

# Runs on Money Market Mutual Funds<sup>†</sup>

Russ Wermers  
Department of Finance  
Smith School of Business  
University of Maryland  
College Park, MD 20742-1815  
[wermers@umd.edu](mailto:wermers@umd.edu)

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## **Runs on Money Market Mutual Funds**

### **Abstract**

This paper studies daily investor flows to and from each money market mutual fund during the period prior to and including the money fund crisis of September and October 2008. We focus on the determinants of flows in the prime money fund category to shed light on the covariates of money fund runs, since this category was, by far, the most heavily impacted by the money fund crisis. We find that institutional investors moved their money simultaneously (or with a one-day delay) into or out of prime money funds, especially within the same fund complex. Specifically, during September and October 2008, flows in a given prime institutional fund are strongly correlated with same-day flows in all other same-complex prime institutional funds, indicating that the money fund crisis was especially focused on certain types of fund complexes. To illustrate, a daily outflow of 1% of total assets from other same-complex prime institutional money funds predicts, on average, a 0.92% outflow in a given prime institutional money fund during the same day; by contrast, prime fund flows are not correlated with same-day, different complex prime fund flows. We also find that investors are sensitive to the liquidity of money fund holdings: correlated flow patterns are less likely to occur in money funds with greater levels of securities with very short maturity (seven days or less). Our analysis also suggests that prime *retail* money funds also exhibited persistent outflows, and that (similar to institutional shareclasses) retail “runs” were focused on certain complexes, as well as on funds holding lower levels of short-maturity securities.

## I. Introduction

Bank runs have long been a subject of academic and regulatory interest. There are two primary and competing theories of how bank runs propagate. One theory (Diamond and Dybvig, 1983) postulates that bank runs, driven by depositors who fear the actions of other investors, can occur as an equilibrium phenomenon—even in banks that would remain fully solvent if no investors withdrew. Once the (self-fulfilling) run starts, all bank customers seek the return of their deposits as quickly as possible, since each customer’s withdrawal imposes a negative externality on all other investors (due to the reduction in bank liquidity that results).

Another theory is that runs may be rationally driven by information: customers seek to discern which banks are solvent and which are not (Jacklin and Bhattacharya, 1988). According to this theory, only insolvent banks (or banks thought to be insolvent on the basis of public information) face runs. These two theories have quite different implications for the potential for bank runs as well as regulatory responses to this threat.

In the eyes of some investors, money market funds have become a substitute for bank deposits. Retail investors often keep much of their liquid assets in money market funds to pay bills, purchase consumer goods, or settle securities trades, and to transfer money back and forth to these funds as liquidity is needed on (if necessary) a daily basis.<sup>1</sup> Although investments in money market funds are not guaranteed (as fund prospectuses and marketing literature clearly state), some investors seem to believe that implicit guarantees exist, either from the management company or from the U.S. Government. In addition, money funds have become a major short-term financing alternative for corporations, who may be able to obtain cheaper financing by

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<sup>1</sup> Indeed, some commentators have referred to money market mutual funds as “shadow banks,” although without any explicit guarantee of capital safety.

selling their short-term debt to these funds, compared to bank loans or other financing methods. And, financial institutions, including regulated banks, often invest in money market mutual funds to gain a higher yield with their excess overnight liquidity.

In this paper, we study a run on money market mutual funds that developed in September 2008. Money market funds, as we explain, have certain characteristics in common with banks, but also have significant differences. Owing to these similarities and differences, we believe that the episode of September 2008 presents a unique opportunity to add perspective to the literature on bank runs. This money market run is unique, relative to commercial bank runs, because data is available on the types of investors who withdrew money each day, as well as the characteristics of fund and management companies that suffered runs. Our main goal in this paper is to explore the determinants of this episode, such as the institutional characteristics of different money market funds, their portfolio holdings, and their investors, with a view to shedding light on the mechanisms by which runs propagate.

Following the failure of Lehman Brothers on September 14, 2008, a single money market fund that held Lehman debt securities, the Reserve Primary Fund, “broke the buck,” that is, marked the net asset value of the fund below the \$1 per share that investors normally expect. This was the first time that a major money market fund had failed to return principal of \$1.00 per share to investors on demand.<sup>2</sup> The event sparked vast outflows from the Reserve Primary Fund. Within a few days, the panic spread to other money funds. Prime money market funds—those that hold investment grade money market instruments such as commercial paper, repurchase agreements, bank certificates of deposit and Eurodollar deposits—suffered outflows totaling

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<sup>2</sup> In 1994, a single small money market fund failed. However, that money market fund was closely held by a group of banks. Consequently, its failure had little implication for other money market funds and their investors. The incidents of September 2008 were different: the Reserve Primary Fund was a very large fund, and its investors included a broad range of retail and institutional customers.

roughly \$300 billion, even though many of these funds held little or no Lehman Brothers debt. In contrast, government-only money market funds—those that invest primarily or exclusively in Treasury and Agency securities—experienced vast inflows.

On September 19, 2008, the U.S. Treasury announced an optional program to “insure the holdings of any publicly offered eligible money market mutual fund—both retail and institutional—that pays a fee to participate in the program.” This insurance was available to money funds with a shadow NAV of at least \$0.995—ensuring that the NAV would be restored to \$1—only for assets invested prior to September 19, 2008. On the same day, the Federal Reserve instituted programs to help provide liquidity to money market funds and the money markets more generally. Within a few weeks, large “panic-driven” outflows from prime money market funds diminished and, ultimately, ceased.

We study the daily flows in money market mutual funds during this crisis period in an effort to determine whether they were sparked by a widespread withdrawal of all investors (as modeled by Diamond and Dybvig), or whether withdrawals were more information-based (as in Jacklin and Bhattacharya). For instance, we wish to determine who initiated runs (institutional vs. individual investors), as well as the timing of their withdrawals (e.g., whether they developed over several days). Further, we wish to observe the reaction of the fund management companies, to determine how they met the liquidations. Finally, we wish to determine the features of funds that were susceptible to large-scale withdrawals, using characteristics such as reported net-asset-value or credit quality and maturity of holdings.

We begin by analyzing money funds at the category level. We study two broad categories: Prime Institutional money funds and Prime Retail money funds. If investors as a group moved away from prime funds during the crisis, regardless of the quality of their portfolio

holdings or the perceived backing by the fund's management company, then it might be natural to see outflows at the category level (in other words, investors do not simply withdraw from one group of prime money market funds to reinvest in another group of prime money market funds). Using a VAR approach, we find low predictability of daily flows (as a percentage of category assets) from both prime institutional and prime retail categories before the crisis (December 31, 2007 to August 1, 2008). To some extent, retail prime daily flows are predictable from lagged flows and CRSP NYSE/AMEX/Nasdaq index returns, but the economic magnitude of the predictability seems low.

However, when we re-estimate our VAR system over the crisis period—the month of September 2008—we find much different results. Specifically, we find a large increase in the predictability of daily flows, both for prime institutional and prime retail categories. For the prime institutional category, one- and two-day lagged prime institutional fraction flows strongly predict daily flows. For instance, a 10% outflow from the prime institutional category predicts a 6.9% outflow from the category on the following day. This level of positive autocorrelation is quite large, and does not appear to be related to investor sentiment about current or lagged CRSP stock index returns—which exhibit insignificant predictive coefficients. Prime retail daily flows during the crisis exhibit similar one-day persistence in flows, although these flows appear to be somewhat related to prior-day institutional prime flows.

We next explore whether redemptions from money funds during the crisis were correlated across funds within a fund complex.<sup>3</sup> Such correlations might arise either from Diamond-Dybvig concerns or for more information-based reasons. For example, a fund might

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<sup>3</sup> A mutual fund “complex” is a family of mutual funds sponsored by a single provider who typically also manages the group of funds. For example, some of the largest mutual fund complexes are those operated by Fidelity, Vanguard, Federated, and JP Morgan Chase.

impose externalities to other same-complex funds if investors believe that the fund's management company implicitly guarantees a NAV per share of \$1.00 for its money market funds, but does not have unlimited ("deep pockets") resources. In that case, once redemptions occur at one fund in a complex, investors in the complex's other money market funds might seek to also redeem. Information-based redemptions might be sparked if money market funds in the same complex are known (or thought) to hold the same securities (e.g., if all funds in the same complex had held Lehman Brothers securities). In that case, if one fund in the complex "breaks the buck" owing to the default on a particular security (e.g., Lehman Brothers commercial paper), investors may infer that other same-complex funds will suffer the same fate (or worse, if outflows from the first fund further devalue the commonly-held Lehman securities).

In our complex-level analysis, we do not find strong evidence of persistent flows. Indeed, we find that same-day overall category level flows (i.e., flows to/from all prime institutional funds across all complexes, excluding the complex being predicted) strongly and positively predict, but that lagged same complex prime institutional flows weakly *negatively* predict complex-level prime institutional flows. Taken at face value, these results imply that investors may not view all funds within the complex equally due to the shared implicit promise of the complex to support its funds. Instead, we seem to find evidence of a "clientel  effect," where certain funds in the complex are more likely to be exposed to autocorrelated outflows.

However, when we reexamine flows, using an estimate of exchanges between government and prime money funds (i.e., flows between these categories within a single complex), we find much more compelling evidence of the risk of runs on money funds at the complex level during the crisis. Specifically, we find that lagged exchanges significantly predict current exchanges better than contemporaneous other-complex flows to prime funds, as we

would expect in a run that occurs at the complex level. Further, complexes with more liquid assets, as represented by the percentage of their prime portfolios that are invested in securities maturing within seven days, exhibit a lower tendency to develop severe autocorrelated withdrawals—lagged exchanges show a lower economic impact on the predictability of current exchanges for such complexes.

Our complex-level findings imply that runs from prime to government money funds occur contemporaneously within a complex/category at the individual fund level. Following this logic, we would expect the strongest potential for runs to occur at the individual fund level, since investors are directly impacted by the actions of other same-fund investors. While these investors may also be impacted by investors in other same-complex funds, we might expect this impact to be smaller since their investments are not legally pooled with that of investors in other funds.

The fund-level results strongly indicate that investors sell prime institutional money funds together at the complex level. Specifically, a sell-off of 10% of the assets of other prime institutional funds within the same complex is associated with a 9.2% same-day sell-off of assets of a given prime institutional fund. Contrary to our earlier results at the complex level, which could only examine lagged same-category, same-complex flows, we find that highly contemporaneously correlated flows do apparently occur in prime institutional funds at the complex level. This indicates that investors infer that there are externalities between prime funds at the complex level. There is slightly stronger economic evidence of runs in outflows, but the statistical precision of this evidence is somewhat weak.

We further investigate whether the quality of fund portfolio holdings significantly influence investor withdrawals within a complex for a given category. Specifically, we interact the percentage holdings of U.S. Treasuries by a prime money fund with several of our predictive



variables to examine whether funds holding more safe debt exhibit a lower predictability in flows. We find only weak evidence of an impact of Treasury holdings on the predictors of flows. However, our prime money funds may not have sufficient Treasury holdings to strongly test this hypothesis.

Finally, we examine whether individual prime retail funds have predictable daily fraction inflows. Here, we find strong, negative first-order autocorrelation in FRACFLOW, consistent with investors parking their money from securities sales (or in anticipation of security purchases) for one day before moving the money. The evidence for runs in prime retail funds, therefore, is much weaker than the evidence in prime institutional funds.

To summarize, our results indicate that withdrawals occurred unevenly across funds and fund complexes during the September 2008 crisis. Funds that cater to institutional investors, which are the most sophisticated and informed investors, were hardest hit. Certain fund complexes were harder hit than others, suggesting that the events following September 15, 2008 were not purely panic driven. Instead, investors were, to some extent, discerning. Thus, during September 2008, investor flows from money market funds seem to have been driven both by externalities (a la Diamond-Dybvig) and information (a la Jacklin and Bhattacharya).<sup>4</sup>

Our paper proceeds as follows. Section II provides a background on money market mutual funds, and reviews the events of the crisis. In section III, we provide a short literature

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<sup>4</sup> This seems consistent with steps taken by regulators and fund managers in an effort to stem the crisis. For example, on the regulatory side, the Treasury's approach of guaranteeing money market funds makes sense to the extent that investor flows were driven by externalities: if investors simply panicked, a federal government guarantee would likely dampen fears. The programs the Federal Reserve put in place to provide liquidity would also help, allowing money market funds that were otherwise stable to meet vast redemptions by nervous investors. On the fund manager side, many funds addressed information issues by publishing fund portfolio holdings more often and in greater detail than required by the SEC. Thus, in many cases, investors were able to tell on a daily basis what securities their money market funds were holding.

review on bank runs. Section IV discusses our dataset and methodology, while section V presents our empirical results. We conclude in section VI.

## II. Background

Banks and money market funds are similar in some respects (e.g., the presumption of dollar-in-dollar-out) but quite different in others (e.g. vastly different regulatory structures). Thus, in our view, money funds provide a unique laboratory to study the mechanics of runs. In addition, money fund data provide a unique opportunity, since we can observe daily flows from investor types in each money market fund—institutional versus retail, as well as some information on the particular type of institutional or retail investor (e.g. defined benefit pension plans versus bank trust accounts). Further, we can observe characteristics of the management company running the money fund.

In principle, money market funds are much like other mutual funds. For instance, like other mutual funds, they are regulated under Investment Company Act (ICA). However, they operate under a special provision of the ICA, Rule 2a-7, which lets them value assets at “amortized cost,” that is, the purchase price of securities minus computed premium or discount amortized over the securities’ remaining life. This provision of the ICA allows money funds to maintain essentially a constant \$1.00 per share net asset value. For investors, this has many advantages. It allows retail investors to use their money market funds for transactions purposes, such as paying bills and settling securities trades. They are also able to tie their money market funds to bank products, such as checking accounts, ATMs, and credit cards. A constant \$1.00 NAV allows many kinds of institutions (e.g. state and local governments) to hold their liquid balances in money market funds. For both retail and institutional investors, a constant \$1.00

NAV vastly simplifies tax accounting by eliminating the need to track the capital gains and losses that arise with a long-term mutual fund.

However, valuing money funds at amortized cost creates the potential for a run, because the fund's price per share (which is based on a book value) can diverge from the market value of the fund's underlying portfolio securities. Like banks, money market funds seek to offer highly liquid liabilities, while holding less liquid assets. To be sure, this maturity mis-match is much less extreme for money market funds, but still raises the possibility that a money market fund might become liquidity-constrained, unable to meet redemption requests despite holding highly liquid assets.<sup>5</sup>

These risks have been controlled differently in banks and money funds. Banks are required to maintain capital, and depositors are insured, but banks may generally hold highly illiquid assets (e.g. 30-year mortgages), hold assets that may be lower-rated or difficult to rate or price, and may employ leverage. Money market funds, in contrast, under Rule 2a-7, must hold only highly liquid, high quality assets, and generally may not use leverage.<sup>6</sup> The Securities and Exchange Commission (SEC) and others have long recognized the potential exposure of money market funds; the SEC has recently tightened the provisions under which money market funds operate, and are currently considering further regulations to control this potential exposure.<sup>7</sup>

Prior to September 2008, Rule 2a-7 had worked well to control risks. From the point at which Rule 2a-7 was first adopted by the SEC in 1983 to September 2008, a period during which

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<sup>5</sup> This issue can also arise with long-term mutual funds. Mutual funds are required by law to offer investors the ability to redeem their shares on a daily basis at the fund's net asset value per share. It is at least theoretically possible that requests for redemptions could outstrip a fund's ability to liquidate its underlying portfolio in order to satisfy those redemptions. This possibility is more meaningful for bond mutual funds, such as during a financial crisis if liquidity were to dry up in certain fixed income instruments (e.g., high yield bonds).

<sup>6</sup> Over the years, the provisions of Rule 2a-7 have been tightened to further reduce systemic risks (see Collins and Mack).

<sup>7</sup> See "SEC Proposes Rule Amendments to Strengthen Regulatory Framework for Money Market Funds," at <http://www.sec.gov/news/press/2009/2009-142.htm>.

hundreds of banks and thrifts failed, only a single money market fund had “broken the buck” (i.e. failed to return \$1.00 per share). Even that event went largely unnoticed because the fund was small and held by a limited number of institutional investors (primarily banks).<sup>8</sup> However, this changed on September 15, 2008, when the Reserve Primary Fund “broke the buck.”

Numerous traumatic economic events had occurred since August 2007, putting considerable pressure on money market funds as investors sought liquidity. From August 2007 to August 2008, several unregulated liquidity pools used by institutional investors failed, both in the US and elsewhere. This led to a vast inflow of dollars to money market funds, as these institutional investors turned to the tighter regulatory provisions required of money market funds under Rule 2a-7. Also, the federal government declined to assist a reeling Lehman Brothers, which failed on September 15, 2008. On September 16, 2008, one large money market fund, the Reserve Primary Fund, which held about \$750 million in commercial paper issued by Lehman Brothers, disclosed that it had broken the buck. Immediately, prime money market funds began to see vast outflows, which totaled over \$300 billion within a few days. With credit markets seizing up, prime money market funds struggled to sell securities to meet these redemptions.

On Friday, September 19, 2008, the U.S. Treasury offered a guarantee to money funds in exchange for an “insurance premium” payment. On that same day, the Federal Reserve announced The Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility to provide funding to U.S. depository institutions and bank holding companies to finance purchases of high-quality asset-backed commercial paper (ABCP) from money market mutual funds under certain conditions. This program was set up to assist money funds holding such paper to meet redemption demands and to promote liquidity in the ABCP market and money

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<sup>8</sup> Add reference.

markets more generally. This program began operations on September 22, 2008, and was closed on February 1, 2010.

In addition, the Fed announced The Commercial Paper Funding Facility on October 7, 2008, followed by additional details on October 14, 2008. This program took effect on October 27, 2008, and was designed to provide credit to a special purpose vehicle that would purchase three-month commercial paper from U.S. issuers.

On October 21, 2008, the Federal Reserve announced another program, The Money Market Investor Funding Facility (MMIFF). The MMIFF was a credit facility provided by the Federal Reserve to a series of special purpose vehicles established by the private sector. Each SPV was able purchase eligible money market instruments from eligible investors using financing from the MMIFF and from the issuance of asset-backed commercial paper (ABCP). Eligible Assets included certificates of deposit, bank notes and commercial paper with a remaining maturity of at least seven days and no more than 90 days.

In addition, the SEC took a number of actions, perhaps the most important of which was to allow money market funds to price their underlying securities at amortized cost at a point during the crisis when quotes on commercial paper were generally regarded as unreliable. Following these developments, for several weeks, investors continued to redeem shares from prime money market funds, but at a diminishing rate. By the end of October 2008, redemptions essentially ceased.

To illustrate, Figure 1 (top panel) shows daily changes in the net assets of the Reserve Primary fund during September 2008. Severe outflows began on September 13, 2008—perhaps due to some sophisticated investors anticipating that the fund's holdings of Lehman securities were in peril. By the end of September 2008, the Reserve Primary Fund had stemmed outflows.

The bottom panel of Figure 1 shows flows for all six aggregate fund categories of funds over the same month. Clearly, prime institutional funds were most severely affected, with prime retail and tax-free funds also showing significant daily outflows.

In contrast, money market funds holding U.S. Government-backed securities (mainly Treasuries and agencies) experienced strong inflows, as investors sought the liquidity of the Treasury market as safety. Figure 2 shows, for government and prime money funds, the daily flows in billions of dollars. Note that the magnitude of the outflows in prime institutional funds is magnified, due to the large scale of these investments, relative to the outflows in prime retail funds.

### III. Literature Review

The seminal theory on bank runs is developed by Diamond and Dybvig (DD; 1983). DD develop a model of bank runs that illustrates how a bank run can be an equilibrium outcome with bank deposits; in this equilibrium, investors think the bank is going to fail, and it becomes a self-fulfilling prophecy. Investors judge whether to deposit money, depending on the probability of a run. The DD model also finds that bank deposits can provide allocations of capital superior to those of disintermediated security markets. Postlewaite and Vives (1987) extend DD by modeling how bank runs are an equilibrium outcome even if investors cannot observe public information about the probability of a particular bank's failure beforehand.

Goldstein and Pauzner (2005) further extend DD by tying the probability of bank runs to observable fundamentals. Using this concept, they find conditions under which banks increase welfare overall, as well as constructing a demand-deposit contract that trades off the benefits of

liquidity against the costs of runs. Peck and Shell (2003) extend DD to show, by examples, that under an optimal demand deposit contract, a post-deposit game can have a run equilibrium.

Jacklin and Bhattacharya (1988) contrast panics and information-based bank runs to provide a model of how bank runs are triggered. Information-based runs are driven by two-sided asymmetric information—the bank cannot observe the liquidity needs of the depositors, and the depositors cannot observe the bank asset quality. Finally, Bryant (1980) shows how demand deposits backed by fractional currency reserves and public insurance can be beneficial, depending on the costs of illiquidity and incomplete information.

To our knowledge, this is the first study of the high-frequency flows to and from individual U.S. money market funds surrounding the September 2008 crisis. Jank and Wedow (2010) study German money funds during the crisis. They find that German money funds competed for flows, which respond to past performance of funds, by investing in less liquid securities. Funds that engaged in this risk-shifting to the greatest degree suffered larger outflows during the crisis, i.e., investors appeared to understand the potential for runs in funds with less liquid holdings. Therefore, less liquid funds attract flows at the risk of developing an investor run if a market distortion occurs (such as the Lehman default).

## IV. Data and Methodology

### IV.A. Data

Our data are derived from iMoneyNet ([www.imoney.net](http://www.imoney.net)). iMoneynet collects daily information for over 2,000 U.S. registered money market mutual funds that invest primarily in U.S. short-term, dollar-denominated debt obligations. These money funds are offered to retail as

well as institutional investors. The iMoneyNet data consists of daily total net assets by share class, as well as data on the fund investment objective, fund family/adviser (i.e., “complex”), fund type (i.e. retail vs. institutional), portfolio average maturity, and asset breakdown. Our daily money fund dataset from iMoneyNet covers the period December 31, 2007 to June 30, 2009. We approximate daily fund share class flows as the daily change in share class assets (this ignores the negligible effect of the small daily dividends that money market funds declare).<sup>9</sup>

Table 1 shows the total net assets and number of shareholder accounts in these funds at the end of each year from 1990 to 2008. The total assets held in money market funds increases from almost \$500 billion at the end of 1990 to more than \$3.8 trillion at the end of 2008, reflecting the huge increase in popularity of these funds among individuals and institutions. As of December 2008, the total M2 money supply in the United States was \$8.3 trillion, of which \$1.3 trillion was invested in retail share classes of money market mutual funds.<sup>10</sup> Therefore, money market funds are a substantial share of liquid assets for individuals in the U.S. Note that, until the crisis of 2008, money market funds holding predominantly non-government securities dominated the asset value of the sample. During 2008, assets held in government money market funds nearly doubled to \$1.45 trillion. Note, also, that there were 38 million shareholder accounts as of December 2008, most of which were retail accounts. Therefore, a large cross-section of individuals in the U.S. hold assets in money market funds, indicating that any perceived instability of money funds may impact a large proportion of U.S. investors. In terms of assets,

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<sup>9</sup> Almost all money fund dividends are reinvested in the same money fund share class, so distributions (and their passive reinvestments) have a negligible effect on our estimates of flows.

<sup>10</sup> M2 consists of currency, traveler’s checks, demand deposits, other checkable deposits, retail money market mutual funds, savings, and small time deposits. See [www.federalreserve.gov/releases/h6/hist/h6hist1.txt](http://www.federalreserve.gov/releases/h6/hist/h6hist1.txt) for yearly values of M2 and [www.ici.org](http://www.ici.org) for yearly retail money fund assets.



institutions own about two-thirds of money funds. Therefore, even outflows from a relatively small number of institutional accounts could impact money funds.

Table 2 explores the yearly number of money market mutual funds and the yearly number of shareclasses within each asset-class category. Note that the average number of shareclasses per fund has increased from slightly over one to almost three during the sample period. This trend indicates that the actions of one class of investors has a greater potential to affect other classes over time, such as institutions affecting individuals, and vice-versa.

Table 3 shows the net cash inflows, as well as a breakdown into sales and redemptions for each year from 1984 to 2008. The table shows that flows into money market funds have been vastly increasing over the sample period, especially since about 1995. Note, also, the movement toward money funds during the market crisis of 2007 and 2008.

It is important to understand the characteristics of portfolio holdings of money funds to explore the liquidity and other risks that they carry. Table 4 shows that funds that focus on non-governmental securities made a secular movement from commercial paper to bank CDs, repurchase agreements, and corporate notes over our sample period. Clearly, funds have become more diversified among asset classes, while retaining a weighted-average asset maturity of almost 50 days.

## IV.B. Methodology

Our intention in this paper is to study the potential causes for runs in money market mutual funds. In order to achieve this goal, we first estimate a model of money market fund flows during normal (non-crisis) periods. We start by modeling the fund and investor characteristics that we conjecture are covariates of money fund flows:

$$FRACFLOW_{i,t} = f(FRACFLOW_{i,t-j}, FRACFLOW_{-i,t-j}, CRSPVW_{t-j}, Ind_{i,t-1}, Liq_{i,t-1}, Mgmt_{i,t-1}) + \varepsilon_{i,t}, \quad (1)$$

where  $FRACFLOW_{i,t}$  equals the net flows into money fund  $i$  during day  $t$  (computed as the change in total net assets), divided by end-of-day  $t-1$  total net assets;  $FRACFLOW_{-i,t-j}$  equals the same variable, measured across all other same-category (e.g., high-quality corporate) money funds excluding fund  $i$  and lagged  $j$  days ( $j=0$  to  $J$ );  $CRSPVW_{t-j}$  equals the return on the CRSP value-weighted NYSE/AMEX/Nasdaq market index during day  $t-j$ ,  $Ind_{i,t-1}$  indicates whether the shareclass for the money fund being observed is predominantly an institutional shareclass (rather than a retail shareclass) at the end of day  $t-1$ ,  $Liq_{i,t-1}$  is the liquidity characteristics of the most recently available portfolio holdings of fund  $i$  at the end of day  $t-1$ , and  $Mgmt_{i,t-1}$  is the day  $t-1$  characteristics of the management company that offers money fund  $i$  at day  $t$ .

We add the following additional fund and management company characteristics which are also likely related to the potential for money fund runs:

- Management company size
- Fund size
- Maturity structure of fund holdings
- Credit quality of fund holdings.

Our first tests estimate the above model in a VAR setting at the aggregate money fund category level, separated by clientele; specifically, daily flows to all prime (non-government) money market funds in retail shareclasses and daily flows to all prime money funds in institutional shareclasses. In our second tests, we apply panel regressions at the complex/category level, such as the prime money funds (in aggregate) of Fidelity or Vanguard. Finally, we apply panel regressions at the individual shareclass level, using daily flows from

(essentially all) money funds over the period December 31, 2007 to September 30, 2008 to investigate the causes of money fund runs. We stop our analysis at September 30, 2008, as abnormal money fund outflows had virtually stopped by October 2008.

## V. Empirical Results

### V.A. Category Level Flows

Our first analysis of flows is at the category level. We wish to determine whether current money flows from one category are related to lagged money flows from another category. For instance, if flows out of institutional funds predict flows out of retail funds, then retail investors may be following institutions in their decisions.

Our dataset has six categories of money market funds:

1. Government Retail
2. Government Institutional
3. Prime Retail
4. Prime Institutional
5. Tax-Free National
6. Tax-Free State

In this paper, we focus on categories 3 and 4, prime fund flows in retail and institutional shareclasses, since these are shareclasses that were most affected by the crisis. We implement a vector autoregression (VAR) with four lags to predict daily prime retail and daily prime institutional fraction flows,

$$\begin{aligned}
PIF_t &= a_{PIF} + \sum_{i=1}^4 b_{PIF,i} \cdot PIF_{t-i} + \sum_{i=1}^4 c_{PIF,i} \cdot PRF_{t-i} + \sum_{i=0}^3 d_{PIF,i} \cdot CRSPVW_{t-i} + \varepsilon_{PIF,t} \\
PRF_t &= a_{PRF} + \sum_{i=1}^4 b_{PRF,i} \cdot PIF_{t-i} + \sum_{i=1}^4 c_{PRF,i} \cdot PRF_{t-i} + \sum_{i=0}^3 d_{PRF,i} \cdot CRSPVW_{t-i} + \varepsilon_{PRF,t} ,
\end{aligned} \tag{3}$$

where  $PIF_t$  = day  $t$  aggregate fraction flows to all prime institutional shareclasses, and  $PRF_t$  = day  $t$  aggregate flows to all prime retail shareclasses (where a negative value indicates an aggregate outflow). We also add the contemporaneous and three lags of the daily return of the CRSP value-weighted NYSE/AMEX/Nasdaq index to control for flows related to current or prior market conditions.

The results for this VAR estimation are shown in Table 5 over the pre-crisis period, January 2 to August 1, 2008. Note that the predictability of flows is low for the prime institutional category, and only the two-day lagged fraction flow (negatively) predicts daily fraction flows (likely due to settlement delays when moving money into, then out of a money fund). Interestingly, there is a negative two-day lagged correlation for prime retail fraction flows, but this may also reflect that some transactions occur with a settlement delay.<sup>11</sup> Overall, the predictability of daily flows prior to the crisis seems economically weak.

In Table 6, we explore whether this VAR system has similar estimated coefficients during the crisis period—the months of September and October 2008. Note the very large increase in predictability of daily fraction flows, as indicated by the very large and significantly positive coefficient on one-day lagged flows as well as the large adjusted R-squareds, both for prime institutional and prime retail categories. For the prime institutional category, one-day

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<sup>11</sup> This negative coefficient may reflect that some investors exchange into a same-complex government money market fund, while others redeem and buy a government fund at a different complex. The former would not involve any settlement delay, but the latter would.

lagged prime institutional fraction flows strongly predict daily flows, while one-day prime retail flows (which are much smaller in magnitude) negatively predict these prime institutional flows. The economic magnitude of the predictability may be illustrated as follows. With a 10% inflow to the prime institutional category, our estimation predicts an expected 6.9% inflow the following day. This level of herding behavior is quite large, and does not appear to be related to the CRSP stock index return—which exhibits insignificant coefficients, both contemporaneously and at all three lags.

Similar to institutional prime funds, prime retail funds exhibit fraction flows during the crisis that are strongly predictable from their one-day lagged values. In addition, retail flows are predictable from one-day lagged institutional prime flows. In untabulated results, we find stronger evidence of this cross-correlation in flows when we include only the one-day lag of prime institutional flows. This simpler specification improves the power of one-day lagged prime institutional flows in predicting prime retail flows due to the high serial correlation in prime institutional flows of different lags (as exhibited in the results of Table 5 above).

To summarize the results of this section, we find evidence that flows during the crisis are strongly autocorrelated over two-day horizons for both institutional and retail prime money market funds. The strongest predictive variable is one-day lagged flows within each channel, although there are some cross-channel effects. In our tests to follow, we will analyze these two categories, prime institutional and prime retail, separately in more depth. First, we will investigate whether persistent flows occur at the fund complex level. We turn to this question in the next section.

## V.B. Complex/Category Level Flows

### V.B.1. Analysis of Flows

We have an unbalanced panel of 75 complexes that have prime institutional shareclass money funds, and 94 complexes that have prime retail funds. We separately examine each of these categories using a panel OLS.

Table 7 explores the determinants of prime institutional flows during the crisis period, aggregated at the complex level. For example, we aggregate all flows (divided by aggregated prior-day end assets) of Fidelity's prime institutional funds at the end of each day, and this becomes one observation. We aggregate at the complex level for several reasons. First, we might expect that investors view all funds in the complex as having highly correlated credit risk, due to correlated holdings. Second, investors may view the level of implicit backing of a money fund to be a complex-level decision; many complexes have injected capital or bought depreciated assets during the crisis period to keep the NAV at \$1 per share, to maintain the reputation of the complex or the money fund itself. Third, clientele of a complex may be similar. For instance, if a large 401(K) plan, using one or two fund complexes, consists of many employees who communicate about a particular money fund event, then individual money funds within these complexes may have correlated outflows. If so, we would expect that lagged flows at the complex level, for prime institutional funds, would predict current flows at the complex level.

However, Table 7 shows that this is not what we find. Indeed, we find that lagged overall category level flows (i.e., flows to/from all prime institutional funds across all complexes) strongly and positively predict next-day complex-level institutional prime flows, but that lagged

complex-level prime institutional flows have almost no predictive power.<sup>12</sup> Prime retail flows show qualitatively similar results to those for prime institutional funds: lagged prime retail flows, aggregated across all complexes, positively predict, while lagged complex-level prime retail flows do not seem to predict current-day complex-level prime retail flows very well.

## V.B.2. Analysis of Exchanges

In a recent article, Ben Rephael, Kandel, and Wohl (2009) find evidence that within-complex exchanges are a better indicator of investor sentiment than total net flows. While their analysis focuses on equity vs. bond funds, we believe that an improved proxy (relative to total flows) for investor views on the creditworthiness of a prime money fund (or a simple investor “panic”) are exchanges from government to prime money funds. Investors can very easily move money from one fund to another within a family on most trading platforms. In addition, total net flows are subject to the views of investors of money funds vs. stock, bond, or other risky investments. We wish to focus on investor views on prime vs. government money funds, rather than their views on prime money funds vs. risky non-money fund investments.<sup>13</sup> One additional advantage of analyzing exchanges is that they occur without a settlement delay.

Since we do not have information on exchanges, we build a conservative estimate of daily exchanges between government and prime funds within a complex as follows. First, we require that the total net flows to government and prime funds have an opposing sign that day

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<sup>12</sup> Interestingly, two-day lagged CRSP value-weighted returns negatively predict prime retail inflows, which may be a result of a two-day settlement delay when individuals sell their stock funds during a negative stock market return day.

<sup>13</sup> Another advantage of exchanges is that they do not involve a settlement delay, so we see the flows on the day that the investor makes the exchange.

(inflows to one, outflows to the other). If not, we assume zero exchanges that day for that complex. Second, we attribute the minimum (absolute value) of total net flows to government or prime money funds within a complex as exchanges. Specifically, we measure fraction exchanges—when net flows in prime money funds within a complex run counter to net flows to government money funds as

$$FEXCH\_INST\_GOVT\_TO\_PRIME_{i,t} = \frac{\min[(GovtFlow_{i,t-1} - GovtFlow_{i,t}), (PrimeFlow_{i,t} - PrimeFlow_{i,t-1})]}{TNAGovt_{i,t} + TNAPrime_{i,t}}, \quad (4)$$

where  $GovtFlow_{i,t}$  equals day t total net flows (in dollars) to complex i, aggregated across all same-complex government money funds, and  $PrimeFlow_{i,t}$  equals the same statistic for same-complex aggregated prime money funds.  $TNAGovt_{i,t}$  and  $TNAPrime_{i,t}$  are day t total net assets in aggregate government and prime money funds in complex i, respectively.

Table 8 shows the results of this analysis, using panel OLS on unbalanced panels of 48 complexes having both government and prime institutional funds, and 55 complexes having both government and prime retail funds (so that exchanges are possible between government and retail funds by each investor type). The dependent variable in the first column of the table is daily fraction estimated exchanges from government institutional to prime institutional money market funds, while the dependent variable in the second column is daily fraction estimated exchanges from government retail to prime retail money market funds. The period of September and October 2008 are defined as the “crisis period.” Note, also, that dummy variables for four days on which the Federal Reserve or the Treasury (or both) made announcements about money-fund guarantee programs are included. During these days, the normal correlations may have been broken, or even reversed, so we wish to dummy these.



Note the much stronger evidence of predictability using exchanges, as both lagged same-complex exchanges and contemporaneous category (excluding complex) fraction flows positively predict daily exchanges from government to prime funds among institutional investors. It is noteworthy that lagged exchanges are a much more economically significant predictor of exchanges than contemporaneous category-level flows. For instance, a 10% movement of money from institutional prime to government same-complex funds implies a 3.1% next-day movement, as a percentage of combined assets of both types of money funds within the complex. A similar, but slightly weaker, complex-effect occurs among retail funds: a 10% movement of money from retail prime to government same-complex funds predicts a 1.4% next-day same-direction flow.

Table 9 investigates correlated flows on a conditional basis: the regression is conditional on one-day lagged exchanges being negative (flows from same-complex prime to government funds, which might represent a run). Clearly, runs are more likely with outflows from prime funds, as we might expect—since the primary motivation for a run comes from investors fleeing prime funds that they fear will “break the buck,” even though a result of this might be that they also exhibit autocorrelated *inflows* into prime funds that are perceived to be a safer.

The panel regressions of Table 9 also include a portfolio characteristic that may reasonably affect investor perception of fund stability has been added: the fraction of portfolio holdings that mature within seven days. This statistic is widely publicized by information services such as iMoneynet and Crane, so investors likely see this information relatively frequently.

The results show even stronger evidence that persistent outflows occur more strongly at the complex level than at the category level. A 10% aggregate exchange from the prime to the

government money funds of a complex predicts a 5.6% aggregate exchange the following day. By comparison, a 10% outflow from all same-category prime funds predicts a 1.1% following day aggregate exchange from prime to government for a given complex.

Investors, both retail and institutional, also condition their tendency to redeem shares during the crisis on the liquidity of the complex holdings. Specifically, the negative and significant coefficient on the interaction of  $CCE(-1)$  and  $MAT7DAYS$  indicates that an outflow from a complex's prime funds has a lower effect on the following day's outflows when the complex holds higher levels of securities that mature within seven days. Interestingly, coefficients are somewhat similar for both  $CCE(-1)$  and for the interaction term. This may either indicate that retail and institutional investors react similarly, or it could also indicate that there may be some overlap between the types of investors within each category. That is, some institutional classes may consist of omnibus accounts containing the accounts of many individuals.

## V.C. Individual Fund Level Flows

We would expect the strongest evidence of fund runs to occur at the individual fund level, since investors are directly impacted by the actions of other investors. Across funds within the same complex, there are externalities, due to correlated asset holdings (and the impact of runs on those asset values) as well as the creditworthiness of the implicit complex guarantee. But, these relations seem to be second-order in nature. We now turn to our individual money funds in the prime retail and prime institutional categories for further evidence of the influences on daily fund fraction flows during the crisis. At the individual fund level, we would expect that the fund

clientele and portfolio characteristics, which vary between funds, would be important in predicting money fund runs.

In Table 10, we show the results of a panel OLS analysis on the unbalanced panel of prime funds. In panel A, we show results for the unbalanced panel of 341 prime institutional funds, while, in panel B, we show results for the unbalanced panel of 295 prime retail funds.

We predict daily fraction flows to/from individual prime institutional money funds during September and October 2008 in panel A1. We include two lags of the prime institutional fund daily flow (*FRACFLOW*), as well as the contemporaneous and two lags of the complex-level prime institutional daily flows (*COMPCAT\_EXCL\_FUND\_FLOW*) excluding the subject fund represented in the dependent variable; and the contemporaneous and two lags of the category-level prime institutional daily flows (*CAT\_EXCL\_COMPL\_FRACFLOW*) ; excluding the flows of the complex containing the subject fund represented in the dependent variable). Note that the exclusion of the fund flows, or the complex flows, helps us to pinpoint the external influences on the fund-level fraction flows.

The results indicate that lagged fund flows (*FRACFLOW(-1)*) significantly predict daily fund flows, but with a low economic magnitude. Specifically, the coefficient on the one-day lagged *FRACFLOW* indicates that a 10% sell-off yesterday leads to another 0.2% sell-off today for a given prime institutional fund. However, we must interpret this low positive relation with caution. Investors selling stocks or other securities tend to park their money for only a short time (such as one day) before moving the money to a checking account or making another trade. This normal activity may reduce (make more negative) the level of autocorrelation in the fund-level fraction flows.

However, examining the influence on a prime institutional fund's flows of contemporaneous and lagged fraction flows to other prime institutional funds within the same complex (*COMPCAT\_EXCL\_FUND\_FLOW*) provides a clean test of whether investors move into or out of prime funds at the complex level. We would not expect investors to move from one prime institutional fund to another within the same complex for liquidity reasons, although they could do so to avoid a money fund run within the first fund. If such same-complex substitutions are occurring, we would expect the contemporaneous influence of other prime funds within the same complex to be negative: one prime fund's outflows become another prime fund's inflows.

Note, also, that including the influence of contemporaneous and lagged fraction flows to other prime institutional funds outside of the subject fund's complex (*CAT\_EXCL\_COMPL\_FRACFLOW*) helps us to determine whether investors do not pay much attention to the implicit guarantees or correlated holdings within a complex and, instead, sell prime institutional funds across all complexes.

While we also find statistically significant (but economically weak) autocorrelation in flows at the share class level, the results strongly indicate that investors sell prime institutional money funds together at the complex level. Specifically, the coefficient on *COMPCAT\_EXCL\_FUND\_FLOW* indicates that a sell-off of 10% of the assets of other prime institutional funds within the same complex is associated with a 9.2% sell-off of assets of the subject prime institutional fund. Contrary to our results of Tables 7 and 8 at the complex level, which could only examine *lagged* same-category, same-complex flows, our share class level results confirm that runs do apparently occur in prime institutional funds at the complex level. This indicates that investors infer that there are externalities between prime funds at the complex level.

Panel A2 repeats the panel regression for prime institutional funds, dropping the insignificant lagged variables and adding variables that are conditioned on the original variables being negative. For example,  $FRACFLOW(-1) < 0$  is a variable that equals  $FRACFLOW$ , when  $FRACFLOW$  is less than 0, and equals zero, otherwise. Including these one-way flow variables indicates that lagged fund-level outflows more strongly predict future outflows than lagged fund-level inflows predict future fund inflows, but the coefficients are not statistically significant.

In panel A3, we explore whether the creditworthiness of individual prime institutional fund holdings significantly impacts the tendency of investors to exhibit money fund runs within a complex for a given category. Specifically, we interact the percentage holdings of U.S. Treasuries ( $TREAS$ ) by a prime money fund with several of our predictive variables to examine whether funds holding more safe debt exhibit a lower predictability in flows.

The results do not indicate much of an impact of Treasury holdings on the predictors of flows. However, our prime money funds may not have sufficient Treasury holdings to strongly test this hypothesis. Another approach is to measure the amount of debt holdings within a prime fund that mature within seven days. However, in untabulated results, we also do not find much of an impact of this variable on our fund-level predictors.

Finally, we examine whether individual prime retail funds have predictable daily fraction inflows in panel B. Here, we find strong, negative first-order autocorrelation in  $FRACFLOW$ , consistent with investors parking their money from securities sales (or in anticipation of security purchases) for one day before moving the money.

Further, we find much weaker evidence of fund investors in individual prime retail funds having flows that are predictable through other same-complex prime retail flows, or with other outside-complex retail flows, at least with two daily lags. While there is some evidence of same-

complex prime retail fund fraction flows positively predicting a prime retail fund's fraction flows, this coefficient (0.022) is statistically weak ( $p=0.17$ ). We conclude this section with similar results as the category-level and complex level results of prior sections regarding prime retail vs. prime institutional fund flows: institutional fund flows appear to be much more predictable during the crisis than prime retail fund flows, and runs appear to develop most sharply at the complex level in funds with low holdings of short-term (highly liquid) securities.

## VI. Conclusion

This paper studies money fund runs during the crisis period of September and October 2008. We find that correlated withdrawals were especially pronounced among money funds that catered predominantly to institutional investors, although we also find weak evidence of correlated withdrawals among retail money funds during the crisis. This finding indicates that “sophisticated” investors mainly present a “bank-run” risk (a negative externality) to each other, and present a weaker risk to “passive” (retail) investors in same-complex money funds.

Second, we find that runs were more pronounced among funds that had less liquidity, in terms of their lower holdings of securities that matured with seven days. We also find that money fund runs were more likely when the fund didn’t have “deep pocket backing,” indicating that investors infer that funds are guaranteed by their management company. And, finally, institutional investors, for the most part, moved their money into U.S. government (only) money market funds in the same fund complex, indicating that they were sophisticated enough to know when not to rely on the management company’s liquidity-provision.

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Table 1: Total Net Assets and Number of Shareholder Accounts (year-end)

Year	Total net assets (billions of dollars)				Number of shareholder accounts* (thousands)			
	Total	Taxable		Tax-exempt	Total	Taxable		Tax-exempt
		Government	Prime			Government	Prime	
1990	\$498.3	\$107.6	\$307.1	\$83.6	22,969	2,273	19,305	1,391
1991	542.4	138.0	314.6	89.9	23,556	2,547	19,316	1,693
1992	546.2	151.3	300.1	94.8	23,647	2,817	18,954	1,876
1993	565.3	148.7	313.2	103.4	23,585	2,806	18,780	1,998
1994	611.0	147.1	353.5	110.4	25,383	3,049	20,295	2,039
1995	753.0	179.2	450.8	123.0	30,144	3,824	24,035	2,285
1996	901.8	217.9	544.1	139.8	32,200	4,147	25,760	2,292
1997	1058.9	245.0	653.1	160.8	35,624	4,548	28,413	2,663
1998	1351.7	302.8	860.4	188.5	38,847	4,384	32,058	2,405
1999	1613.1	325.9	1082.8	204.4	43,616	4,793	36,385	2,438
2000	1845.2	352.5	1254.7	238.0	48,138	4,888	40,592	2,659
2001	2285.3	437.2	1575.7	272.4	47,236	5,124	39,290	2,821
2002	2272.0	447.7	1549.5	274.8	45,380	5,092	37,634	2,655
2003	2052.0	403.5	1360.1	288.4	41,214	4,111	34,301	2,802
2004	1913.2	372.4	1230.4	310.3	37,636	3,651	31,143	2,842
2005	2040.5	382.5	1324.0	334.0	36,837	3,117	30,916	2,805
2006	2338.5	405.8	1566.2	366.4	37,067	3,292	30,714	3,061
2007	3085.8	726.1	1894.6	465.1	39,130	3,481	32,181	3,467
2008	3832.2	1450.3	1890.4	491.5	38,112	4,160	30,339	3,613

Source: ICI Factbook, 2009

Table 2: Number of Funds and Number of Share Classes  
(Year-end)

Year	Number of funds				Number of share classes			
	Total	Taxable		Tax- exempt	Total	Taxable		Tax- exempt
		Government	Prime			Government	Prime	
1990	741	174	332	235	762	180	343	239
1991	820	211	342	267	871	228	364	279
1992	864	234	351	279	914	247	369	298
1993	920	260	368	292	1,009	280	393	336
1994	963	271	375	317	1,261	360	493	408
1995	997	279	395	323	1,380	394	555	431
1996	988	271	395	322	1,453	404	596	453
1997	1,013	271	411	331	1,549	428	642	479
1998	1,026	275	410	341	1,627	459	674	494
1999	1,045	284	418	343	1,730	493	733	504
2000	1,039	277	426	336	1,855	531	793	531
2001	1,015	273	416	326	1,948	575	822	551
2002	989	265	414	310	2,006	588	876	542
2003	974	258	404	312	2,031	584	879	568
2004	943	247	392	304	2,046	589	882	575
2005	871	220	375	276	2,031	565	900	566
2006	847	212	362	273	2,012	567	888	557
2007	805	197	349	259	2,018	553	897	568
2008	784	195	341	248	1,989	568	880	541

\*Number of shareholder accounts includes a mix of individual and omnibus accounts.

Note: Data for funds that invest primarily in other mutual funds were excluded from the series. Components may not add to the total because of rounding.

Source: ICI Factbook, 2009

Table 3: Net New Cash Flow<sup>1</sup> and Components of Net New Cash Flow of Money Market Funds  
(\$Billions/year)

Year	Net new cash flow	Sales			Redemptions		
		New + exchange	New <sup>2</sup>	Exchange <sup>3</sup>	Regular + exchange	Regular <sup>4</sup>	Exchange <sup>5</sup>
1984	\$35.1	\$640.0	\$620.5	\$19.5	\$604.9	\$587.0	\$18.0
1985	-5.3	848.5	826.9	21.6	853.7	831.1	22.7
1986	33.6	1026.7	978.0	48.7	993.2	948.7	44.5
1987	10.1	1147.9	1049.0	98.8	1137.8	1062.7	75.1
1988	0.1	1130.6	1066.0	64.6	1130.5	1074.3	56.2
1989	64.1	1359.6	1296.5	63.2	1295.5	1235.5	60.0
1990	23.2	1461.5	1389.4	72.1	1438.4	1372.8	65.6
1991	6.1	1841.1	1778.5	62.6	1835.1	1763.1	72.0
1992	-16.0	2449.8	2371.9	77.8	2465.8	2383.0	82.8
1993	-13.9	2756.3	2666.0	90.3	2770.2	2673.5	96.7
1994	8.5	2725.2	2586.5	138.7	2716.7	2599.4	117.3
1995	89.4	3234.2	3097.2	137.0	3144.8	3002.0	142.9
1996	89.4	4157.0	3959.0	198.0	4067.6	3868.8	198.8
1997	103.5	5127.3	4894.2	233.1	5023.9	4783.1	240.8
1998	235.5	6407.6	6129.1	278.4	6172.1	5901.6	270.5
1999	193.7	8081.0	7719.3	361.6	7887.3	7540.9	346.4
2000	159.4	9826.7	9406.3	420.4	9667.3	9256.4	411.0
2001	375.3	11737.3	11426.8	310.5	11362.0	11065.5	296.5
2002	-46.5	12035.8	11739.6	296.2	12082.2	11810.7	271.5
2003	-258.4	11235.9	11011.3	224.6	11494.3	11267.7	226.6
2004	-156.6	10953.4	10786.9	166.5	11110.0	10939.7	170.3
2005	63.1	12596.5	12420.4	176.1	12533.4	12362.6	170.8
2006	245.2	15707.3	15496.0	211.3	15462.0	15269.4	192.6
2007	654.5	21315.2	21040.1	275.1	20660.7	20409.4	251.3
2008	636.8	24574.2	24189.1	385.1	23937.3	23620.7	316.7

<sup>1</sup>Net new cash flow is the dollar value of new sales minus redemptions, combined with net exchanges.

<sup>2</sup>New sales are the dollar value of new purchases of mutual fund shares. This does not include shares purchased through reinvestment of dividends in existing accounts.

<sup>3</sup>Exchange sales are the dollar value of mutual fund shares switched into funds within the same fund group.

<sup>4</sup>Redemptions are the dollar value of shareholder liquidation of mutual fund shares.

<sup>5</sup>Exchange redemptions are the dollar value of mutual fund shares switched out of funds and into another fund in the same group.

Note: Data for funds that invest primarily in other mutual funds were excluded from the series.

Components may not add to the total because of rounding. Source: ICI Factbook, 2009

Table 4: Asset Composition of Taxable Non-Government Money Market Funds as a Percent of Total Net Assets  
(Year-End)

Year	Total net assets (billions of dollars)	U.S. Treasury bills %	Other Treasury securities %	U.S. government agency issues %	Repurchase agreements %	Certificates of deposit %	Eurodollar CDs %	Commercial paper %	Bank notes <sup>1</sup> %	Corporate notes <sup>2</sup> %	Other assets <sup>3</sup> %	Average maturity (days)
1990	\$307.1	4.3	2.3	4.7	3.3	6.8	8.8	65.0	–	–	4.7	48
1991	314.6	5.8	3	4.3	4.1	10.5	6.9	59.7	–	–	5.8	56
1992	300.1	2.8	2.6	7.5	5.1	10.3	6.7	57.4	–	–	7.4	59
1993	313.2	2.7	2.5	11.9	6.4	7.9	3.2	52.2	–	–	13.2	58
1994	353.5	2.6	1.3	11.3	6	6.3	4.5	53.2	2.4	–	12.4	38
1995	450.8	1.5	1	9.2	6.5	8.8	4.4	52.2	3.7	–	12.6	60
1996	544.1	0.7	1.9	8.9	5.4	12.7	4.3	50.5	2.3	–	13.3	56
1997	653.1	0.5	0.8	5.5	5.6	14.6	3.7	51.5	3.2	–	14.8	57
1998	860.4	0.6	0.9	9.5	4.9	12.9	3.6	48.3	3.9	5.8	9.6	58
1999	1082.8	0.5	0.3	6.7	5.1	12.7	3.9	48.9	3.1	8.3	10.4	49
2000	1254.7	0.5	0.1	6.2	4.5	10.2	7.8	50.2	3.6	10.4	6.6	53
2001	1575.7	0.6	0.3	12.4	6.4	13.2	8.8	41.2	1.5	10.9	4.6	58
2002	1549.5	1.5	0.3	12.1	8.4	12.4	8.2	39.7	1.3	11.8	4.3	54
2003	1360.1	1.5	0.4	15.2	8.5	10.5	6	35.1	2	15.9	4.7	59
2004	1230.4	0.5	0.1	12.2	9	12.7	6.9	33.4	2.6	17.6	5	41
2005	1324.0	0.8	0.1	4.6	12.4	13.3	6.9	37.9	2.3	17.6	4.2	37
2006	1566.2	0.2	0.2	3	10.9	12.5	5.5	39	2.2	21.3	5.3	49
2007	1894.6	0.9	0.2	3.3	12.4	13.4	6.9	36.2	3.9	16.4	6.4	44
2008	1890.4	2.4	0.5	13.1	9.1	18.6	7	33.4	3	9.1	3.8	47

<sup>1</sup>Prior to 1994, bank notes are included in other assets.

<sup>2</sup>Prior to 1998, corporate notes are included in other assets.

<sup>3</sup>Other assets include banker's acceptances, municipal securities, and cash reserves.

Note: Data for funds that invest primarily in other mutual funds were excluded from the series. Source: ICI Factbook, 2009

Table 5: Vector Autoregression Estimates of Institutional and Retail Category-Level Prime Money Market Fraction Flows, Pre-Crisis

This table presents VAR estimates of a 2-equation system, where daily Prime Institutional Flows (PIF) and Prime Retail Flows (PRF) (in fraction of prior-day TNA) are the endogenous variables. The exogenous variable is the daily CRSP value-weighted NYSE/AMEX/Nasdaq return, dividends included. This VAR system is estimated over the period January 2 to August 1, 2008. T-statistics are shown in parentheses.

	PIF	PRF
C	0.0010 ( 1.32)	0.0002 ( 0.71)
PIF(-1)	0.0752 ( 0.81)	0.0025 ( 0.10)
PIF(-2)	-0.2111** (-2.23)	-0.0396 (-1.51)
PIF(-3)	0.0267 ( 0.28)	-0.0342 (-1.30)
PIF(-4)	-0.1276 (-1.34)	-0.0205 (-0.77)
PRF(-1)	0.0598 ( 0.18)	0.0237 ( 0.26)
PRF(-2)	0.0323 ( 0.10)	0.2656*** ( 3.05)
PRF(-3)	0.2092 ( 0.66)	0.1725* ( 1.97)
PRF(-4)	0.3514 ( 1.10)	0.1076 ( 1.21)
CRSPVW_RET	0.0918 ( 1.48)	0.0163 ( 0.95)
CRSPVW_RET(-1)	0.0293 ( 0.47)	0.0094 ( 0.54)
CRSPVW_RET(-2)	-0.0024 (-0.04)	-0.0419** (-2.44)
CRSPVW_RET(-3)	0.0343 ( 0.53)	-0.0032 (-0.18)
R-squared	0.0868	0.1859
Adj. R-squared	0.0031	0.1113
F-statistic	1.0373	2.4924
Log likelihood	479.9	664.2
Akaike AIC	-6.48	-9.04
Schwarz SC	-6.22	-8.78

Table 6: Vector Autoregression Estimates of Institutional and Retail Category-Level Prime Money Market Fraction Flows, Crisis-Period

This table presents VAR estimates of a 2-equation system, where daily Prime Institutional Flows (PIF) and Prime Retail Flows (PRF) (in fraction of prior-day TNA) are the endogenous variables. The exogenous variable is the daily CRSP value-weighted NYSE/AMEX/Nasdaq return, dividends included. This VAR system is estimated over the period September 2 to October 31, 2008. T-statistics are shown in parentheses.

	PIF	PRF
C	-0.0033 (-0.86)	-0.0002 (-0.29)
PIF(-1)	0.6940** ( 3.79)	0.0851*** ( 2.77)
PIF(-2)	0.3520 ( 1.54)	0.0140 ( 0.36)
PIF(-3)	0.1154 ( 0.51)	-0.0146 (-0.38)
PIF(-4)	-0.3071 (-1.48)	-0.0076 (-0.22)
PRF(-1)	-2.1083* (-1.71)	0.3730* ( 1.80)
PRF(-2)	-0.8007 (-0.62)	-0.0009 (-0.004)
PRF(-3)	0.6055 ( 0.48)	0.01229 ( 0.06)
PRF(-4)	0.9311 ( 0.92)	0.1154 ( 0.68)
CRSPVW_RET	0.0586 ( 0.67)	-0.0035 ( -0.24)
CRSPVW_RET(-1)	0.0062 ( 0.07)	0.0031 ( 0.21)
CRSPVW_RET(-2)	-0.0334 (-0.37)	-0.0320** (-2.11)
CRSPVW_RET(-3)	-0.0840 ( -0.95)	0.0128 (-0.86)
R-squared	0.5585	0.6189
Adj. R-squared	0.3819	0.4664
F-statistic	3.1626	4.0595
Log likelihood	119.5	196.2
Akaike AIC	-4.95	-8.52
Schwarz SC	-4.42	-7.99

Table 7: Panel OLS Estimates of Complex/Category-Level Prime Money Market Fraction Flows, Crisis Period (Institutional and Retail)

This table presents Panel OLS estimates of the covariates of daily Prime Institutional (Panel A) and Prime Retail (Panel B) Flows aggregated at the complex level, respectively (in fractions of prior-day TNA). CCF is defined as single complex/single category flow. CAT\_EXCL\_CCF is defined as aggregate category fraction flows (e.g., for all prime institutional shareclasses), excluding the flows to the complex/category represented by CCF. Our dataset covers 75 complexes with prime institutional funds and 94 complexes with prime retail funds. This unbalanced panel system is estimated over the period September 2 to October 31, 2008.

	CCF(Inst.)	CCF(Retail)
C	0.0024 (0.81)	-0.0007 (-0.65)
CCF(-1)	-0.0836** (-4.63)	-0.0793*** (-5.09)
CCF(-2)	-0.0082 (-0.45)	0.0465*** (2.96)
CCF(-3)	0.0018 (0.10)	-0.0257 (-1.63)
CCF(-4)	-0.0027 (-0.15)	0.1795*** (11.4)
CAT_EXCL_CCF	0.3788*** (2.61)	0.5268* (1.87)
CAT_EXCL_CCF(-1)	0.1320 (0.77)	0.4593 (1.22)
CAT_EXCL_CCF(-2)	0.1532 (0.68)	-0.2526 (-0.70)
CAT_EXCL_CCF(-3)	-0.0913 (-0.47)	-0.1864 (-0.54)
CAT_EXCL_CCF(-4)	-0.0311 (-0.22)	-0.0637 (-0.24)
CRSPVW_RET	0.0443 (0.69)	-0.0054 (-0.21)
CRSPVW_RET(-1)	-0.0508 (-0.78)	0.0030 (0.11)
CRSPVW_RET(-2)	0.0577 (0.87)	-0.0652** (-2.37)
CRSPVW_RET(-3)	0.0502 (0.76)	0.0067 (1.22)
D(SEP 19, 2008)	0.0104 (0.38)	0.0014 (0.21)
D(OCT 7, 2008)	-0.0078 (-0.53)	0.0068 (1.22)
D(OCT 14, 2008)	0.0020 (0.13)	-0.0018 (-0.30)
D(OCT 21, 2008)	0.0009 (0.06)	0.0001 (0.02)
R-squared	0.017	0.6189
Adj. R-squared	0.116	0.4664
F-statistic	3.19	4.0595
Log likelihood	2309.9	196.2
Akaike AIC	-1.45	-8.52
Schwarz SC	-1.41	-7.99



Table 8: Panel OLS Estimates of Complex/Category-Level Prime Money Market Fraction Exchanges from Government to Prime Funds, Crisis Period (Institutional and Retail)

This table presents Panel OLS estimates of the covariates of estimated exchanges from government money market funds to prime money market funds (in the same complex), for institutions and retail shareclasses (CCE(Inst.) and CCE(Retail), respectively). Exchanges are estimated by Equation (4), then aggregated at the complex level (in fractions of prior-day TNA). CAT\_EXCL\_CCF is defined as aggregate category fraction flows (e.g., for all prime institutional shareclasses), excluding the flows to the complex/category represented by CCE. Our dataset covers 48 complexes with prime and gov't institutional funds, and 55 complexes with prime and gov't retail funds. This unbalanced panel system is estimated over September 2 to October 31, 2008.

	CCE(Inst.)	CCE(Retail)
C	-0.0001 (-0.47)	-0.0001 (-0.86)
CCE(-1)	0.3071*** ( 13.8)	0.1449*** (6.92)
CCE(-2)	-0.0141 (-0.60)	0.0550*** ( 2.60)
CCE (-3)	-0.0389 (-1.65)	-0.0361* (-1.70)
CCE (-4)	0.0831*** (3.70)	0.0802*** (3.73)
CAT_EXCL_CCF	0.0694*** (7.18)	0.1287*** (5.36)
CAT_EXCL_CCF(-1)	0.0180 (1.59)	0.1113 (3.47)
CAT_EXCL_CCF(-2)	0.0553*** ( 3.72)	-0.0882*** (-2.86)
CAT_EXCL_CCF(-3)	-0.0414*** (-3.19)	-0.0035 (-0.12)
CAT_EXCL_CCF(-4)	0.0065 ( 0.69)	0.0305 ( 1.32)
CRSPVW_RET	0.0045 (1.06)	0.0056** ( 2.58)
CRSPVW_RET(-1)	0.0054 ( 1.26)	0.0012 ( 0.52)
CRSPVW_RET(-2)	-0.0010 (-0.25)	-0.0020 (-0.87)
CRSPVW_RET(-3)	-0.0054 (-1.24)	0.0021 (0.94)
D(SEP 19, 2008)	0.0062*** (3.45)	-0.0012* (-2.06)
D(OCT 7, 2008)	0.0005 (0.52)	0.0004 (0.92)
D(OCT 14, 2008)	-0.0005 (-0.48)	-0.0015*** (-2.77)
D(OCT 21, 2008)	-0.0004 (-0.39)	0.0008 (1.45)
R-squared	0.232	0.099
Adj. R-squared	0.226	0.092
F-statistic	36.26	15.06
Log likelihood	7532.9	10153.9
Akaike AIC	-7.32	-8.67
Schwarz SC	-7.27	-8.62

Table 9: Panel OLS Estimates of Complex/Category-Level Prime Money Market Fraction Exchanges from Government to Prime Funds, Crisis Period (Institutional and Retail)

This table presents Panel OLS estimates of the covariates of estimated exchanges from government money market funds to prime money market funds (in the same complex), for institutions and retail shareclasses (CCE(Inst.) and CCE(Retail), respectively). Exchanges are estimated by Equation (4), then aggregated at the complex level (in fractions of prior-day TNA). MAT7DAYS is defined as the proportion of the complex/category holdings that matures in 7 days. CAT\_EXCL\_CCF is defined as aggregate category fraction flows (e.g., for all prime institutional shareclasses), excluding the flows to the complex/category represented by CCE. Our dataset covers 48 complexes with prime and gov't institutional funds, and 55 complexes with prime and gov't retail funds. This unbalanced panel system is estimated over September 2 to October 31, 2008. Controls for the CRSP VW return, day  $t$  through day  $t-3$ , as well as dummies for 9/19, 10/7, 10/14, and 10/21/2008 are included, but are not shown in this table.

	CCE(Inst.)<0	CCE(Retail)<0
C	-0.0025*** (-2.85)	-0.0019*** (-4.83)
CCE(-1)	0.5606*** (5.20)	0.4178*** (4.44)
CCE(-2)	-0.0293 (-0.60)	0.0064 (0.12)
CCE (-3)	-0.0701 (-1.37)	-0.0484 (-1.20)
CCE (-4)	0.1157** (2.65)	0.0013 (0.03)
CCE(-1)*MAT7DAYS	-0.6622* (-1.90)	-0.6904** (-2.49)
CAT_EXCL_CCF	0.1088*** (5.18)	0.1547*** (3.17)
CAT_EXCL_CCF(-1)	0.0184 (0.78)	0.2004*** (2.91)
CAT_EXCL_CCF(-2)	0.0867** (2.52)	-0.1852*** (-2.66)
CAT_EXCL_CCF(-3)	-0.0420 (-1.43)	-0.0066 (-0.10)
CAT_EXCL_CCF(-4)	0.0014 (0.06)	0.0969* (1.99)
MAT7DAYS	-0.0023 (-1.12)	-0.0003 (-0.33)
R-squared	0.387	0.189
Adj. R-squared	0.368	0.166
F-statistic	20.24	8.37
Log likelihood	2161.4	2938.6
Akaike AIC	-6.80	-8.29
Schwarz SC	-6.66	-8.16

Table 10: Panel OLS Estimates of Fund (Shareclass)-Level Prime Money Market Fraction Flows, Crisis Period (Institutional and Retail)

This table presents Panel OLS estimates of the covariates of daily Prime Institutional (Panel A) and Prime Retail (Panel B) Flows (in fractions of prior-day TNA) to 341 individual prime institutional (panels A1, A2, and A3) and 295 prime retail (panel B) fund shareclasses. This panel system is estimated over the period September 2 to October 31, 2008.

Panel A1: Prime Institutional Fraction Flows

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.074897	0.035144	2.131158	0.0331
FRACFLOW(-1)	0.022611	0.011882	1.902926	0.0571
FRACFLOW(-2)	-0.002407	0.011883	-0.202595	0.8395
COMPCAT_EXCL_FUND_FLOW	0.919964	0.464574	1.980229	0.0477
COMPCAT_EXCL_FUND_FLOW(-1)	-0.127703	0.473320	-0.269803	0.7873
COMPCAT_EXCL_FUND_FLOW(-2)	-0.443835	0.469431	-0.945475	0.3444
CAT_EXCL_COMPL_FRACFLOW	0.631110	1.269051	0.497309	0.6190
CAT_EXCL_COMPL_FRACFLOW(-1)	-0.005677	1.444157	-0.003931	0.9969
CAT_EXCL_COMPL_FRACFLOW(-2)	0.241055	1.258353	0.191564	0.8481
R-squared	0.001404	Mean dependent var		0.054510
Adjusted R-squared	0.000276	S.D. dependent var		2.433193
S.E. of regression	2.432857	Akaike info criterion		4.617277
Sum squared resid	41940.57	Schwarz criterion		4.625988
Log likelihood	-16370.79	Hannan-Quinn criter.		4.620277
F-statistic	1.244917	Durbin-Watson stat		2.101118
Prob(F-statistic)	0.268089			

Panel A2: Prime Institutional Fraction Flows  
(Includes Dummy Slope for Lagged 1 Day Flows < 0)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.016507	0.070002	0.235809	0.8136
FRACFLOW(-1)	0.023291	0.011882	1.960255	0.0500
FRACFLOW(-1)<0	0.078881	0.058065	1.358493	0.1744
COMPCAT_EXCL_FUND_FLOW	0.947825	0.473583	2.001390	0.0454
COMPCAT_EXCL_FUND_FLOW<0	0.064765	0.067808	0.955118	0.3396
CAT_EXCL_COMPL_FRACFLOW	0.736245	1.201625	0.612707	0.5401
CAT_EXCL_COMPL_FRACFLOW<0	-0.018168	0.076304	-0.238096	0.8118
R-squared	0.001623	Mean dependent var		0.054487
Adjusted R-squared	0.000778	S.D. dependent var		2.432679
S.E. of regression	2.431733	Akaike info criterion		4.616071
Sum squared resid	41931.38	Schwarz criterion		4.622844
Log likelihood	-16375.44	Hannan-Quinn criter.		4.618403
F-statistic	1.920827	Durbin-Watson stat		2.099305
Prob(F-statistic)	0.073605			

**Panel A3: Prime Institutional Fraction Flows**  
(Includes Influence of % Portfolio Consisting of Treasurys)

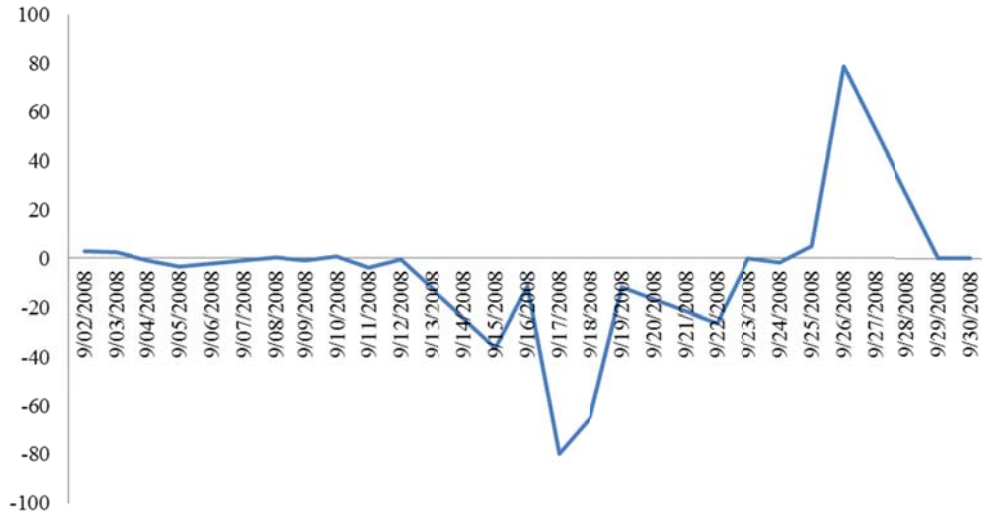
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.076623	0.034460	2.223496	0.0262
FRACFLOW(-1)	0.022679	0.011885	1.908170	0.0564
FRACFLOW(-2)	-0.002671	0.011882	-0.224784	0.8222
TREAS(-1)*FRACFLOW(-1)	0.016214	0.283613	0.057170	0.9544
COMPCAT_EXCL_FUND_FLOW	0.865174	0.461786	1.873537	0.0610
TREAS*COMPCAT_EXCL_FUND_FLOW	-0.094396	0.558430	-0.169038	0.8658
COMPCAT_EXCL_FUND_FLOW(-1)	-0.230811	0.461584	-0.500042	0.6171
CAT_EXCL_COMPL_FRACFLOW	0.717296	1.273950	0.563049	0.5734
TREAS*CAT_EXCL_COMPL_FRACFLOW	0.126867	0.931690	0.136169	0.8917
CAT_EXCL_COMPL_FRACFLOW(-1)	-0.055857	1.270110	-0.043978	0.9649
R-squared	0.001281	Mean dependent var		0.054526
Adjusted R-squared	0.000012	S.D. dependent var		2.433536
S.E. of regression	2.433521	Akaike info criterion		4.617965
Sum squared resid	41945.71	Schwarz criterion		4.627646
Log likelihood	-16367.61	Hannan-Quinn criter.		4.621298
F-statistic	1.009514	Durbin-Watson stat		2.100129
Prob(F-statistic)	0.429530			

**Panel B: Prime Retail Fraction Flows**  
(Includes Influence of % Portfolio Consisting of Treasurys)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001278	0.000872	1.464668	0.1431
FRACFLOW(-1)	-0.184258	0.012542	-14.69128	0.0000
FRACFLOW(-2)	0.014580	0.012588	1.158208	0.2468
COMPCAT_EXCL_FUND_FLOW	0.022270	0.016134	1.380257	0.1676
COMPCAT_EXCL_FUND_FLOW(-1)	0.019208	0.016716	1.149098	0.2506
COMPCAT_EXCL_FUND_FLOW(-2)	0.012539	0.016186	0.774655	0.4386
CAT_EXCL_COMPL_FRACFLOW	-0.033148	0.217182	-0.152629	0.8787
CAT_EXCL_COMPL_FRACFLOW(-1)	0.143211	0.282965	0.506110	0.6128
CAT_EXCL_COMPL_FRACFLOW(-2)	0.017312	0.226337	0.076488	0.9390
R-squared	0.036559	Mean dependent var		0.000832
Adjusted R-squared	0.035312	S.D. dependent var		0.056546
S.E. of regression	0.055539	Akaike info criterion		-2.942014
Sum squared resid	19.07189	Schwarz criterion		-2.932230
Log likelihood	9117.474	Hannan-Quinn criter.		-2.938621
F-statistic	29.32773	Durbin-Watson stat		2.064830
Prob(F-statistic)	0.000000			

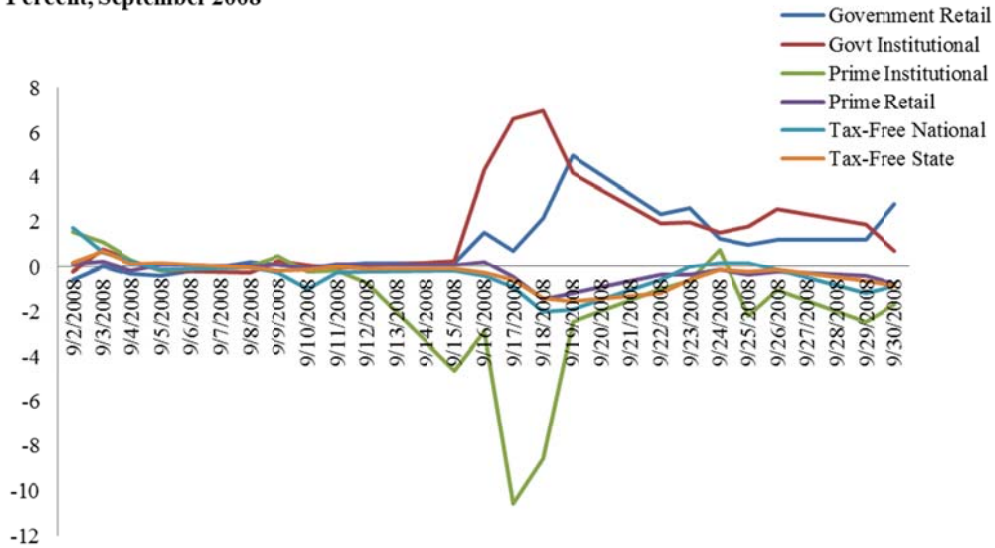
Figure 1: Daily Flows to/from the Reserve Primary Fund During the Period Surrounding the Crisis Week (in %)

**Change in Daily Assets of the Reserve Primary Fund**  
Percent, September 2008



Source: iMoneyNet

**Change in Daily Assets of Money Market Funds**  
Percent, September 2008



Source: iMoneyNet

Figure 2: Daily Flows to/from Money Fund Categories  
During the Period Surrounding the Crisis Week (in \$Billions)

