, we explore another, complementary explanation for outflows from prime MMFs during the eurozone crisis. In particular, we ask whether first-mover incentives nudge sophisticated investors to redeem from riskier funds. To answer this question, we call upon the theoretical model and empirical application of Schmidt et al. (2015), which predicts larger outflows from sophisticated share classes when the portfolio is owned by a larger share of sophisticated investors. Results in columns (1)–(3) of Table 5 show that the estimated coefficients on portfolio sophistication, measured by $SOPH_f$, are negative but consistently insignificant, even when interacted with the sophistication of the class (column 2) or when the sample is limited to only the most sophisticated classes of investors (column 3). Thus, the results are, at best, only weakly supportive of the first-mover hypothesis during the 2011 eurozone crisis.

It is possible that results in Table 5 are, so far, insignificant because investors are unable to perceive the sophistication level of other investors and, instead, must rely on proxies. If investors assume that more sophisticated investors flock to lower expense ratio classes, then they may be more likely to redeem when such classes hold a greater claim on the fund. Columns (4)–(7) test this possibility using the portion of a fund's assets held in classes with an expense ratio in the 50th and in the 25th percentiles ($ER_f < 23$ and $ER_f < 18$ bps, respectively). Results in column (5) are consistent with this hypothesis. Coefficients on the interaction terms between $ER_f < 23$ and the middle and high terciles of investor sophistication are negative and both statistically and economically significant. However, columns (6-7) repeat the analysis when $ER_f < 18$ is used instead of $ER_f < 23$, which corresponds with a narrower definition of sophistication. Coefficients in column (7) are small in magnitude and statistically insignificant.

We interpret these findings as evidence that credit risk, rather than first-mover advantage, was the more important factor explaining outflows during the eurozone crisis. Indeed, it is plausible that the eurozone crisis was not perceived by investors as sufficiently worrisome to drive redemptions on a scale necessary to threaten the safety and liquidity of principal. The source of complementarities in the theoretical framework of Schmidt et al. (2015) is essentially a liquidation externality: investors care about other investors' redemptions if they are likely to be large enough to force fire sales. It seems, ex-post, that the magnitude of redemptions during the eurozone crisis may have been insufficient to give liquidation externalities the same level of importance as was observed by Schmidt et al. (2015) during the 2008 Lehman episode. Importantly, the SEC's 2010 Amendments likely lowered investors' expectations of fund illiquidity. These reforms included, for the first time, minimum liquidity levels, which were specifically targeted at reducing the likelihood that other investors' redemptions would force asset sales and create losses for investors who do not redeem. In addition, the reforms included detailed portfolio disclosure requirements. These lowered monitoring costs for investors, possibly reducing information asymmetries and the benefit of inferring information from other investors' redemption decisions (e.g., Dang et al., 2010).

6 Portfolio Risk Reallocations

In the second-part of our study, we look at heterogeneity in the extent to which portfolio managers reallocated away from the eurozone and to regions presumably more insulated from the eurozone crisis, including the U.S., Canada, and, most notably, the Asia/Pacific region. In some respects, this analysis is motivated by results in Collins and Gallagher (2016), who study the types of investments that contributed most to a fund's total credit risk during the eurozone crisis. They find that, perhaps counterintuitively, the increase in average credit risk in the fall of 2011 (clearly visible in Figure 5) is not primarily attributable to funds'

European bank exposure. Instead, they contend that the European contribution to credit risk was mitigated by efforts to reduce exposures and limit maturities; however, these efforts were partly offset by a shift into Asia/Pacific banks, which grew riskier as eurozone contagion spread throughout banking system.

Although based on an analysis of the average fund's credit risk, the findings of Collins and Gallagher (2016) might indicate that some portfolio managers selectively shifted risk out of Europe even at the expense of adding some credit risk from other regions. This result may have important implications for our understanding of how investor flows influence portfolio management. For example, one possible explanation of the results in Collins and Gallagher (2016), is that some funds adjusted their portfolios in such a way as to appease investors but not necessarily produce a steady level of credit risk throughout the crisis (i.e., by substituting from risky European issuers into equally-risky issuers in other regions). We empirically validate this interpretation using snapshots of fund portfolio characteristics during the eurozone crisis.

6.1 Empirical strategy

The factors contributing to flows, identified during the first part of our study, inform the explanatory variables of interest in the second-part of our study. In particular, we test whether the same variables that drove outflows from funds translated into portfolio risk reallocations. Thus, we run the the following cross-sectional regression at the fund-level:

$$ELM^{date} - CELM^{date}\,(Region) = \alpha + \beta_1 FLOW\ FACTORS + \beta_2 OUTFLOW + \beta_3 CONTROLS + \varepsilon \tag{3}$$

The dependent variable, $ELM^{date} - CELM^{date}\,(Region)$, is the actual contribution of a region to a fund's credit risk (ELM^{date}) on a given $date$ minus the counterfactual contribution ($CELM^{date}$). 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. By taking snapshots at various moments during the eurozone crisis, we test whether such efforts are attributable to the same factors (i.e., fund credit risk, ELM, and investor sophistication, $SOPH$) that drove investors to redeem heavily from prime MMFs at the onset crisis (i.e., during 6/8/2011–7/5/2011). In some specifications, we control for the shock each fund experienced during the onset of the crisis, $OUTFLOW$, and the portion of fund assets maturing before the end of the shock, $LIQUIDITY$ (since more liquid funds may have responded differently to outflows). We also control for logged fund assets, $LOGASSETS$, since larger funds typically have greater credit research capabilities and negotiating power with issuers.

The specification in Equation 3 can be used to evaluate the short-, medium-, and long-run influences of investor discipline on portfolio management. 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. If our results are consistent with those of Strahan and Tanyeri (2015) during the 2008 crisis, we should find that funds with greater outflows become temporarily riskier as the manager feeds redemptions with the safest and most liquid assets. In our setting, this could mean that some managers actually add rather than reduce the contribution of Europe to their funds' credit risk in the short-run.

However, over time, as the eurozone crisis persists and redemptions moderate, behavior might evolve. We hypothesize that fund managers will react less to the relative size of the shock they experienced at the onset of the crisis and more to the fundamental causes of variation in outflows across prime MMFs. If this hypothesis holds true, we should observe risk reallocations that correspond with the underlying factors that drove heavy outflows. Furthermore, reallocations should be larger among those funds with the largest exposures to those underlying factors.

6.2 Empirical findings

We have established that, through their flows, sophisticated investors discipline funds with higher levels of credit risk, particularly when the investor believes the fund to be on a trajectory to become riskier. Consistent with this, during the eurozone crisis, investors expressed a stronger aversion to risk attributable to investments in Europe compared to other regions. In fact, fund investors appear to have disregarded or even pursued risk from the Asia/Pacific region. In a sense, this particular form of investor discipline, imposed at the onset of the eurozone crisis, creates a set of directions for fund managers to follow as they navigate the duration of the crisis. We evaluate the extent to which fund managers responded to these implicit directions in the short-, medium-, and long-run.

Following Equation (3), in Tables 6, 7, and 8, we regress each portfolio's regional risk adjustments, $\left[ELM^{date} - CELM^{date}\left(Region\right)\right]$, on the factors found to significantly drive investors to redeem at the onset of the eurozone crisis. First, we study portfolio managers' short-run responses to these factors using two snapshots of fund portfolios, one at the end of the heavy outflow period (7/5/2011) and one a few weeks later (9/30/2011).[18] In order to understand medium-term responses, we take additional snapshots on 11/30/2011 and 1/31/2012. Finally, we study fund managers' long-run actions by taking snapshots towards the tail-end of the eurozone crisis, on 6/30/2012, and, again, after the markets perceived the eurozone crisis to be essentially over, on 9/30/2012 and on 12/31/2012.

Results suggest that, in the very short-run, fund managers largely ignored the factors driving outflows from their funds, responding only to the need to meet redemptions. Column (2) of Table 6 indicates that, compared to a fund with zero outflows, a fund with outflows of 15% of assets (roughly the 10th percentile of net flows) increased the contribution of Europe to its credit risk by 1 basis point. While this effect seems small, the average prime fund had only about 10 bps of credit risk attributable to Europe at the start (i.e. on 6/7/2011). Regardless, the coefficient on $OUTFLOW$ suggests that funds experiencing heavy outflows had difficulty immediately eliminating riskier European investments from their portfolios. Instead, they met redemptions with their safer, more liquid assets. These observations are largely consistent with the findings of Strahan and Tanyeri (2015) immediately following the failure of Lehman in 2008. Note that this would be the rational response of a fund that expected Eurozone default risk to be sufficiently low in the very near term, in which case the optimal response to outflows would be to first sell out of the more liquid assets and wait for Eurozone holdings to mature. The disinclination to sell eurozone holdings during this period was further exacerbated by the amortized pricing for mmfs which meant that they did not have to record a loss on their Eurozone assets as long as they did not sell them.

By September, it appears that funds began actively trying to reduce the European contribution to their credit risk. The coefficients on $ELM \times SOPH$ are negative and large in scale. They are also, generally, increasing in magnitude with investor sophistication. According to column (4), funds serving highly so-

[18] September 30th may seem too distant to capture short-run effects. However, we wait until September to take another snapshot of fund portfolio risk allocations in order to keep results independent from the debt ceiling crisis, which was resolved on August 2, 2011.

phisticated investors with a one standard deviation higher *ELM* (7 bps) at the start of the crisis, reduced the European contribution to their credit risk by 2.6 bps more (i.e., $7bps \times -0.376 = 2.6bps$). This effect, however, would be nearly offset if the same fund experienced outflows of 15% at the onset of the crisis (i.e., 15%). A likely explanation is that high outflow funds, having used up more of their liquid assets, continued to wait for their longer-dated (and, therefore, riskier) European holdings to mature in order to be run off. The coefficients on $OUTFLOW$ in columns (2), (4), and (6) of the next table, Table 7, indicate that, in the short-term, a portion of the outflows were likely funded by selling or not rolling investments in the Asia/Pacific region, which were perhaps more liquid than funds' European holdings.

Results suggest that, in the medium and long-run, fund managers systematically allocated away from risk originating in certain regions and replaced it with risk from others. Moreover, these cross-sectional differences in risk-shifting behavior line up with the determinants of investor flows early in the crisis. Table 6 shows that by November 2011, fund managers appear to have gained more control over their portfolio risks and began responding to investors' concerns about credit risk from Europe. In columns (5)–(12), coefficients on $ELM \times SOPH$ are negative and significant in most specifications, despite the previously established correlation between these two variables and outflows during the crisis. These coefficients are also economically large. For example, estimates in column (5) entail that, by the end of November 2011, a fund manager with a one standard deviation higher *ELM* (7 bps) and *SOPH* in the top tercile (meaning greater than 60% sophisticated ownership) at the start of the crisis reduces her credit risk attributable to Europe by 18 bps more. Again, this is substantial compared to the average credit risk of funds at the time of 26.2 bps (see Figure 5). Importantly, the significance of $ELM \times SOPH$ proves that portfolio reallocations were, indeed, driven by the demands of fund investors, rather than purely by the risk preferences of fund managers. The R-squared of the regressions also rises markedly, peaking on September 30, 2012 at 40% – which is remarkable considering that by this point the eurozone crisis had been contained and the average fund's actual credit risk was very similar to that of its counterfactual portfolio (see Figure 5). This implies that 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.

Like their investors, fund managers did not treat all origins of credit risk equally. Results in Table 7 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 $ELM \times SOPH$ from January through September 2012. These coefficients are much smaller in magnitude that coefficients for the same period in Table 6. In fact, according to the estimates in Tables 7 and 6, the reallocation of credit risk out of Europe and into the Asia/Pacific was not one-to-one but closer to ten-to-one. Nonetheless, these statistics largely correspond with the revealed preferences of fund investors seen earlier in our study (see Table 4). As a reminder, sophisticated investors in higher risk funds were unresponsive to the contributions of Asia/Pacific investments to their funds' credit risks. At the same time, lower sophistication investors gravitated *towards* funds with more credit risk emanating from the Asia/Pacific. In other words, the Asia/Pacific region was a good bet, more so than the Americas, for funds seeking to park assets and garner yield during the eurozone crisis without a negative reaction by investors of any sophistication level.

Similarly, Table 8 shows that higher risk funds were also more likely to increase the contribution of the Americas to their credit risk over time. However, this effect appears to decline with investor sophistication. In the short- and medium-terms, higher risk funds serving more sophisticated investors were less likely to reallocate risk toward the Americas than similar funds with less sophisticated ownership. Again, these results appear fairly consistent with the revealed preferences of fund investors from Table 4. By late 2012, once the eurozone crisis was under control, even those riskier funds serving highly sophisticated investors began to allocate more credit risk toward the Americas.

To visualize these results, Figure 6 plots the asset-weighted average risk response ($\left[ELM^{date} - CELM^{date}\right]$) of prime fund managers in total and by regional contribution. The top panel shows that by the end of 2011 the average fund in the top tercile of sophisticated ownership (middle column) reduced its total credit risk more than the average fund in the bottom tercile (left column). The right-most column 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. To ensure these results are not driven purely by correlation between investor sophistication and the initial level of portfolio risk (i.e., correlation between *SOPH* and *ELM*), the bottom panel repeats this exercise on a subsample of funds with above median credit risk (*ELM*) as of May 31, 2011. Once again, funds appear to have made substantially larger risk reallocations when serving a more sophisticated clientele. And, consistent with our regression results, the right-most column shows that managers of high *SOPH* funds appear to have responded to European risk exposures 2 months later than managers of low *SOPH* funds, likely due to greater redemption pressures.

Unlike their investors, fund managers were more reactive to certain origins of risk within Europe than others. As discussed in Section 5.2, we do not find that investors redeemed significantly more when credit risk came from specific countries within Europe. Thus, fund managers had some leeway in how they reduced the contribution of Europe to their portfolio risk. Figure 7 plots the average country-specific risk response of prime funds (e.g., the asset-weighted average of $\left[ELM^{date} - CELM^{date}\left(France\right)\right]$). The figure indicates that, 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. This is not unexpected. French investments accounted for the largest portion (30% as of May 2011) of MMFs' European assets. Additionally, on average, French banks were riskier than Germany 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% MMFs' European assets as of May 2011. This reduction occurred primarily in September–December 2011, around the time of the failure of the Franco-Belgian bank, Dexia. MMFs helds \$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 the view that fund managers change their risk preferences to conform to those of their investors. At the onset of the crisis, investors, especially sophisticated cash managers, expressed a clear aversion to the European contribution to their fund's credit risk and an indifference to the contribution from other regions, notably the Asia/Pacific. While, in the short-run, managers used their liquidity to meet outflows, forcing some to become temporarily riskier, in the medium-to-long-run managers headed calls from their investors to reallocate risk. 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 risk credit risk from the Asia/Pacific and, to a lesser extent, the Americas. As expected, this reallocation from Europe to the Asia/Pacific was significantly stronger among funds serving more sophisticated investors – which proves that the risk reallocation was driven, at least in part, by the demands of fund investors. The pull back from European credit risk persists for at least 3 months after the eurozone crisis was resolved.

7 Discussion and Conclusions

Our results illustrate how sophisticated investors closely monitor fund portfolios and, by redeeming during the early stages of a crisis, are able to steer portfolio managers away from risks they deem intolerable. This finding has implications for evaluations of the stability of the MMF industry after the SEC's 2010 Amendments, and also following implementation of the 2014 Amendments, which will completely segregate into different funds "true" institutional (i.e., sophisticated) investors from retail investors

An important difference between the 2008 Lehman crisis and the 2011 eurozone crisis is the moment at which investors redeemed from MMFs. Despite the ongoing ABCP crisis, the rescue of Bear Stearns, and significant stress in repo markets, between June of 2007 and August of 2008, taxable MMF assets rose from \$2.1 trillion to \$3.0 trillion. Indeed, prime MMFs did not experience heavy outflows until Lehman's bankruptcy on September 15, 2008. This delayed reaction is quite remarkable when juxtaposed against the 2011 eurozone crisis, when investors began redeeming from prime MMFs nearly 2 months before CDS premiums rose sharply (Figures 1 and 2). This earlier response by investors – which our results suggest was facilitated by the 2010 reforms' enhanced disclosure rules – could be interpreted as both a positive and a negative development. On the one hand, it suggests sophisticated investors are now, at least, capable of shaping manager behavior and curtailing risk-taking before a crisis escalates. Earlier reactions can sometimes be stabilizing. For example, MMFs may have avoided another Lehman-like event by eliminating their exposure to Dexia before October 2011. On the other hand, the fact that investors impose discipline om fund managers by redeeming, suggests that the risk tolerances of sophisticated investors and MMF managers remain, on occasion, out of sync. Had the crisis been more sudden and had the outflows of June and July 2011 far surpassed fund liquidity, it is conceivable that short-term markets, particularly those in Europe, might have been more seriously impaired.[19]

Results in this study also inform our understanding of the extent to which enhanced portfolio disclosure interacts with investor sophistication to encourage safer portfolios during a crisis. It is clear from Table 4 that sophisticated investors look beyond simple risk indicators, such as the relative weight of European banks in a portfolio, and, instead, use holdings data to perform advanced credit analysis of individual securities. However, the fact that investors reacted only to the European contribution to their fund's credit risk and largely disregarded other sources is puzzling. It may reflect foresight on the part of sophisticated fund investors. Those funds with a greater contribution from European holdings to their overall credit risk ex-ante did, indeed, become riskier ex-post. Simply put, it could be that investors are generally comfortable with the typical risk level of prime MMFs but, in June and July of 2011, came to believe that risks from Europe were on a uniquely upward trajectory. Although European bank CDS premiums did not move sharply upward until August of 2011, the timing of the outflows from MMFs is consistent with a number of media reports and statements from public officials in June of 2011 encouraging investors to be particularly wary of the European risk in their prime MMFs (for examples, see Footnote 6). Sophisticated investors appear to have headed these early warnings.

We also show that sophisticated investors are able to alter the portfolio choice of fund managers (i.e., Tables 6–8). During the eurozone crisis, this meant that managers of funds owned by more sophisticated investors were more likely to reallocate risk exposures away from Europe, albeit at the cost of adding more limited risk exposures to other regions. To the extent that this mechanism produced safer portfolios, it follows that unsophisticated investors may free-ride on the credit research of their more sophisticated counterparts in the same fund.

In turn, this implies that the SEC's 2014 Amendments, may have two effects, one risk-reducing, the

[19] However, as it stood, eurozone banks seem to have adapted to the reduction in funding from MMFs without triggering a systemic crisis – evidenced by the fact that eurozone banks did not heavily utilize the European Central Bank's (ECB) dollar swap lines during 2011.

other unknown. As we show, during a market stress event, concentration of investor types will create a concentration of redemption-risk in funds having “true” institutional investors, with little or no risk in funds held by retail investors. That is, the buffer of slow money in institutional classes, documented in Figures 3 and 4, will be substantially reduced once the new regulations are fully implemented. This should help protect retail investors from any risks associated with the flow behavior of institutional investors. However, our findings imply an unintended consequence of separating investors: managers of retail funds may have less incentive to adjust portfolio risks during the the early-stages of a crisis.

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 the period of rapid outflows. 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. $\left[ELM^{date} - CELM^{date}\left(Europe\right)\right]$ 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	0.8	8.6
ELM_f (bps)	5.5	13.3	21.7	13.5	6.3
$ELM_f^{9/30/2011}$ (bps)	6.5	20.6	41.9	22.0	12.4
$CELM_f^{9/30/2011}$ (bps)	9.5	29.0	46.0	28.9	13.1
$ELM_f\left(Europe\right)$ (bps)	1.0	9.6	15.6	9.0	5.3
$ELM_f\left(Asia/Pac\right)$ (bps)	0.1	2.2	7.0	2.8	2.8
$ELM_f\left(Americas\right)$ (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)	8.1	199.4	3,144.0	1,989.3	9,716.3
Institutional Classes					
$FLOW_c$ (%)	-19.8	-3.5	7.7	-4.0	12.6
ELM_f (bps)	6.9	17.4	26.8	17.1	6.7
$ELM_f^{9/30/2011}$ (bps)	11.4	29.7	46.0	29.5	14.0
$CELM_f^{9/30/2011}$ (bps)	14.8	37.3	52.4	36.7	13.5
$ELM_f\left(Europe\right)$ (bps)	4.0	12.8	19.8	12.6	5.8
$ELM_f\left(Asia/Pac\right)$ (bps)	0.3	2.5	6.4	3.3	3.1
$ELM_f\left(Americas\right)$ (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)	24.7	681.3	11,634.6	4,250.6	9,956.6
Fund Portfolios					
$\left[ELM^{7/5/2011} - CELM^{7/5/2011}\right]$ (bps)	-3.5	-0.4	2.1	-0.6	2.4
$\left[ELM^{11/30/2011} - CELM^{11/30/2011}\right]$(bps)	-44.1	-14.1	-1.0	-20.6	22.6
$\left[ELM^{7/5/2011} - CELM^{7/5/2011}\left(Europe\right)\right]$ (bps)	-3.4	-0.6	1.2	-0.8	2.1
$\left[ELM^{11/30/2011} - CELM^{11/30/2011}\left(Europe\right)\right]$ (bps)	-43.2	-15.7	0.0	-21.5	23.9
$\left[ELM^{7/5/2011} - CELM^{7/5/2011}\left(Asia/Pac\right)\right]$ (bps)	-0.7	0.0	1.6	0.2	1.6
$\left[ELM^{11/30/2011} - CELM^{11/30/2011}\left(Asia/Pac\right)\right]$ (bps)	-1.8	0.7	5.0	1.2	3.9
$\left[ELM^{7/5/2011} - CELM^{7/5/2011}\left(Americas\right)\right]$ (bps)	-0.3	0.0	0.3	0.0	0.3
$\left[ELM^{11/30/2011} - CELM^{11/30/2011}\left(Americas\right)\right]$ (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)	158.0	1,461.5	20,209.0	8,241.1	18,696.0
Number of classes	1.0	2.0	6.0	3.0	2.3

Table 2: Flow regressions: the influence of credit risk and investor sophistication

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 measures include the annualized gross yield ($GYIELD_f$) and the expected-loss-to-maturity (ELM_f) on the fund's portfolio, averaged across days during the period of rapid outflows. 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 investor sophistication terciles based on the distribution of $SOPH_c$across institutional share classes (e.g., $LowSOPH_c$). These binary variables are used in interactions. We control for the logged average balance size ($BALANCESIZE_c$} and the logged historical asset variation ($FLOWSTD_c$) of the class. Class-level and fund-level (a.k.a., portfolio-level) variables are denoted by the subscript "c" and "f", respectively. When using the full sample of prime share classes, we also include a dummy variable to control for whether the class is labeled "institutional" ($INST_c$) in its prospectus. Selected results show weighted least squares estimates, where observations are weighted by class assets ($ASSETS_c$). To manage a handful of outliers, the dependent variable is winsorized at the 1st and 99th percentiles. Standard errors are clustered by fund . Estimates with a p-value below 0.10, 0.05, and 0.01 are marked with a *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Constant$	4.354	4.002	1.664	-1.856	-3.883	-7.565	1.412
	(3.762)	(3.656)	(2.061)	(3.201)	(2.519)	(5.328)	(4.089)
$GYIELD_f$	-0.174	-0.058					
	(0.146)	(0.140)					
ELM_f		-0.170*					-0.331*
		(0.099)					(0.195)
$ELM_f \times LowSOPH_c$			-0.081	0.023	0.161	0.351	
			(0.131)	(0.203)	(0.152)	(0.286)	
$ELM_f \times MidSOPH_c$			-0.350***	-0.309**	-0.241	-0.171	
			(0.113)	(0.132)	(0.149)	(0.203)	
$ELM_f \times HighSOPH_c$			-0.490***	-0.539***	-0.584**	-0.524**	
			(0.184)	(0.195)	(0.245)	(0.254)	
$SOPH_c$	-0.006	-0.004	0.073*	0.112**	0.066	0.086	-0.090**
	(0.023)	(0.023)	(0.042)	(0.053)	(0.074)	(0.087)	(0.038)
$BALANCESIZE_c$	-0.219	-0.208	-0.187	-0.476	-0.494*	-0.712*	
	(0.187)	(0.189)	(0.188)	(0.314)	(0.291)	(0.412)	
$FLOWSTD_c$	-0.479	-0.383	-0.298	-1.035	-0.313	-0.281	
	(0.472)	(0.472)	(0.481)	(0.847)	(0.686)	(1.408)	
$INST_c$	-2.786**	-2.703**	-2.665**		-1.478		
	(1.321)	(1.355)	(1.322)		(1.440)		
R-squared	0.06	0.07	0.08	0.07	0.46	0.29	0.13
DOF	184	184	184	108	184	108	108
N	501	501	501	253	501	253	253
Weight	None	None	None	None	$ASSETS_c$	$ASSETS_c$	$ASSETS_c$
Sample	Full	Full	Full	$INST_c$	Full	$INST_c$	$INST_c$

Table 3: Flow regressions: the influence of 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. Contemporaneous credit risk is measured as the expected-loss-to-maturity (ELM_f) on the fund's portfolio, averaged across days during the period of rapid outflows. We include two measures of a fund portfolio's future credit risk: $ELM_f^{9/30/2011}$ 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. 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 investor sophistication terciles based on the distribution of $SOPH_c$across institutional share classes (e.g., $LowSOPH_c$). These binary variables are used in interactions. We control for the logged average balance size ($BALANCESIZE_c$} and the logged historical asset variation ($FLOWSTD_c$) of the class. Class-level and fund-level (a.k.a., portfolio-level) variables are denoted by the subscript "c" and "f", respectively. When using the full sample of prime share classes, we also include a dummy variable to control for whether the class is labeled "institutional" ($INST_c$) in its prospectus. To manage a handful of outliers, the dependent variable is winsorized at the 1st and 99th percentiles. Standard errors are clustered by fund. Estimates with a p-value below 0.10, 0.05, and 0.01 are marked with a *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
$Constant$	3.198*	3.663*	2.263	-0.893
	(1.864)	(2.026)	(2.269)	(3.625)
ELM_f	-0.361**	0.280	0.283	0.324
	(0.181)	(0.261)	(0.263)	(0.415)
$ELM_f^{9/30/2011}$	0.092			
	(0.089)			
$CELM_f^{9/30/2011}$		-0.246*		
		(0.144)		
$CELM_f^{9/30/2011} \times LowSOPH_c$			-0.192	-0.170
			(0.152)	(0.246)
$CELM_f^{9/30/2011} \times MidSOPH_c$			-0.318**	-0.326
			(0.143)	(0.219)
$CELM_f^{9/30/2011} \times HighSOPH_c$			-0.380***	-0.428**
			(0.141)	(0.198)
$SOPH_c$	-0.008	0.002	0.078*	0.118**
	(0.024)	(0.023)	(0.040)	(0.053)
$BALANCESIZE_c$	-0.227	-0.213	-0.195	-0.510
	(0.186)	(0.191)	(0.190)	(0.313)
$FLOWSTD_c$	-0.430	-0.387	-0.303	-1.054
	(0.474)	(0.477)	(0.483)	(0.897)
$INST_c$	-2.583*	-2.713**	-2.624*	
	(1.352)	(1.368)	(1.330)	
R-squared	0.07	0.08	0.09	0.07
DOF	184	184	184	108
N	501	501	501	253
Sample	Full	Full	Full	$INST_c$

Table 4: Flow regressions: the influence of regional 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 regional contribution (Asia/Pacific, Americas, Europe) to a fund's overall expected-loss-to-maturity (ELM_f), averaged across days during the period of rapid outflows. In other words, the fund's overall credit risk is parsed into the regional source of that credit risk (based on the headquarters of the companies that issued debt to the fund). 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 investor sophistication terciles based on the distribution of $SOPH_c$across institutional share classes (e.g., $Low\,SOPH_c$). These binary variables are used in interactions. In select regressions, we control for the portion of fund assets invested in European banks, $EXPOSURE_f\,(Europe\,bank)$. We also control for the logged average balance size ($BALANCESIZE_c$} and the logged historical asset variation ($FLOWSTD_c$) of the class. Class-level and fund-level (a.k.a., portfolio-level) variables are denoted by the subscript "c" and "f", respectively. When using the full sample of prime share classes, we also include a dummy variable to control for whether the class is labeled "institutional" ($INST_c$) in its prospectus. Selected results show weighted least squares estimates, where observations are weighted by class assets ($ASSETS_c$). To manage a handful of outliers, the dependent variable is winsorized at the 1st and 99th percentiles. Standard errors are clustered by fund. Estimates with a p-value below 0.10, 0.05, and 0.01 are marked with a *, **, and ***, respectively.

Interaction region:	*None*				*Asia/Pac*	*Americas*	*Europe*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	3.005*	2.032	2.061	-34.720***	1.205	0.839	-0.346	-2.656
	(1.741)	(2.610)	(3.210)	(8.869)	(2.560)	(2.591)	(3.344)	(4.359)
$ELM_f\,(Asia/Pac)$	0.187	0.196	0.195	-0.023		0.180	0.174	0.425
	(0.191)	(0.259)	(0.259)	(0.753)		(0.271)	(0.274)	(0.374)
$ELM_f\,(Americas)$	-0.089	-0.241	-0.246	-1.254	-0.210		-0.410	-2.058
	(0.299)	(0.739)	(0.823)	(1.744)	(0.790)		(0.752)	(1.512)
$ELM_f\,(Europe)$	-0.343***	-0.404**	-0.401	-1.025**	-0.411**	-0.453***		
	(0.127)	(0.160)	(0.312)	(0.435)	(0.163)	(0.169)		
$EXPOSURE_f\,(Europe\,bank)$			-0.001	0.139				
			(0.101)	(0.153)				
$ELM_f\,(Region) \times Low\,SOPH_c$					0.631**	1.076	-0.105	0.107
					(0.285)	(1.147)	(0.314)	(0.365)
$ELM_f\,(Region) \times Mid\,SOPH_c$					-0.096	0.413	-0.501***	-0.518*
					(0.270)	(1.114)	(0.172)	(0.281)
$ELM_f\,(Region) \times High\,SOPH_c$					-0.002	-1.978	-0.656***	-0.805***
					(0.634)	(1.407)	(0.193)	(0.233)
$SOPH_c$	0.005	0.022	0.022	0.455***	0.039	0.063*	0.093*	0.069
	(0.024)	(0.026)	(0.026)	(0.099)	(0.035)	(0.037)	(0.052)	(0.065)
$BALANCESIZE_c$	-0.232	-0.642**	-0.642**	-0.424	-0.608*	-0.658**	-0.560*	-0.961**
	(0.188)	(0.321)	(0.320)	(0.659)	(0.319)	(0.317)	(0.318)	(0.395)
$FLOWSTD_c$	-0.334	-1.036	-1.035	0.011	-0.900	-0.849	-1.038	0.199
	(0.482)	(0.901)	(0.907)	(1.075)	(0.887)	(0.874)	(0.896)	(1.277)
$INST_c$	-2.633*							
	(1.350)							
R-squared	0.08	0.06	0.06	0.18	0.07	0.07	0.07	0.32
DOF	184	108	108	46	108	108	108	108
N	501	253	253	89	253	253	253	253
Weight	None	None	None	None	None	None	None	$ASSETS_c$
Sample	Full	$INST_c$	$INST_c$	$High\,SOPH_c$ $INST_c$	$INST_c$	$INST_c$	$INST_c$	$INST_c$

Table 5: Flow regressions: the influence of strategic complementarities

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. The key explanatory variable, μ_f, measures the sophistication of all investors with a claim on fund portfolio f. We measure μ_f in three ways: (1) $SOPH_f$ is the percentage of portfolio assets held by sophisticated investors (for funds with only one share class $SOPH_f = SOPH_c$); (2) $ER_f < 23$ is the portion of portfolio assets held in institutional share classes with an expense ratio below 23 bps (the median); (3) $ER_f < 18$ is the portion of portfolio assets held in institutional share classes with an expense ratio below 18 bps (the bottom quartile). The other key explanatory variable is the portion of class assets held by sophisticated investors ($SOPH_c$). In select regressions, observations are binned into low, mid, and high investor sophistication terciles based on the distribution of $SOPH_c$across institutional share classes (e.g., $Low SOPH_c$). These binary variables are used in interactions. We control for the fund portfolio's credit risk (ELM_f) as well as the logged average balance size ($BALANCESIZE_c$} of the class. 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 labeled "institutional" ($INST_c$) in their prospectuses. To manage a handful of outliers, the dependent variable is winsorized at the 1st and 99th percentiles. Standard errors are clustered by fund . Estimates with a p-value below 0.10, 0.05, and 0.01 are marked with a *, **, and ***, respectively.

$\mu_f =$	$SOPH_f$			$ER_f < 23$		$ER_f < 18$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Constant$	1.689	1.274	-32.304***	-33.514***	1.977	-34.507***	2.228
	(2.459)	(2.512)	(8.356)	(7.401)	(2.812)	(7.331)	
μ_f	-0.028		-0.049	-0.027		0.001	
	(0.035)		(0.058)	(0.034)		(0.033)	
$SOPH_c$	0.021	0.059	0.462***	0.450***	0.049	0.442***	0.004
	(0.033)	(0.047)	(0.094)	(0.097)	(0.037)	(0.099)	(0.027)
$\mu_f \times Low SOPH_c$		0.020			-0.016		-0.022
		(0.053)			(0.034)		(0.036)
$\mu_f \times Mid SOPH_c$		-0.051			-0.058**		-0.022
		(0.043)			(0.022)		(0.020)
$\mu_f \times High SOPH_c$		-0.066			-0.067*		-0.009
		(0.053)			(0.039)		(0.036)
ELM_f	-0.243*	-0.262*	-0.470***	-0.413**	-0.204	-0.433**	-0.258*
	(0.131)	(0.133)	(0.167)	(0.166)	(0.129)	(0.162)	(0.133)
$BALANCESIZE_c$	-0.659**	-0.638**	-0.284	-0.271	-0.553*	-0.324	-0.651**
	(0.300)	(0.305)	(0.689)	(0.716)	(0.320)	(0.723)	(0.318)
R-squared	0.04	0.04	0.17	0.17	0.06	0.16	0.04
DOF	108	108	46	46	108	46	108
N	253	253	89	89	253	89	253
Sample	$INST_c$	$INST_c$	$High SOPH_c$ $INST_c$	$High SOPH_c$ $INST_c$	$INST_c$	$High SOPH_c$ $INST_c$	$INST_c$

Table 6: 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 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 2 to motivate investors to redeem from funds. These include the fund's expected-loss-to-maturity (ELM), 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 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. As a robustness check, we control for logged fund assets as of 6/7/2011, $LOGASSETS$, since larger funds may have greater credit research capabilities and negotiating power with issuers. We also control for the portion of fund assets that are maturing or highly liquid during the shock (6/1/2011–7/5/2011), $LIQUIDITY$, 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.

date :	7/5/2011		9/30/2011		11/30/2011		1/31/2012		6/30/2012		9/30/2012	12/31/2012
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$ELM \times low\,SOPH$	-0.020	-0.059	-0.307***	-0.217*	-1.068***	-1.236***	-0.857***	-0.906***	-0.889***	-0.928***	-0.302***	-0.465***
	(0.017)	(0.037)	(0.094)	(0.117)	(0.182)	(0.288)	(0.112)	(0.178)	(0.129)	(0.199)	(0.064)	(0.120)
$ELM \times mid\,SOPH$	-0.019	-0.071*	-0.293***	-0.235*	-1.274***	-1.470***	-1.180***	-1.234***	-1.294***	-1.400***	-0.401***	-0.749***
	(0.024)	(0.039)	(0.105)	(0.124)	(0.235)	(0.329)	(0.171)	(0.239)	(0.192)	(0.266)	(0.065)	(0.158)
$ELM \times high\,SOPH$	-0.028	-0.087	-0.414***	-0.376**	-2.458***	-2.627***	-1.895***	-1.937***	-2.178***	-2.317***	-0.592***	-1.369***
	(0.065)	(0.081)	(0.155)	(0.172)	(0.631)	(0.724)	(0.463)	(0.536)	(0.479)	(0.556)	(0.117)	(0.392)
$SOPH$	-0.003	-0.006	0.023	0.017	0.182*	0.152	0.111	0.101	0.126*	0.109	0.027	0.084
	(0.011)	(0.011)	(0.030)	(0.032)	(0.096)	(0.100)	(0.069)	(0.072)	(0.073)	(0.074)	(0.018)	(0.053)
$OUTFLOW$		0.059**		0.145*		0.060		-0.010		0.284	0.068	0.155
		(0.028)		(0.080)		(0.301)		(0.218)		(0.201)	(0.054)	(0.106)
$LIQUIDITY$		-0.023		0.073*		-0.026		-0.000		0.033	0.019	0.002
		(0.022)		(0.038)		(0.146)		(0.103)		(0.114)	(0.026)	(0.077)
$LOGASSETS$		0.208**		0.101		1.782**		0.713		0.821	0.223	0.786**
		(0.095)		(0.282)		(0.900)		(0.571)		(0.590)	(0.154)	(0.351)
R-squared	0.01	0.11	0.09	0.11	0.18	0.19	0.32	0.31	0.35	0.35	0.40	0.29
N	184	184	184	184	184	184	184	184	184	184	184	184

Table 7: Portfolio reallocation regressions: Asia/Pacific

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, $\left[ELM^{date} - CELM^{date}(Asia/Pac)\right]$, is the actual contribution of 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). The first three explanatory variables capture the factors found in Table 2 to motivate investors to redeem from funds. These include the fund's expected-loss-to-maturity (ELM), 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 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. As a robustness check, we control for logged fund assets as of 6/7/2011, $LOGASSETS$, since larger funds may have greater credit research capabilities and negotiating power with issuers. We also control for the portion of fund assets that are maturing or highly liquid during the shock (6/1/2011–7/5/2011), $LIQUIDITY$, 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.

$date$:	7/5/2011		9/30/2011		11/30/2011		1/31/2012		6/30/2012		9/30/2012	12/31/2012
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$ELM \times low\,SOPH$	-0.029	-0.043	-0.004	-0.008	0.017	-0.008	0.103**	0.043	0.104***	0.074**	-0.002	-0.032
	(0.028)	(0.039)	(0.036)	(0.076)	(0.053)	(0.079)	(0.045)	(0.052)	(0.029)	(0.035)	(0.045)	(0.029)
$ELM \times mid\,SOPH$	-0.028	-0.036	0.050	0.067	0.098*	0.092	0.182***	0.130**	0.150***	0.127***	0.042	-0.032
	(0.024)	(0.027)	(0.046)	(0.082)	(0.051)	(0.078)	(0.044)	(0.051)	(0.037)	(0.043)	(0.059)	(0.026)
$ELM \times high\,SOPH$	-0.089	-0.093	0.124	0.165	0.189	0.205	0.300***	0.259**	0.236***	0.223***	0.222**	-0.015
	(0.071)	(0.069)	(0.140)	(0.181)	(0.172)	(0.195)	(0.096)	(0.105)	(0.049)	(0.058)	(0.102)	(0.037)
$SOPH$	0.017	0.018	0.007	0.005	-0.004	-0.007	-0.019	-0.020	-0.012	-0.014	-0.011	0.003
	(0.014)	(0.015)	(0.020)	(0.020)	(0.025)	(0.024)	(0.016)	(0.017)	(0.010)	(0.011)	(0.017)	(0.008)
$OUTFLOW$		-0.030**		-0.101**		-0.091*		-0.049		-0.035	-0.049	0.010
		(0.013)		(0.051)		(0.047)		(0.036)		(0.035)	(0.047)	(0.020)
$LIQUIDITY$		-0.016		0.009		-0.004		-0.039**		-0.011	-0.034	-0.028***
		(0.011)		(0.047)		(0.037)		(0.017)		(0.018)	(0.024)	(0.010)
$LOGASSETS$		-0.032		0.086		0.174		0.190		0.190	0.150	0.167*
		(0.101)		(0.133)		(0.145)		(0.137)		(0.122)	(0.135)	(0.092)
R-squared	0.05	0.08	0.07	0.10	0.07	0.10	0.15	0.19	0.16	0.17	0.16	0.10
N	184	184	184	184	184	184	184	184	184	184	184	184

Table 8: Portfolio reallocation regressions: Americas

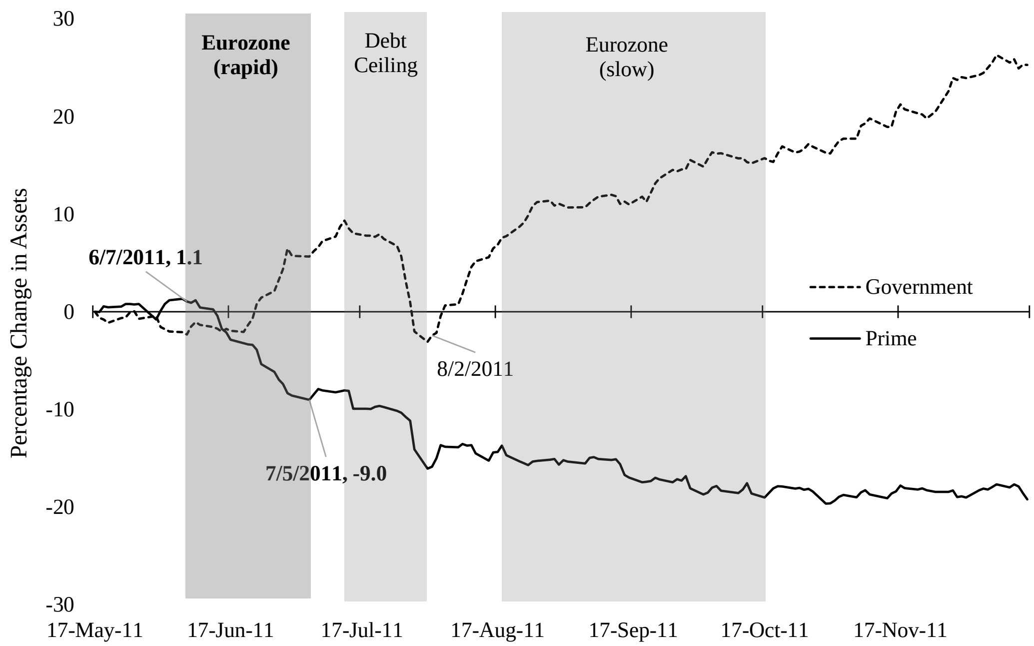
These are cross-sectional regressions at the fund portfolio-level on selected dates. All variables are measured at the fund (a.k.a. portfolio) level. The dependent variable, $\left[ELM^{date} - CELM^{date}(Americas)\right]$, is the actual contribution of the Americas to a fund's credit risk on a given 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 2 to motivate investors to redeem from funds. These include the fund's expected-loss-to-maturity (ELM), 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 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. As a robustness check, we control for logged fund assets as of 6/7/2011, $LOGASSETS$, since larger funds may have greater credit research capabilities and negotiating power with issuers. We also control for the portion of fund assets that are maturing or highly liquid during the shock (6/1/2011–7/5/2011), $LIQUIDITY$, 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.

date :	7/5/2011		9/30/2011		11/30/2011		1/31/2012		6/30/2012		9/30/2012	12/31/2012
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$ELM \times low\,SOPH$	0.010***	0.013***	0.029**	0.015	0.092***	0.105***	0.061***	0.067***	0.059***	0.068***	0.140***	0.130***
	(0.003)	(0.004)	(0.014)	(0.016)	(0.021)	(0.027)	(0.017)	(0.021)	(0.021)	(0.024)	(0.039)	(0.035)
$ELM \times mid\,SOPH$	0.012***	0.014***	0.012	-0.001	0.075***	0.086***	0.059***	0.066***	0.050**	0.061**	0.165***	0.153***
	(0.003)	(0.003)	(0.016)	(0.020)	(0.025)	(0.030)	(0.019)	(0.022)	(0.021)	(0.025)	(0.043)	(0.040)
$ELM \times high\,SOPH$	0.008	0.008	-0.055*	-0.064*	-0.003	0.006	0.017	0.026	0.008	0.024	0.194**	0.211**
	(0.005)	(0.005)	(0.030)	(0.033)	(0.061)	(0.066)	(0.035)	(0.037)	(0.038)	(0.042)	(0.090)	(0.093)
$SOPH$	0.001	0.001	0.009	0.005	0.010	0.008	0.004	0.000	0.004	-0.001	-0.021	-0.018
	(0.001)	(0.001)	(0.006)	(0.006)	(0.009)	(0.009)	(0.007)	(0.007)	(0.008)	(0.008)	(0.015)	(0.014)
$OUTFLOW$		0.006**		0.001		0.009		-0.008		-0.001	0.012	0.000
		(0.002)		(0.018)		(0.020)		(0.015)		(0.023)	(0.033)	(0.026)
$LIQUIDITY$		0.003		0.006		0.027**		0.028***		0.028***	0.058***	0.052**
		(0.002)		(0.010)		(0.011)		(0.010)		(0.010)	(0.020)	(0.022)
$LOGASSETS$		0.006		0.128*		0.120		0.213***		0.194***	0.295***	0.239**
		(0.011)		(0.072)		(0.089)		(0.061)		(0.071)	(0.112)	(0.105)
R-squared	0.08	0.12	0.03	0.05	0.08	0.10	0.08	0.15	0.05	0.09	0.15	0.17
N	184	184	184	184	184	184	184	184	184	184	184	184

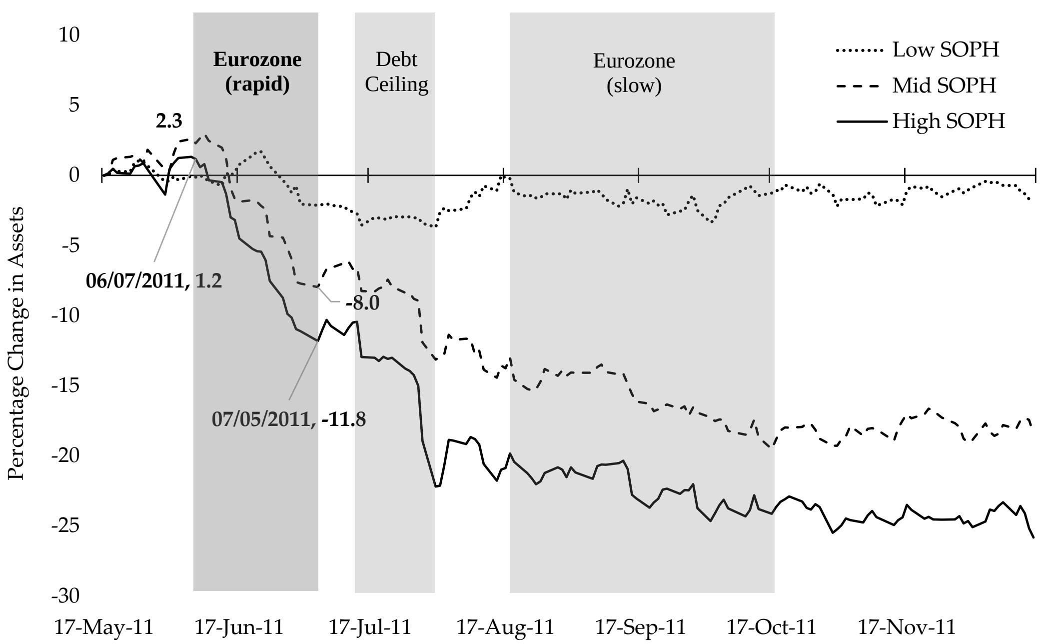
Figure 1: Aggregate MMF institutional share class flows

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 top panel shows flows split by investment objective (i.e., prime versus government-only MMFs). The bottom panel shows flows for prime MMFs only, split by the portion of class assets owned by sophisticated investors. Classes are binned into terciles based sophisticated ownership.

(a) Prime vs. government-only MMFs



(b) Prime MMFs, split by sophisticated ownership tercile



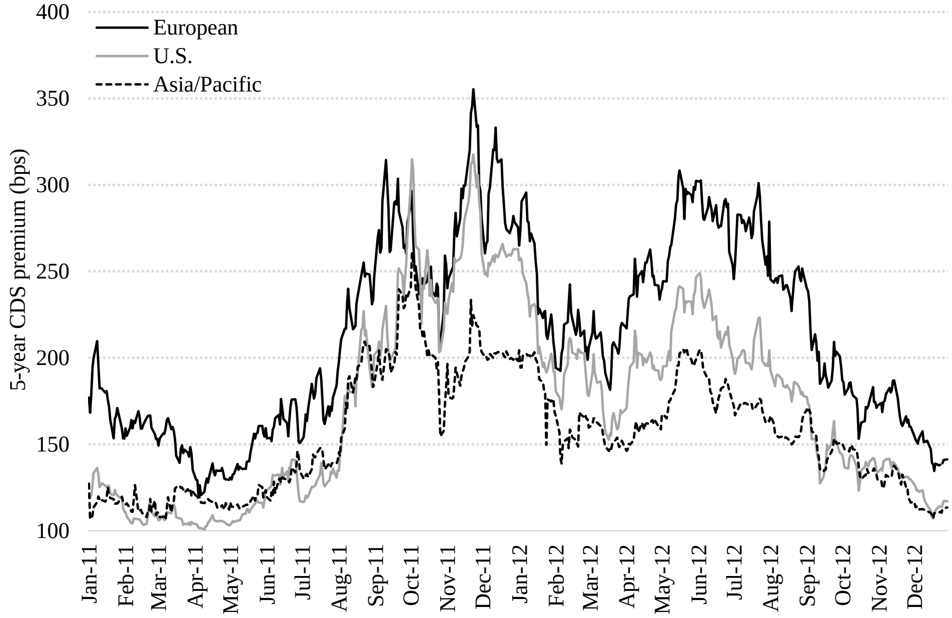


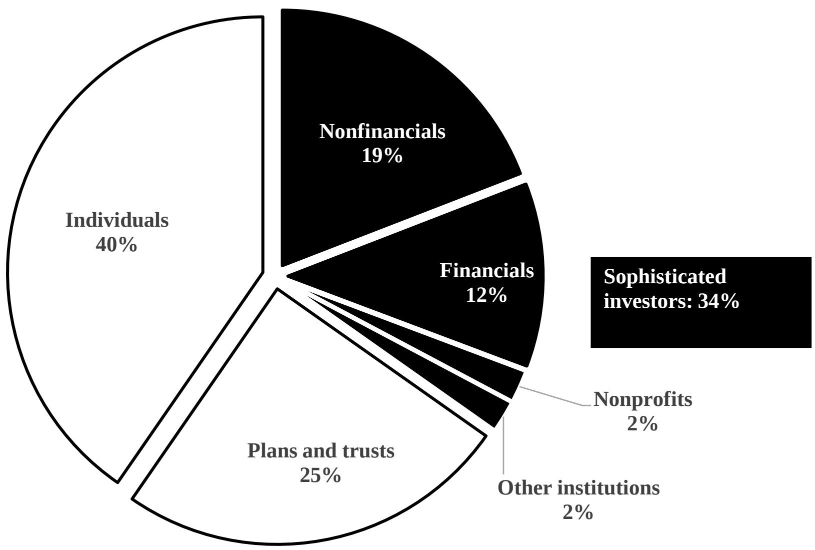
Figure 2: 5-Year CDS premiums for banks by region, 2011

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: Prime MMF shareholder-types

This figure shows the portion of aggregate assets of prime MMFs owned by different types of investors. For simplicity, in some cases, investor categories are grouped together: "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) All Share Classes



(b) Institutional Share Classes

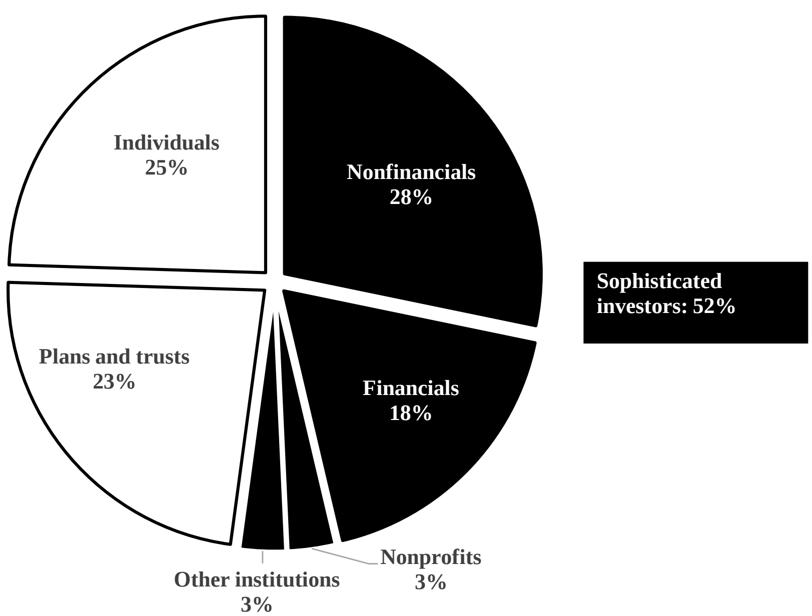
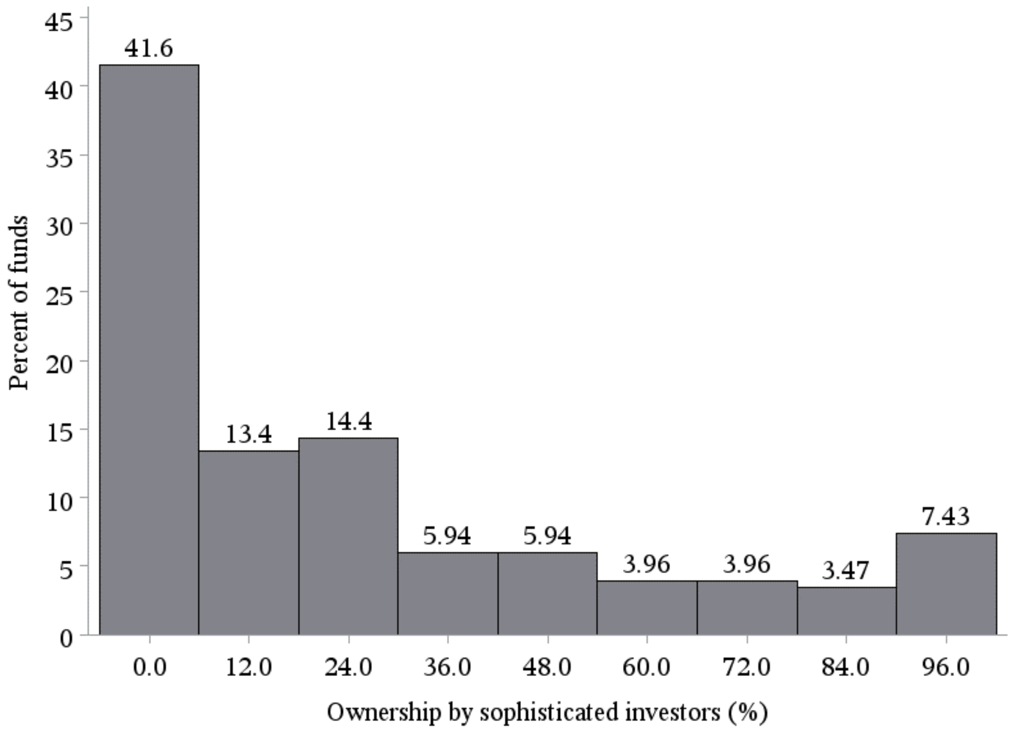


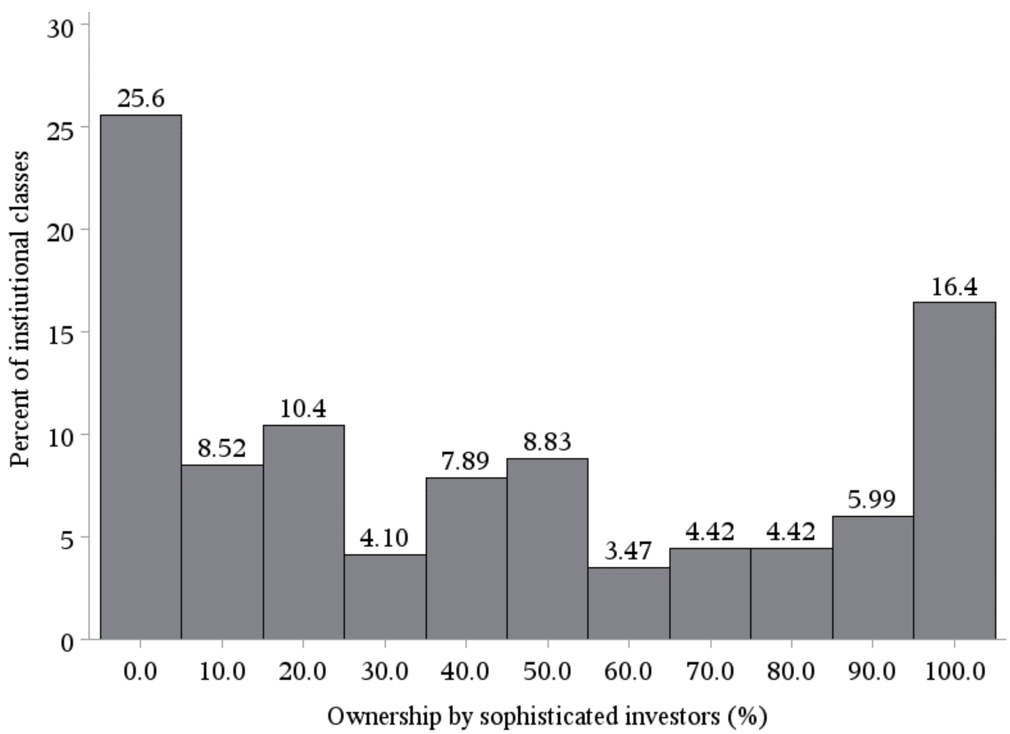
Figure 4: The distribution of prime MMFs' ownership by sophisticated investors

This figure shows the distribution of investor sophistication (*SOPH*) across prime MMFs. For example, 7.43% of prime funds and 16.4% of institutional share classes of prime funds have nearly 100% of their assets owned by sophisticated investors.

(a) All Share Classes (Fund-level)



(b) Institutional Share Classes



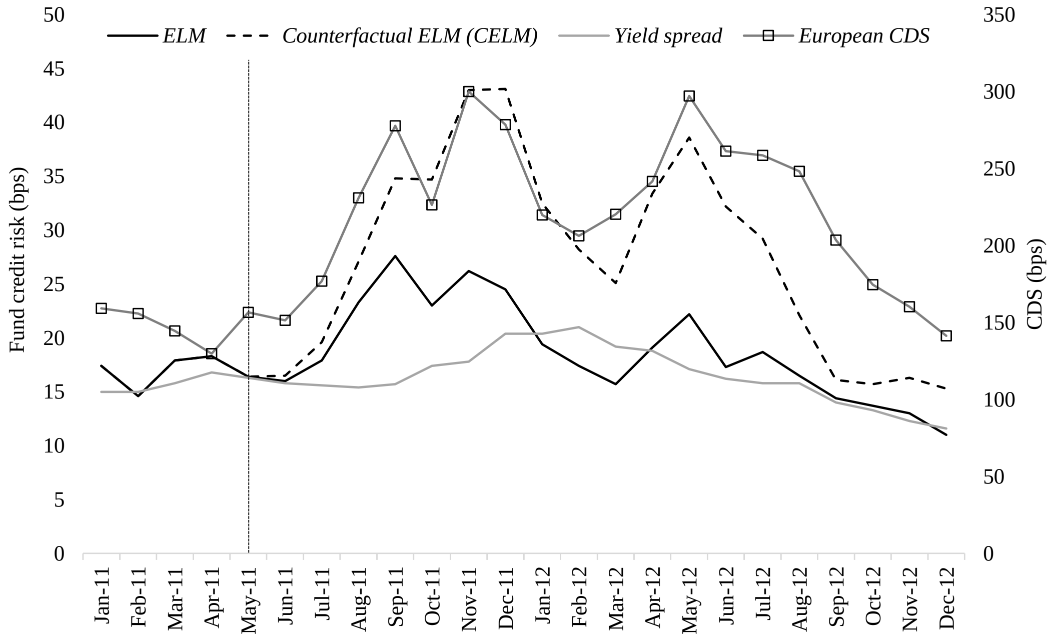


Figure 5: Credit risk measures over time

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 expected-loss-to-maturity had prime funds continued to hold their end-May portfolio allocations ($CELM$), and the annualized gross yield on each prime MMF minus the gross yield on the average government MMF ($Yield\,spread$).

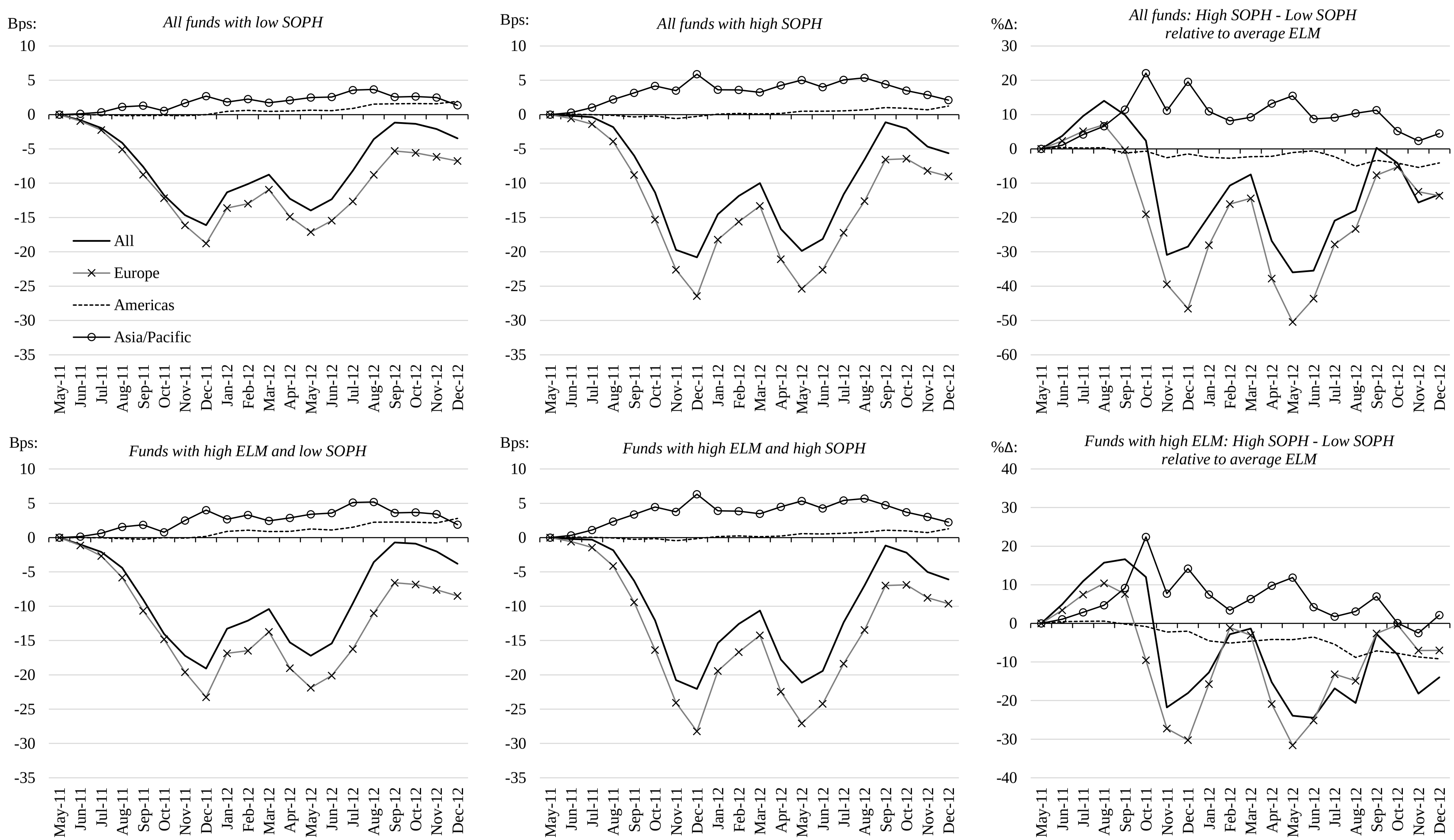


Figure 6: Regional credit risk reallocations, $\left[ELM^{date} - CELM^{date}(Region)\right]$

This figure shows the asset-weighted average $\left[ELM^{date} - CELM^{date}(Region)\right]$ across 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). The top panels include all prime funds. The bottom panels include only those prime funds with above median ELM on May 31, 2011 (i.e., "riskier" funds). The left panels include only those funds with ownership by sophisticated investors ($SOPH$) in the bottom tercile. The middle panels include only those funds with $SOPH$ in the top tercile. The right panels 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. The resulting difference is normalized by the average fund ELM as of May 31, 2011 (17.5bps).

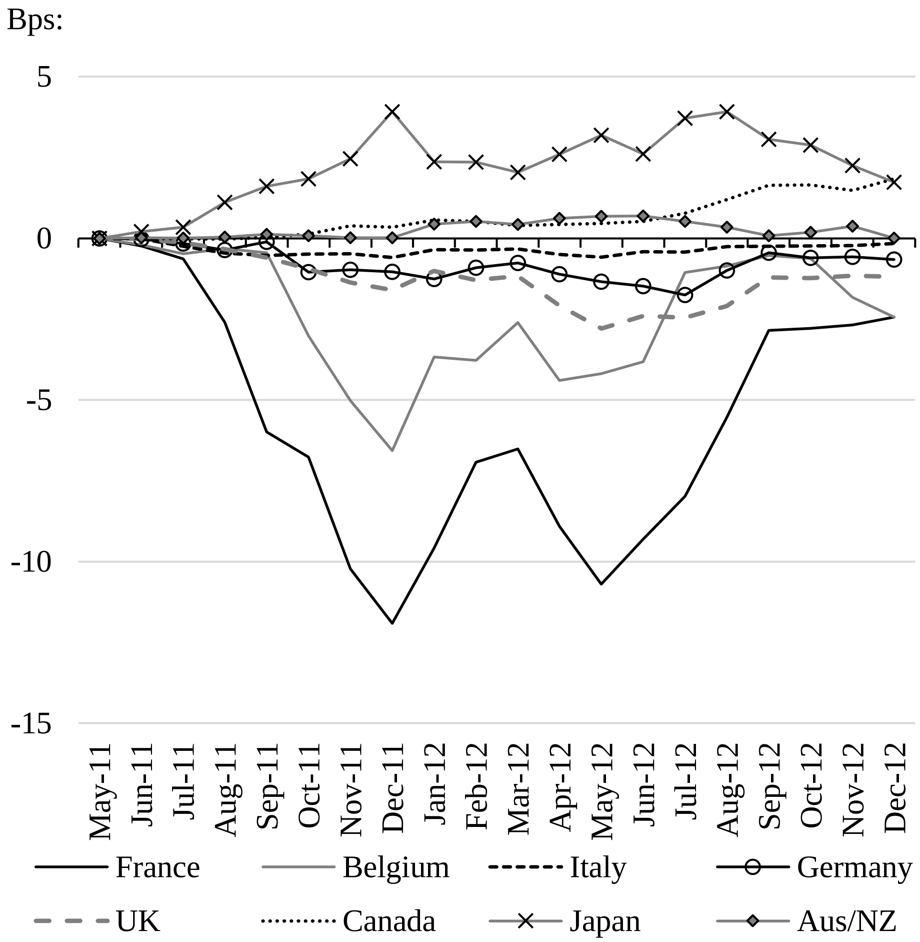


Figure 7: Country credit risk reallocations, $\left[ELM^{date} - CELM^{date}(Country)\right]$

This figure shows the asset-weighted average $\left[ELM^{date} - CELM^{date}(Country)\right]$ 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 Assumptions Used to Calculate *ELM*

We must make a number of assumptions when calculating *ELM*. In general, the assumptions we use are consistent with those in Collins and Gallagher (2016). This appendix details our treatment of different security types as well as of securities issued by parents for which there is no default probability in RMI data (representing roughly 10% of fund assets).

- 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 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 Description of the Shareholder Dataset

This appendix provides further information on the ICI's shareholder dataset used in this study.

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 dataset tells us that the high-level category of fiduciary accounts consists of subcategories such as estates and inheritance trusts. Although we only know aggregate shareclass 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: non-financial 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 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 dataset, including estimates. We do this for a 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. In sum, we believe this to be the best dataset in existence on MMF shareholders.

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