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INTERACTION BETWEEN MUTUAL FUND MANAGERS AND FUND INVESTORS

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Contents

Declaration

I hereby declare that this work has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Chanyuan Ge, Sydney, 12 February 2019

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MACQUARIE UNIVERSITY

Abstract

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This PhD thesis evaluates fund managers' risk-taking incentives and performance outcomes in the money market mutual fund and equity mutual fund segments. The thesis consists of three key chapters based on three research papers.

The research paper entitled '*Out of Sight, Out of Mind: Information Insensitivity and Risk-taking of Prime Institutional Money Market Funds*' analyzes the economic implications of a more informationally sensitive net asset value (NAV) for prime institutional money market funds' (PIFs) risk-taking incentives. In July 2014, the Securities and Exchange Commission (SEC) introduced a new reform requiring PIFs to disclose daily portfolio mark-to-market prices to the public on a daily basis and adopt the floating NAV (FNAV) trading rule. The results show that in response to the new reform, PIFs have: (i) shortened aggregate portfolio maturity; (ii) lowered gross yields; (iii) boosted daily and weekly portfolio liquidity; and (iv) increased their holdings of safe assets in an attempt to eliminate the greater informational advantage of investors. Interestingly, PIF managers have proportionally readjusted their risk-taking under the FNAV pricing system, confirming the existence of lower dilution cost and weaker adverse selection under this regime. The overall evidence supports the view that the new SEC reform has contributed to improving the overall resiliency of PIFs.

The research paper entitled '*Floating NAV Pricing under Single- versus Multi-strike Prime Institutional Money Market Funds*' is the first to assess the implications of the intraday FNAV strike system for PIFs' risk-taking incentives. PIFs have begun to offer multiple redemption windows to cater to investors with greater liquidity needs; however, this is at the cost of greater exposure to unanticipated asset–liability mismatches during the day. Using unique data on the intraday striking system of PIFs, this study shows that in an attempt to limit their exposure to heightened intraday flow-related liquidity risk, multi-strike funds have: i) reduced maturity risk; ii) increased portfolio liquidity; iii) reduced portfolio holdings of risky assets relative to safe assets; and iv) intensified their reach for yield. This study finds that institutional investors are prepared to pay a premium for their more frequent access to intraday liquidity. Importantly, this study finds no evidence that this heterogeneity in PIFs' risk-taking behavior across multi- and single-strike funds is explained by cross-sectional differences in investors' risk preferences.

The research paper titled '*Jack of All Trades versus Specialists: Fund Family Specialization and Mutual Fund Performance*' explores, for the first time, the impact of specialization decisions by a fund family, as reflected by its asset-based concentration in the active management segment (ACF), on the performance of its equity mutual funds. This study finds that active funds of fund families with higher ACF enjoy superior performance and greater investor capital allocation. Importantly, funds of fund families with higher ACF exhibit greater reliance on private information production, a clear signal of managerial skill. These findings are not explained by heterogeneity in total ownership costs and outsourcing arrangements of the fund family. By exploiting a quasi-experiment involving fund families' sponsorship acquisition events, it is shown that fund performance deteriorates markedly when the acquiring fund family has lower ACF than the selling fund family. Last, this study shows that funds affiliated to fund families with higher ACF enjoy significant institutional advantages from better family-level allocation of resources to information production.

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Chapter 1

Introduction

1.1 The Mutual Fund Industry

The mutual fund industry has experienced rapid growth in the past century as a result of increasing demand from both households and institutions. According to the 2018 Investment Company Institute (ICI) Fact Book, United States (US) households have continued to rely on investment companies for their investments and allocated 24% of their financial assets in mutual funds, well above the 13% allocation in bank deposits. The industry of open-ended mutual funds plays a major role in financial markets with assets under management exceeding $18 trillion as of 2017, 55% of which is managed by equity mutual funds, 22% by bond mutual funds, 8% by hybrid mutual funds, and the remaining 15% by money market mutual funds. While equity, bond, and hybrid mutual funds provide investors with the management services of long-term investments, money market funds (MMFs) serve short-term investments and are typically considered an alternative cash management vehicle to more traditional bank deposits. Mutual funds are also important liquidity providers to financial and nonfinancial institutions through their holdings of equity securities and both short-term and long-term debt securities (see e.g. Musto, 2011).

This thesis uses a quantitative framework to investigate the interaction between two key market players in the mutual fund industry, namely, fund managers and their investors. The characteristic feature of mutual funds is that they provide investors with alternatives to direct investment in individual securities. Investors buy or sell fund shares at the net asset value (NAV) of a mutual fund based on their assessment of the quality of its asset management services in terms of fund performance, risk profile, and liquidity management. Many studies have shown that investors chase past performance by allocating more capital to outperforming funds (Spitz, 1970; Sirri & Tufano, 1998). Cash flows between investors and mutual funds reflect the volume and direction of investors' trading activities as a result of this quality assessment. Since the fee revenue generated by a fund (and its fund sponsor) depends on fund size, and hence ultimately on investors' net money flows, investors' capital allocation decisions inevitably affect funds' ex-ante risk-taking behavior and fee-structure decisions. This, in turn, could influence the pricing of their traded assets, and the overall stability of the financial system (Christoffersen *et al.*, 2014).

The topic of delegated asset management has been studied extensively in the literature. Earlier studies have investigated the economic motivations for mutual fund managers to change their risk profile and the implications of their risk shifting for fund performance and investor flows. Mutual fund managers adjust their risk levels for several reasons. One of the drivers of a fund's decision to take a risk is the presence of agency issues in delegated portfolio management, which can be detrimental to investor wealth. To attract additional investor flows and thus enhance their asset-based fee revenue, fund managers can ramp up risk (e.g., Zheng, 1999; Wermers, 2003; Basak *et al.*, 2007), or even manipulate end-of-year performance (Goetzmann *et al.*, 2007). Risk shifting can also be motivated by compensation incentives. Starks (1987) and Elton *et al.* (2011) show that incentive-fee funds take on more risk than do non-incentive-fee funds and are more likely to increase risk after a period of poor performance. Fund managers are also shown to exhibit heterogeneous risk-taking incentives because of career concerns or based on their interim performance ranking in the active fund segment (Brown *et al.*, 1996; Chevalier & Ellison, 1999; Kempf *et al.*, 2009; Schwarz, 2011).[1] Kempf & Ruenzi (2008) argue that tournament-motivated risk-taking also exists within mutual fund families, the degree of which depends on the level of within-family competition, since fund managers need to compete for scarce resources, such as marketing opportunities provided by the fund family. Alternatively, risk shifting could arise as an unintended consequence of skilled fund managers changing their portfolio composition to take advantage of their private information production (see e.g. Huang *et al.*, 2011).

[1] Additional papers on the tournament and on risk-taking incentives include Taylor (2003), Qiu (2003), Chen & Chen (2009), and (Hu *et al.*, 2011).

This thesis contributes to the asset management literature by concentrating on two macro issues related to the causes and consequences of mutual fund managers' risk-taking decisions across two different mutual fund groups. First, this thesis assesses the relation between fund liquidity risk and the risk-taking incentives of MMF managers. A defining feature of MMF products is their ability to offer investors means to achieve high yields while preserving their access to intraday liquidity. Flow-related liquidity management is critical to the functioning of MMFs because unlike other mutual funds, they are typically "hold-to-maturity" vehicles that meet next day redemptions using primarily previous-day maturing assets.[2] The liquidity management skill of MMF managers is reflected in their ability to project future cash flows and deal with unanticipated asset–liability mismatches. To attract additional investor flows and thus maximize fee income, MMF managers boost performance by increasing their holdings of illiquid debt securities, such as (asset-backed) commercial papers and bank obligations. However, excessive risk-taking can enhance investor wealth at the cost of heightened liquidity risk which can destabilize the fund and in turn the entire MMF industry. Chapters 2 and 3 of the thesis examine the implications of a change in the regulatory environment of MMF for fund managers' ex-ante risk-taking incentives.

Second, this thesis analyzes the performance implications of the fund family product offering and its relation to the degree of active risk-taking of equity mutual funds. Mutual funds are owned and managed by their affiliated investment companies, also known as fund families. While some fund families prefer to diversify their fund product offering across both active and passive fund management in an attempt to minimize investors' redemption risk and maximize fee revenue (see e.g. Elton *et al.*, 2007), others specialize their product offering in one of these segments. Chapter 4 of the thesis examines whether, and if so, how a fund family's degree of specialization in the active fund management segment affects the active risk-taking decisions of its active funds, and, importantly, the performance implication of this active risk-taking. As previously discussed, increasing risk-taking does not necessarily improve investor wealth. This chapter

[2] A recent study conducted by the Institutional Money Market Association estimated that only 0.33% of MMFs sell their portfolio assets before maturity (see e.g., "The Use of Amortised Cost Accounting by MMFs"). Similarly, the Division of Risk, Strategy, and Financial Innovation (DERA) of the Securities and Exchange Commission (SEC) finds that most MMF securities are held to maturity, and it justifies this trend by noting that securities held until maturity will eventually yield a NAV equivalent to market-based valuations, under ordinary circumstances. Notably, MMFs also tend to hold less than 1% of their assets in cash, which could otherwise absorb unanticipated outflows without triggering instant trading.

also identifies the channel that links the risk-taking of funds offered by actively concentrated fund families to improved performance.

1.2 Thesis Structure and Contribution

The three main chapters of the thesis (Chapters 2–4) are based on three research papers, with the first two chapters (Chapters 2 and 3) focusing on fund risk-taking incentives in the money market industry and the last chapter (Chapter 4) on fund performance of active equity mutual funds affiliated with fund families with different degrees of active management specialization.

Chapter 2: *Out of Sight, Out of Mind: Information Insensitivity and Risk-taking of Prime Institutional Money Market Funds*

In July 2014, the Securities and Exchange Commission (SEC) introduced a new reform requiring prime institutional money market funds (PIFs) to disclose extensive portfolio information to the public including daily mark-to-market NAVs, and float their prices. We examine the economic implications of the mark-to-market NAV pricing framework for PIF risk-taking incentives. Using daily information on PIFs' characteristics, we find that in response to the new reform, PIFs have lowered their aggregate portfolio maturity, increased their portfolio liquidity, and tilted away from risk assets. Interestingly, PIF managers have proportionally increased their risk-taking under the floating NAV (FNAV) pricing system confirming the existence of weaker investors' adverse selection under this regime. Our results highlight for the first time the benefits of a more informationally sensitive NAV in terms of improving PIFs' overall risk profile.

This study is the first to examine empirically how enhanced disclosure of the mark-to-market NAV affects PIFs' ex-ante risk-taking incentives from greater investors' informational advantage. Focusing on the money market industry, we contribute to the literature on MMFs' risk-taking incentives by showing that a more informationally sensitive NAV improved the overall risk profile of PIFs as a result of fund managers' stronger incentives to eliminate investors' greater informational advantage. The evidence supports that the subsequent transition from constant NAV (CNAV) to mark-to-market NAV of PIF shares reduced markedly investors' adverse selection and thus the overall financial fragility.

Chapter 3: *Floating NAV Pricing under Single- versus Multi-strike Prime Institutional Money Market Funds*

This is the first study to assess the implications of the intraday FNAV strike system of PIFs for the funds' risk-taking incentives. Prime funds offer multiple redemption windows to cater to investors with greater liquidity needs at the cost of greater exposure to unanticipated asset–liability mismatches during the day. Using unique data on the intraday striking system of PIFs, it is shown that to limit this exposure to heightened flow-related liquidity risk, multi-strike funds have: i) reduced their maturity risk; ii) increased their portfolio liquidity; iii) reduced their portfolio holdings of risky assets relative to safe assets; and iv) intensified their reach for yield. We find that institutional investors are prepared to pay a premium for their more frequent access to intraday liquidity. Importantly, we find no evidence that this heterogeneity in PIFs' risk-taking behavior across multi- and single-strike funds is explained by cross-sectional differences in investors' risk preference.

This study contributes to the current literature on MMFs' risk choices by investigating the cross-sectional difference in the risk-taking behavior of PIFs under the new FNAV system, and its association with a fund's flow-related liquidity risk. Importantly, this study emphasizes for the first time that the intraday striking system allows prime funds to preserve their money-likeness at the cost of marginally lower shareholder annualized yields.

Chapter 4: *Jack of All Trades versus Specialists: Fund Family Specialization and Mutual Fund Performance*

This study explores, for the first time, the impact of specialization decisions by a fund family, as reflected by its asset-based concentration in the active management segment (ACF), on the performance of its equity mutual funds. We find that active funds of fund families with higher ACF enjoy superior performance and greater investor capital allocation. Importantly, funds of fund families with a higher ACF exhibit greater reliance on private information production, a clear signal of managerial skill. Our findings are not explained by heterogeneity in total ownership costs and outsourcing arrangements of the fund family. By exploiting a quasi-experiment involving fund families' sponsorship acquisition events, we show that fund performance deteriorates markedly when the acquiring fund family has lower ACF than the selling fund family. Last, we show that funds affiliated to fund families with higher ACF enjoy significant institutional advantages from better family-level allocation of resources to information production.

This study contributes to the growing literature on the effect of a fund family's product diversity on investor wealth and capital allocation by highlighting the performance implications of fund families' product diversity across the unrelated segments of active and passive investing. In this light, the study contributes to the extant literature on the effect of side-by-side management of different fund products of a fund family on fund performance. Finally, by emphasizing the performance benefits of a fund family's decision to pursue segment specialization, this study also contributes to the debate on the value of active management in the mutual fund industry.

To conclude the thesis, Chapter 5 summarizes the main findings of Chapters 2, 3 and 4 and the major contributions to the current mutual fund literature. It also identifies several directions for future research in the mutual fund industry.

Chapter 2

Out of Sight, Out of Mind: Information Insensitivity and Risk Taking of Prime Institutional Money Market Funds

Chanyuan Ge (contribution 80%), Lorenzo Casavecchia (contribution 20%)

2.1 Introduction

As the largest investors in short-term liabilities of financial institutions and corporations (Kacperczyk & Schnabl, 2013), money market funds (MMFs) play an essential role in financial markets. Despite their track record of principal stability, MMFs experienced an unprecedented investor run exceeding $300 billion in September 2008. The resulting flight-to-quality of MMFs from risky collateralized debt (e.g., commercial paper) to safe treasury debt increased their liquid assets but froze short-term funding for financial and nonfinancial institutions. The United States (US) Department of the Treasury responded promptly by injecting large volumes of liquidity to stabilize the money market and support the $3 trillion MMF industry.

Many commentators interpreted this investor run as evidence of adverse selection in the MMF segment.[1] To reduce the run risk among MMFs while preserving, as much as possible, their money-likeness nature, the Securities and Exchange Commission (SEC) proposed on 23 July 2014 an amendment to Rule 2a-7 under the Investment Company Act of 1940. The new regulation required all MMFs to enhance disclosure by reporting their daily mark-to-market NAV from 14 April 2016, while allowing all prime institutional MMFs (PIFs) to trade at constant NAV (CNAV) until 13 October 2016. A second fundamental change was the requirement for PIFs to trade their shares at floating NAV (FNAV) from 14 October 2016. The reform did not alter the existing CNAV trading rule among government and retail MMFs.

Since the initial adoption of Rule 2a-7 in 1983, the SEC has allowed open-end MMFs to trade their shares at the CNAV of $1.00. Their historical ability to meet redemptions at par contributed to the general perception of PIFs as riskless debt-on-debt-like securities, whose trading requires only limited information production, despite their holdings of (illiquid) collateralized debt securities such as commercial papers.[2] The opacity of the CNAV has allowed PIFs to create money-like liquidity and provide investors with access to intraday liquidity at par (see e.g., Hanson & Sunderam, 2013). Dang *et al.* (2015) argue that by raising information production costs, the information insensitivity of debt-on-debt securities creates value for investors who trade primarily for liquidity purposes since this reduces adverse selection costs. However, they demonstrate that a liquidity shock to the collateral value causes debt to become suddenly information-sensitive, and that this could amplify investor-run risk owing to adverse selection (Gorton, 2010; Holmström, 2015).

Why would a PIF decide to (over) invest in risky collateralized debt securities

1 Under the constant net asset value (CNAV) regime, an MMF would be forced to liquidate (i.e., "break-the-buck") if the "shadow" mark-to-market NAV declines below the threshold of $0.995. Importantly, should the NAV decline from the CNAV of $1.00 to the mark-to-market NAV of $0.998, an investor who withdraws first will receive the CNAV of $1.00, and face no dilution costs ("first-mover advantage"). The next redeeming investor, however, will receive only $0.996 (= 2 x $0.998 – $1.00) and pay a significant dilution cost of 40 basis points per share.

2 Dang *et al.* (2015) refer to MMFs as debt-on-debt securities. This definition applies primarily to PIFs, where the information sensitivity of their CNAV is further minimized by the information insensitivity of their portfolio holdings of collateralized debt securities, such as commercial paper and bank obligations. In the presence of asset-backed commercial paper holdings, it is possible to think of PIFs as debt-on-debt-on-debt securities.

if its information insensitivity worsens its liquidity risk?[3] After all, it could simply reduce its exposure to risky assets to prevent unanticipated asset–liability mismatches. Hanson *et al.* (2015) suggest that the stability of the CNAV incentivizes PIFs to overinvest in risky collateralized debt securities even when there are early warning signs of future financial stress. Kacperczyk & Schnabl (2013) show that PIFs' "reaching-for-yield" behavior is rewarded with substantial asset growth even during the early stages of a financial crisis (see also Chernenko & Sunderam, 2014). This is unsurprising under a CNAV system: if investors believe that they can continue to redeem at par despite the (unobserved) liquidity risk posed by collateralized debt holdings, they would be less inclined to seek private information on the "shadow" mark-to-market NAV of PIFs. In other words, if the dislocation of the mark-to-market NAV from the CNAV is out of sight, it is likely to also remain out of mind. Holmström (2009) and Pagano & Volpin (2012) argue that this blissful state of "symmetric ignorance" among investors may be broken by enhanced information disclosure which reduces private information production costs. Similarly, Dang *et al.* (2017) suggest that by increasing information acquisition costs, opacity offers efficient risk-sharing between investors, and eliminates the informational advantage of expert investors to acquire information. They show that when the cost of information acquisition drops, banks could choose to relax the information acquisition incentives of expert investors by reducing (increasing) their investments in risky (safe) assets, equal conditions.[4]

This study is the first to test whether a more informationally sensitive debt strengthens managers' incentives to reduce investment in risky assets as a result of investors' greater informational advantage. We test this prediction using the 2014 reform requiring MMFs to start disclosing their daily mark-to-market NAV after the proposal date of 23 July 2014—and no later than 14 April 2016—without altering the CNAV trading rule.[5] We expect a more informationally sensitive NAV

[3] Under Rule 22e-4(a)(7), the SEC defines liquidity risk as "the risk that the fund could not meet requests to redeem shares issued by the fund that are expected under normal conditions, or are reasonably foreseeable under stressed conditions, without materially affecting the fund's net asset value."

[4] Dang *et al.* (2017) show that banks could alternatively distort money provision rather than increase their holdings of safe assets when investors' liquidity needs are small. This is obviously not the case for PIF investors.

[5] Prior to the 2014 reform, MMFs reported their monthly portfolio holdings but were not required to disclose the daily mark-to-market NAV. As suggested by Holmström (2015), this represented a "purposeful effort to avoid a continuous flow of information into the market."

to weaken the ex-ante managerial incentives to hold risky assets (e.g., commercial papers) in an attempt to eliminate the experts' informational advantage.[6] This strategy would be optimal from PIFs' perspective if it helps reduce the volatility of the NAV, thus preserving their previous money-like nature.

Importantly, we evaluate whether PIFs' transition to an FNAV trading rule on 14 October 2016 has altered their choice of risky assets. Hanson *et al.* (2015) posit that the transition to FNAV trading could reduce the advantage of informed investors to redeem first because the fund's liquidation threshold would mechanically drop from \$0.995 of the CNAV to \$0 under the FNAV. If the FNAV reduces investors' dilution costs and expected value of private information production, we should then expect PIFs to respond to the implementation of the FNAV regime by readjusting their holdings of less liquid and risky assets. Our findings offer a fresh perspective on the current state of play of the PIF segment in the wake of the growing bipartisan support for a new bill that could roll back the MMF reform and reinstate the CNAV trading rule.[7]

We use high frequency (i.e., daily) information on PIFs' characteristics from January 2012 to March 2018, and highlight for the first time the benefits of a more informationally sensitive NAV in terms of aggregate portfolio liquidity, maturity risk, and excess annualized yield of PIFs.[8] In the time series, we show that PIFs have reduced their aggregate portfolio maturity by more than 37 days during the compliance period, and by 32 days during the implementation period. We also document an economically meaningful reduction in the dollar-weighted maturities across different security types, which confirms the post-reform improvement in prime MMFs' portfolio liquidity. Additionally, we find an increase in

6 A related study examines the impact of enhanced transparency on financial institutions(see Goldstein & Sapra, 2014, for a comprehensive literature review). A widely used argument in favor of disclosure is that it improves market discipline thus leading investors to monitor financial institutions closely. Arguments against transparency refer to the possible reduction of risk-sharing opportunities (Hirshleifer, 1971) or inefficient market discipline in the presence of information externalities (Morris & Shin, 2002). Our study is more closely related to the literature on the effect of information sensitivity.

7 On 3 May 2017, representative Keith Rothfus introduced H.R. 2319–Consumer Financial Choice and Capital Markets Protection Act (`https://www.congress.gov/congressional-report/115th-congress/house-report/903`). The bill would reverse parts of the MMF reform such as the requirement of PIFs to trade at FNAV.

8 It is important to distinguish two implementation periods of the MMF reform. The SEC announced the of amended Rule 2a-7 on 23 July 2014, but set the implementation date of the disclosure of portfolio date on 14 April 2016 to allow enough time for MMFs to adjust to the new regulatory environment. Although our main empirical identification comes from an event study analysis of the implementation date, we also quantify any changes in fund's risk-taking behavior during the compliance period 23 July 2014 to 13 October 2016.

the percentage of daily and weekly liquid assets by 11% and 27% after the implementation of the FNAV regime. This confirms the disincentives for PIFs to reach for yield as a result of the increase in investors' informational advantage following the disclosure of the mark-to-market NAV. The negative relationship between investors' informational advantage and the risk-taking incentives of PIFs is further confirmed by the increase in PIFs' risk-taking behavior following the implementation of the traded FNAV on 14 October 2016. The reduction in the dilution costs associated with the new FNAV regime provides stronger incentives for PIFs to heighten their relative exposure to maturity risk.

Using maturity- and holdings-matched yield spreads of prime funds, we confirm the positive effect of the lower portfolio average maturity on the post-reform search-for-yield behavior of PIFs. On average, the maturity- and holdings-adjusted yield spreads decreased by 1 and 2 basis point(s) during the two-year transition period, indicating a weakened incentive of PIFs to search for yield. The yield spreads were readjusted upward following the FNAV implementation as a result of the lower dilution costs and thus the reduced value of private information product.

These findings are enhanced by using weekly information on fund portfolio holdings and separating asset holdings into safe assets (e.g., treasury securities and repurchase agreements collateralized by treasury securities) and risky assets (e.g., bank obligations, commercial papers, and asset-backed commercial papers). Our results show that the improvement in a fund's aggregate risk profile is driven primarily by the reduction in its holdings of risky assets. Importantly, we observe that PIFs have readjusted their holdings in risky asset classes after their transition into the FNAV regime.

One empirical concern is the identification of the results on risk-taking. The new reform caused several funds to exit the prime segment as a result of either fund closure or changes in their label from prime to government MMFs and from institutional to retail share classes. If riskier funds are more likely to exit, our results on the post-reform change in funds' risk profiles could also be consistent with the survival of the safer funds. We address this concern by first estimating a probit model of the probability of fund exit on several risk-taking proxies and find that the decision to exit is not limited to riskier funds. We then re-estimate our main tests by removing funds that exit the sample during the transition period 23 July 2014 to 13 October 2016, and reach qualitatively similar conclusion. This suggests that funds' positive selection is unlikely to explain our findings regarding the change in the strategic behavior of PIFs.

Our study contributes to the recent debate on the implication of the FNAV regime for PIFs. We provide, for the first time, the empirical evidence that suggests the enhanced disclosure of mark-to-market NAV strengthens PIFs' incentives to reduce risk-taking under normal market conditions. This study also contributes to the literature on information sensitivity of debt-on-debt securities. While early studies have mostly focused on the effect of information sensitivity during distress periods, we contribute to this strand of literature by examining the implications of an exogenous shock to investors' informational advantage for the risk-taking incentives of PIFs. Overall, our findings suggest that the disclosure and implementation of mark-to-market NAV increases investors' informational advantage and improves the overall resiliency of the prime segment by disincentivizing PIFs from holding illiquid over-collateralized debt securities.

2.2 Industry Background

Prime MMFs are open-ended mutual funds commonly used by institutional and retail investors as cash management tools. PIFs accounted for about 55% of the entire $3 trillion money market fund industry. They offer single deposit-like accounts, which provide investors with a diversified pool of high quality and short-term instruments. Historically, PIF investors have enjoyed the high yield provided by PIF products while being able to access their cash rapidly at a stable NAV rounded to $1.00. For financial and nonfinancial institutions, PIFs are a vital provider of short-term financing since prime funds invest largely in commercial papers and certificates of deposit.

The industry was known for its long track record of stability and safety until 16 September 2008. With an exposure of $784 million to Lehman Brothers' debt securities, the Reserve Prime Fund received $25 billion's worth of redemption orders on the day of Lehman's failure. As a result, it "broke the buck" and was forced to liquidate the following day, which in turn caused a market-wide investors' run from prime to government MMFs (see e.g., Brady *et al.*, 2012; Chernenko & Sunderam, 2014). The prime institutional segment suffered a 29% reduction in total assets under management in the two weeks following the failure of the

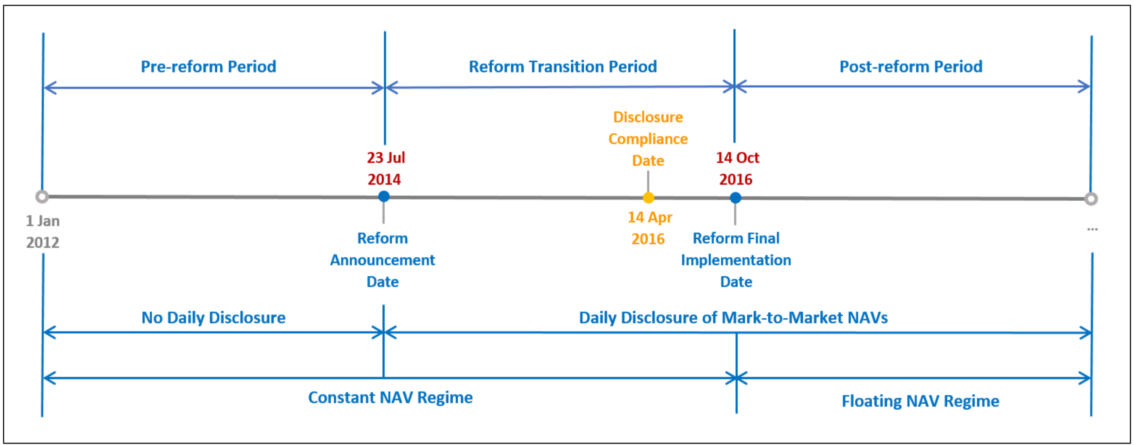

Figure 2.1. 2014 SEC Reform Timeline.

Reserve Prime. The investor run was eventually backstopped by the government's temporarily guarantee offered on 19 September. The US Department of the Treasury provided extraordinary support to the industry to help stabilize the funding of global financial institutions.[9] It is important to note that because large financial firms rely heavily on PIFs for short-term funding, in the absence of a government intervention, the run on PIFs could have resulted in a cascading wave of intermediary defaults and a system-wide financial collapse.

In February 2010, the SEC adopted amendments to Rule 2a-7 as a response to the financial turmoil of 2008. These included a reduction of the maximum portfolio weighted average maturity from 90 days to 60 days, a tightening in the illiquid asset holdings from 10% to 5%, the introduction of a minimum requirement of 10% of daily liquid assets and 30% of weekly liquid assets out of a fund's total assets, and the requirement of the additional disclosure of a fund's month-end portfolio holdings. Despite this more stringent regulatory framework, PIFs were hit for the second time in 2011 by two financial market shocks: the US federal debt ceiling standoff, and the Eurozone debt crisis, which triggered again panic-driven investor redemptions. This led the SEC to propose a second round of amendments to Rule 2a-7 in July 2014, which were fully implemented on 14 October 2016. Figure 2.1 illustrates the detailed reform timeline.

[9] The Federal Reserve was forced to expand a set of emergency liquidity facilities including the Primary Dealer Credit Facility, the Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility to support finance purchases of asset-backed commercial paper from MMFs, and the Commercial Paper Funding Facility to support the tri-party repo market in the aftermath of MMF withdrawals and finance purchases of(asset-backed) commercial papers from MMFs.

There are two major changes compared with the 2010 reform.[10] First, after the announcement date of 23 July 2014, PIFs were required to start reporting daily market-based NAV on their company websites by no later than 14 April 2016 while maintaining trade at a constant \$1.00 per share.[11] PIFs invest largely in over-collateralized debt such as (asset-backed) commercial papers and certificates of deposit, which are information-insensitive during normal times (see e.g., Holmström, 2015). When PIFs trade at constant \$1.00 NAV and are not required to disclose their mark-to-market prices, PIF investors operate in the market without price discovery such that investors' need for private information production is minimized simply because this information is unreachable or the cost of information production outweighs the potential benefits. This leaves PIFs enough time to adjust to fluctuations in the daily NAV. The enhanced disclosure of daily mark-to-market NAVs improves investors' oversight of PIFs' risk profiles because now PIFs are less likely to mask fluctuations in the market value of collateralized debt holdings, which in turn leads to PIFs' stronger incentives to reduce their holdings of these risky assets.

Second, a fundamental change is that PIFs have been required to abandon the current constant \$1.00 NAV and trade at the mark-to-market or FNAV from 14 October 2016. The CNAV rule has been a pricing convention to the MMF industry, and it enables a fund to trade at a constant \$1.00 per share as long as the "shadow" mark-to-market NAV has not fallen below \$0.995. If the penny-rounded NAV falls below \$0.995–also known as the "breaking-the-buck" event–the fund is then forced to liquidate all its assets. The CNAV regime has been criticized by many because it incentivizes PIFs to "search for yield" during normal times. In the event of an investor run, the early redeeming investors can be met with cash generated from maturing assets and/or by selling off the safest and most liquid holdings (Manconi *et al.*, 2012). This, in turn, leaves the remaining investors with illiquid assets, and heightened liquidity risk (see e.g., Strahan & Tanyeri, 2015). The later redemption

[10] The new reform also introduces a liquidity fee and redemption gate rule as amendments to the existing liquidity ratio test and gating rules under the 2010 amended Rule 2a-7. For all prime funds, a fund's board of directors is given the discretion to impose liquidity fees of up to 2% upon redemptions, and/or gate redemptions for up to 10 business days in a 90-day period, whenever the fund's weekly liquid assets fall below 30% of its total assets. Further, the board would be required to impose a 1% liquidity fee if its weekly liquid asset level falls below 10%.

[11] Other required daily disclosure includes daily and weekly liquid asset levels, flows, and instances of sponsor support. Prior to 23 July 2014, MMFs only had to file monthly reports with the SEC. However, the reported NAV has limited informativeness because it is not the current NAV (see Holmström, 2015).

requests can only be met with liquidity-motivated fire sales of illiquid assets which can generate great dilution costs to the existing investors or even cause the fund to break the buck.

However, the FNAV pricing requires PIFs to obtain mark-to-market prices of their holdings and report the basis point–rounded unit share price (i.e., to the nearest 1/100th of one cent). Contrary to the CNAV system, the floating unit price of PIFs eliminates entirely the possibility of the breaking-the-buck event since every share now must be redeemed at the latest available market value. This mark-to-market NAV would reflect the latest market value of the fund portfolio as well as the potential cost of liquidity-motivated trades associated with investors' redemption orders. The greater transparency of investors' residual claims, as reflected by the FNAV, weakens investors' incentives to run ahead of others and reduces adverse selection problems. However, it is unclear whether the adoption of the FNAV system is as beneficial to the MMF segment as the regulator expected. Parlatore (2016) argues that the FNAV system would decrease the probability of sponsor support, reduce fund managers' risk-taking incentives, and in turn increase the aggregate portfolio liquidity of PIFs. In contrast, Gordon & Gandia (2014) and Hanson *et al.* (2015) believe that the FNAV system may work in a similar fashion to the existing stable NAV system because of the illiquidity of the secondary markets for commercial papers and other private money market assets, such as certificates of deposit, such that the share price would almost fluctuate between $0.9990 and $1.0010.

2.3 Data and Methodology

2.3.1 Empirical Design

In our empirical tests we use an array of risk-taking proxies of PIFs. Our main focus is on the effects of the MMF reform implemented by the SEC. Since MMFs adjust their interest rate risk exposure through weighted average maturity (WAM), this also represents the risk-taking proxy in this study. For robustness, this study considers three alternative proxies. Our second proxy is weighted average life (WAL). While WAM is computed using the interest rate reset date (e.g., 30-day interest rate reset), WAL is based on the security's stated final maturity (e.g., 365-day maturity). By using the interest rate reset date, WAM effectively measures a prime fund's exposure to interest rate changes and their potential impact on fund portfolio yield. By contrast, for a fund required to hold its entire portfolio of securities until maturity, *WAL* would better reflect any deteriorating credit or tightening liquidity conditions.

Our third proxy relies on the maturity-adjusted annualized portfolio yield of prime funds. In their study, Di Maggio & Kacperczyk (2017) use the spread between the annualized yield and the federal target rate as one of their risk-taking proxies to evaluate the effect of the Federal Reserve (FED) zero-interest-rate policy (ZIRP) introduced in December 2008. However, this proxy may not be appropriate to distinguish the effect on the portfolio yield of a fund's risk-taking behavior from that of changes in the FED policy rate during periods of rising interest rates. For instance, assume that the market on 1 June 2015 discounts the price of US government securities in anticipation of a 25 basis points interest rate hike, which is expected to be announced by the FED at the next Federal Open Market Committee (FOMC) meeting on 16 December 2015. This adjustment in market expectations will immediately affect the annualized spread between the yield of a prime fund portfolio of US government securities and the (current) FED target rate, even when the prime fund did not alter the portfolio *WAM*. To address this issue, this study uses two excess yield measures to quantify better the risk-taking behavior associated with prime fund portfolio decisions. The first fund spread variable is *SpreadWAM*, which is the difference between a fund portfolio yield and the average yield of a portfolio of funds with matched portfolio *WAM*. The second fund spread variable, *SpreadHR*, is computed as the excess yield of a fund over the average yield of a portfolio of funds with a matched portfolio holdings risk (*HR*). Following Di Maggio & Kacperczyk (2017), this study defines *HR* as the difference between a fund's percentage holdings of risky assets (i.e., bank obligations) and safe assets (i.e., US treasury and agency securities and repurchase agreements). This study computes the first (second) spread yield variable by first assigning prime funds to quintile portfolios of sorted *WAM* (*HR*) at the end of day $t-1$. For each quintile portfolio of sorted *WAM* (*HR*), we then calculate the equally weighted average gross yield in day t, and subtract it from the gross yield of all prime funds belonging to that *WAM* (*HR*) quintile portfolio. The resulting excess gross yield is more likely to reflect the "active" decisions of prime funds to change their risk profiles than the confounding effect of (expected) policy rates on prime funds' portfolio yields.

The fourth and last proxy of funds' risk-taking is the percentage of daily liquid asset (DLA) and the percentage of weekly liquid asset (WLA). Daily (weekly) liquid assets include any: (i) cash, (ii) direct obligations of the US government, (iii) securities that will mature or are subject to a demand feature[12] that is exercisable and payable within one (five) business day(s), and (iv) amounts receivable and due unconditionally within one (five) business day(s) pending sales of portfolio securities. For instance, an increase in the percentage of daily liquid asset maturing in a day would indicate an increase in the liquidity available to the fund to face next-day net cash outflows. MMFs are not required to disclose their fund liquidity on a daily basis until the announcement of the new reform. To obtain historical information on portfolio liquidity covering the whole sample period, we strictly follow the SEC definitions and compute our liquidity measures based on the portfolio-holdings data provided by iMoneyNet. Since holdings information is only reported on a monthly basis, our liquidity measures are computed at month end. The accuracy of the liquidity measures is confirmed by performing data checks using the available iMoneyNet data on daily and weekly liquidity information. We also replace the liquidity measures calculated from portfolio holdings with those available from iMoneyNet, which collected fund liquidity measures as soon as they started to be disclosed by PIFs, and yield similar conclusions.

2.3.2 Data and Summary Statistics of the Sample

The sample includes the universe of US institutional taxable prime money market mutual funds over the period of January 2012 to March 2018. We obtained daily money market fund data from iMoneyNet. This dataset is the leading provider and most comprehensive source of information on MMF portfolio attributes such as investment objectives, fund family/adviser names, share class information, total net assets, daily gross yield, fund fees (charged and incurred), portfolio average maturity, portfolio average life, and portfolio security holdings. More recently, iMoneyNet has also started reporting information on the percentages of daily liquid assets and weekly liquid assets of MMFs. We use this information to examine any change in the daily liquidity positions of PIFs around the introduction and implementation dates of the SEC reform.

[12] A demand feature is defined as a feature permitting the holder of a security to sell the security at an exercise price equal to the approximate amortized cost of the security plus accrued interest, if any, at the time of exercise. All definitions are sourced from the amended Rule 2a-7 published on the SEC website.

We complement the iMoneyNet sample with data from the CRSP Mutual Fund Database (CRSP MFDB) and Form N-MFP filed by all MMFs with the SEC since November 2010. From the CRSP MFDB, we collect data on total assets under management and fund product offerings of mutual fund sponsors and then matched with these sponsor characteristics with iMoneyNet using unique NASDAQ tickers. From the Form N-MFP, we collect monthly fund portfolio holdings information, which includes CUSIPs, maturity dates, asset classes, weights, and issuers. The N-MFP data is then linked to iMoneyNet using unique central index keys of the registrants and unique series identifiers of individual MMF portfolios.

We conduct our analysis at the institutional share class level for several reasons. First, share class level information allows superior estimates of changes in institutional investors' risk appetite regarding the introduction of the new policy. Second, share class level fees enable the construction of cross-sectional proxies for investors' sophistication, as shown in Schmidt *et al.* (2016). Third, since PIFs could cater their portfolios to individual investors via retail share classes until 14 October 2016, an institutional class-level analysis would yield less noisy estimates of the risk-taking incentives of PIFs[13].

Panel A of Table 2.1 provides the descriptive statistics of our sample of PIFs from January 2012 to March 2018. The average prime fund class has \$3.3 billion in assets under management, has been in operation for at least 15 years, and manages a portfolio of securities with a *WAM* of 37 days, and a *WAL* of 62 days. Importantly, *DLA* and *WLA* in the prime fund portfolio average at 33% and 50%, respectively. It is also interesting to note that the 5th percentile of funds' *DLA* (*WLA*) distribution of 16% (34%) is well above the minimum regulatory thresholds of 10% (30%) that would put pressure on the PIF board to impose liquidity fees or temporarily suspend institutional investor redemptions for up to 10 days. Panel A of Table 2.1 shows that the average prime fund experiences net cash inflows of 18.6%, varying between –5% (5th percentile) and +5% (95th percentile), and offers a daily net annualized yield of 18 basis points which reflects a daily gross

[13] Using proprietary data from the Investment Company Institute (ICI), Schmidt *et al.* (2016) estimate that some self-declared institutional share classes comprise less than 5% of sophisticated institutional ownership. Since our hypotheses are concerned with the (expected) response of institutional investors to fund liquidity shortfalls, the presence of less sophisticated investors (e.g. omnibus accounts) among some self-declared institutional share classes is likely to weaken our findings on PIFs incentives to reduce their liquidity risk. Schmidt *et al.* (2016), for instance, show that the presence of retail investor classes mitigates the strategic complementarities among institutional money market funds.

annualized yield of 41 basis points and an annualized expense ratio of 23 basis points.

In Panel B of Table 2.1, we report the descriptive statistics of weekly PIF portfolio holdings. Typically, prime funds invest in an array of asset categories, including US treasury (USTR) and agency debt and repurchase agreements (USOT), domestic and foreign bank obligations (BNKOB), floating rate notes (FRNS), asset-backed commercial papers (ABCP), and financial and nonfinancial commercial papers (CP). Over the sample period, the average prime funds invested 21% in BNKOB, 10% in ABCPs, and an additional 31% of its assets in CP. About 23% of prime fund portfolios are allocated to USTR (3.1%), USOT (3.7%), and 15.9% in tri-party repo contracts (REPO). Repo contracts are among the safest assets that prime funds could invest in because of their daily collateral and overnight maturity.[14]

Next, we decompose the total portfolio maturity and portfolio liquidity at the level of the asset categories. Specifically, we compute the value-weighted *WAM* and *DLA* for some asset classes illustrated previously in Panel B of Table 2.1. The findings are documented in Panel C of Table 2.1. The evidence there indicates that *DLA* comprise bank obligations (7.7%) with average maturities of 42 days. Asset-backed commercial papers and Financial and nonfinancial commercial papers and account for only 3.2% of *DLA*, and have an average *WAM* of 47 and 48 days, respectively.

2.4 Prime Fund Liquidity Risk and 2014 Reform

We begin this section with a preliminary analysis of the effect of the daily disclosure of mark-to-market NAVs on PIFs by examining the change in fund characteristics around the announcement date. To this end, we first separate the sample period into two sub-periods: 1 January 2012 to 22 July 2014 (*Pre-2014*), and 23 July 2014 to 31 March 2018 (*Post-2014*). We then compute the descriptive statistics of the whole sample, which includes both surviving and dead PIFs (*Whole Sample*),

[14] MMFs invest primarily in tri-party repo contracts intermediated by two repo clearing banks, J.P. Morgan Chase and the Bank of New York Mellon. The majority of these repo contracts comprise overnight investments, in which securities are repurchased by the seller on the next business day. Only a minority of tri-party repo contracts mature later than the next business day (term repos), with the clearing banks daily readjusting the collateral value of these contracts. Given the overnight nature of these collateralized repo contracts, they are typically deemed safe investments.

and of the sample of surviving PIFs only (*Subsample Survivors*). The evidence shown in Panel A of Table 2.2 suggests that implementation of the SEC reform contributed to reducing the total net asset (TNA) of the average surviving prime fund (*FNDTNA*) by almost 33% (from \$5.2 billion to \$3.5 billion). This is consistent with the significant cash outflows experienced by prime funds prior to the implementation date of the SEC reform. By contrast, prime fund sponsors experienced an increase in the total assets under management (*FAMTNA*) across all their fund (prime and non-prime) product offerings[15]. The daily net and gross annualized daily yields increased post-2014 as a result of the increase in the FED fund rate from nearly zero to 1.25% in June 2017. Importantly, our proxies of fund risk-taking show a clear change in the behavior of PIFs. In detail, PIFs have lowered their total *WAM* by about 12 days while increasing *DLA* by 2%. A closer inspection of these findings shown in Panel B suggests that this trend applies to most of the asset classes in prime fund portfolios. For instance, prime funds lowered the *WAM* of their BNKOB by 16 days, of their CP by 13 days, and of their ABCP by 6 days. More importantly, they increased the percentage of BNKOB due to mature within 1 business day by more than 4% (from 3.2% to 7.6%) and by 1.2% for ABCP and CP (from 2.6% to 3.8%). We reach qualitatively similar findings when we consider the sample of surviving prime funds. The changes in prime funds' risk-taking proxies illustrated in Table 2.2 are not only statistically significant but also economically meaningful, and they suggest a distinctive reduction in PIFs' risk-taking incentives in response to the greater informational advantage of sophisticated investors as a result of the enhanced disclosure of mark-to-market NAVs.[16]

15 In December 2015, Fidelity reclassified a third of its PIFs as government funds. This reclassification from prime to government funds caused an increase (decrease) in sponsors' government (prime) TNA, but was not follows by any cash flow changes. We will consider the event of fund label switch in Section 2.6

16 Di Maggio & Kacperczyk (2017) show that reaching-for-yield was particularly strong among PIFs during the FED ZIRP. In our sample period, there were four rate hikes on 17 December 2015 (0.25% to 0.50%), 15 December 2016 (0.50% to 0.75%), 16 March 2017 (0.75% to 1.00%), and 15 June 2017 (1.00% to 1.25%) which officially ended the effect of the ZIRP on managerial incentives to take excessive risk. Our adjusted yield spread isolates the effect of the announcements of the FED's open market operations on PIFs' performance.

2.5 SEC Reform and Risk-taking of PIFs

Our empirical strategy uses both cross-sectional and panel variations to examine whether the 2014 reform affects funds' liquidity level and, if so, how this impact varies across funds and fund sponsors. In this section, we test our main model predictions, namely that PIFs decrease significantly their aggregate portfolio riskiness following the enhanced disclosure of the mark-to-market NAV using various risk proxies.

2.5.1 SEC Reform and Fund Maturity Risk

We examine the changes of PIFs' risk-taking decisions by first investigating the aggregate portfolio maturity around the implementation date of the SEC reform. Flow-related liquidity management is critical to the functioning of PIFs because they need to meet daily net cash outflows with maturing short-term assets without risking falling below the mandated liquidity thresholds. We analyze the portfolio maturity risk of prime funds using different proxies. Our first proxy is the funds' aggregate *WAM* and aggregate *WAL* to quantify the level of PIFs' maturity risk under the new regulation. Both, *WAM* and *WAL* have long served as important metrics for SEC and PIF investors when screening funds' risk profiles. Since the 2010 reform, the SEC has restricted PIFs to holding securities with a dollar-weighted maturity of up to 60 days, and a dollar-weighted life of up to 120 days. Earlier studies highlighted the role of *WAM* and *WAL* in measuring funds' exposure to interest rate and credit risks (see e.g., Witmer, 2016). A lower *WAM*/*WAL* indicates that a fund has a higher maturity turnover ratio of its portfolio holdings such that it is more likely to settle expected (and unexpected) redemptions with the cash generated by maturing assets. Additionally, maturity measures are closely linked to the SEC's liquid asset measures of *DLA* and *WLA* because the identifying criteria of liquid assets is based on the remaining time to maturity.

To quantify the impact of the SEC reform on PIF managers' risk-taking decisions, we adopt the following regression specification:

$$RiskProxy_{i,t} = \alpha + \beta_1 POST2014 + \beta_2 POST2016 + \Gamma' X_{i,t-1} + \epsilon_{i,t} \qquad (2.1)$$

where the dependent variable $RiskProxy_{i,t}$ is our fund risk measure of fund i in time t; *POST2014* is a dummy variable, which equals 1 if day t is within the period during which PIFs were required to enhance their disclosure of the mark-to-market NAV from 23 July 2014 to 31 March 2018, and 0 otherwise; *POST2016* is an indicator variable which identifies the FNAV implementation period from 14 October 2016 to 31 March 2018; $X_{i,t-1}$ is a set of lagged control variables in time $t-1$; and $\epsilon_{i,t}$ is the residual term. The coefficients of interest are β_1 and β_2, which capture the changes in the PIFs' average cross-sectional aggregate portfolio risk. In our regression specifications, we control for a host of fund and fund family characteristics that might be correlated with a fund's risk choices, including the logarithm of fund TNA (*LFNDTNA*), the logarithm of fund age since inception (*LFNDAGE*), the expense ratio charged by the prime fund portfolio (*FEERATIO*), the logarithm of fund sponsor's TNA (*LFAMTNA*), and the percentage change in fund assets accounted for capital appreciation (*NFLOW*). We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also apply a time-fixed effect to control for any changes in unobservable economic trends. We cluster standard errors at the day dimension to account for any cross-sectional dependence of residuals.

Table 2.3 reports the estimated findings of the regression model illustrated in equation 2.1 using alternative risk-taking measures of portfolio average maturity and portfolio average life. In columns (i) to (iv), our dependent variables are the daily *WAM* and the daily *WAL*, as reported by PIFs to the regulator. The estimated coefficients of *POST2014* and *POST2016* are both economically and statistically significant and consistent with our expectations of the effect of enhanced disclosure on fund liquidity. For example, compared with the pre-reform period without investors' access to mark-to-market NAV, PIFs' aggregate dollar-weighted maturity drops by more than 37 days, with the *WAL* decreasing by nearly 55 days, as shown in columns (i) and (ii). However, the implementation of the FNAV system led to PIFs' further adjustment of portfolio maturity. In columns (i) and (ii), the positive coefficients on *POST2016* show increases in the average *WAM* by 5 days and in the average *WAL* by 39 days compared with the transition period.

In columns (v) and (vi), we also compute the excess *WAM* (*EXCWAM*) and *WAL* (*EXCWAL*) to capture PIFs' maturity deviation from the average government fund in the segment. Our aim is to capture the differential impact of the reform on

PIFs relative to government institutional MMFs. We find consistent results using excess maturity measures. Overall, PIFs have significantly reduced their portfolio maturity post-regulation to enjoy the ease resulting from greater liquidity buffer by rolling over maturing assets at a higher pace. However, compared with the transition period, the funds' portfolio maturity has been readjusted to a relatively higher level since the implementation of the FNAV trading rule.

We find a positive relationship between *FEERATIO* and *WAM*, indicating that funds that charge a higher expense ratio hold longer maturity securities on average, which suggests that a lower level of investor sophistication, and possibly a lower flow-related liquidity risk, as proxied by higher management fees, allows funds to lengthen the maturity of portfolio holdings and increase their portfolio liquidity risk exposure. Unsurprisingly, the coefficient of the variable *NFLOW* suggests that PIFs experiencing greater net cash outflows are more likely to shorten the dollar-weighted maturity of their portfolio holdings.

According to the 2017 *Investment Fact Book* of the Investment Company Institute (ICI), PIFs' total assets under management dropped by about 70% following the announcement of the new reform, which is equivalent to nearly $900 billion net cash outflows. A possible concern with our previous findings is that prime funds could have appeared to take less maturity risks while in fact they were simply attempting to meet investors' redemption demands by reducing (increasing) portfolio maturity (liquidity). To address this concern, we also include the 30-day standard deviation of fund flows (*FLOWVOL*) in columns (iii) and (iv) of Table 2.3 to capture the heterogeneity in the volatility of fund net cash flows. Our results remain qualitatively similar to those in models (i) and (ii). We find a significant negative relation between fund flow volatility and *WAM*, which suggest that funds hit by more volatile flows tend to hold securities with lower *WAM*.

2.5.2 SEC Reform and Portfolio-holdings Maturity Risk

In this section, we evaluate the portfolio maturity risk by computing the *WAM* and *WAL* at the level of the individual asset categories in prime fund portfolios (e.g., CP, REPO). Equal conditions, a reduction in aggregate portfolio maturity will suggest lower risk-taking if associated with a reduction in the maturity of risky assets (e.g., BNKOB and CP) rather than safe assets (i.e., USTR). Using data on month-end portfolio holdings of PIFs from iMoneyNet, we compute the monthly dollar-weighted maturity of each asset category by asset-weighting the time to maturity of all portfolio securities in that category. Specifically, for each fund i, month t, and asset category c, we estimate the generic variable $ASSET\_MATURITY$ as follows:

$$ASSET\_MATURITY_{c,i,t} = \sum_{j=1}^{n} w_{j,c,i,t} * DTM_{j,c,i,t} \tag{2.2}$$

where n denotes the total number of securities in category c that fund i holds in month t; $w_{j,c,i,t}$ is the weight of security j in category c held by fund i calculated as the fund's holdings of security j as a percentage of fund's total net assets under management at time t; DTM is the number of days to maturity of security j computed using either the maturity date (with interest rate reset date) or the maturity life (without reset date) of a security[17].

Table 2.4 reports the estimated monthly regression coefficients of equation 2.1 using the average maturities of the following asset categories: (i) total portfolio holdings (*Total*), (ii) USTR[18], (iii) REPO, (iv) BNKOB, (v) ABCP, and (vi) CP. In Panel A of Table 2.4 our dependent variable is $ASSET\_MATURITY$, computed using a DTM equal to the interest rate reset date (WAM) of the security. Overall, we find that PIFs have significantly shortened their portfolio maturities across all security types after the compliance date of the reform. For instance, in columns (iv) and (vi) of Panel A, the average fund's $ASSET\_MATURITY$ of BNKOB dropped by 31 days during the enhanced disclosure period, and by 19 days (31 − 12) after the compliance date of 14 October 2016, while that of CP decreased by 32 days post-2014 and 20 days (32 − 12) post-2016. In Panel B of Table 2.4, we yield qualitatively similar conclusions for risky asset classes when we re-estimate equation 2.1 using the variable $ASSET\_MATURITY$ computed using a DTM equal to the stated final maturity date (WAL) of a security. The evidence in Table 2.4 is indicative of an economically meaningful reduction in the dollar-weighted maturities across different security types, and confirms the post-reform improvement in prime MMFs' portfolio maturity risk. Consistent with

17 When calculating WAM (WAL) under Rule 2a-7, a fund adviser is permitted to use the interest rate reset date (security's stated final maturity) for variable and floating rate securities. Therefore, the number of days to maturity for the WAM of a security is the interest rate reset date, while that for the WAL of a security is the lower of the stated final maturity date or next demand feature date.

18 The US Treasury securities include US Treasury debt and US Repurchase Agreement, if collateralized only by US Treasuries (including Strips) and cash.

our previous findings, the adoption of the FNAV system in the post-2016 period increases in funds' portfolio maturity compared with the two-year transition period of enhanced disclosure.

2.5.3 Daily and Weekly Liquid Assets of Prime Funds before and after the SEC Reform

We now examine the *DLA* and *WLA* levels to quantify the change in prime fund's portfolio liquidity around the reform date. *DLA* is an important indicator of flow-related liquidity risk since a higher *DLA* would signal a fund's superior ability to face unanticipated net cash outflows on the next business day. Prior to 14 April 2016, MMFs were not required to disclose their mark-to-market NAV on a daily basis. Since portfolio-holdings data are only available on a monthly basis, our liquidity measures are computed at the end of each month using the information from iMoneyNet. Specifically, for each fund i and month t we estimate its aggregate percentage daily and weekly liquidity by first identifying the daily and weekly liquid securities in the fund portfolio following the SEC's official definition of *DLA* and *WLA*. We then compute the monthly *DLA* and monthly *WLA* measures as a percentage of the total assets under management of fund i in month t.[19]

Table 2.5 reports the estimated coefficients of equation 2.1 using the portfolio *DLA* and *WLA* measures as our dependent variables. In models (i) and (ii), we focus on the portfolio aggregate *DLA*/*WLA* as defined by the SEC. The coefficients of *POST2014* and *POST2016* are both economically and statistically significant. This evidence suggests that PIFs have increased their aggregate portfolio daily liquidity ratio by 3% during the enhanced disclosure period and by 11% in the *POST2016* period, while they have boosted their aggregate *WLA* by over 3% and 17% over the two periods.

However, we would like to stress that, as previously noted, PIF managers tend to carefully match daily redemptions with daily maturing assets because they are unlikely to sell their holdings before maturity. As the SEC also classifies US

[19] The accuracy of our liquidity measures is confirmed by performing data checks using the data from iMoneyNet on daily and weekly liquidity information when they start being reported by PIFs. We also replace our liquidity measures with the latest available reported figures from iMoneyNet and confirm that the replacement does not cause any significant change.

treasury securities as eligible daily liquid assets regardless of their remaining time to maturity, we compute the percentage of daily liquid assets in column (iii) of Table 2.5 as the percentage of assets that will mature on the next day (*1DAY*). This is a more precise estimate of the exact cash flow that will be generated by next-day maturing assets. Interestingly, the loading of the dependent variable *1DAY* is positive on *POST2014* and negative on *POST2016*, which is consistent with our previous findings concerning funds' maturity risk. Importantly, this trend of liquidity adjustment is also consistent across various asset types. In columns (iv) to (vii), we estimate the percentage of daily liquidity contributed by each asset class. Our results show that since the announcement date of the new regulation, PIFs' holdings of daily maturing assets have significantly increased. While the percentages of daily maturing USTR, ABCP, and CP have slightly increased, the percentage of daily maturing BNKOB has significantly increased, thus confirming their contribution to the daily liquidity of PIFs. The negative coefficients of the dummy variable *POST2016* indicate that funds' aggregate liquidity level has decreased since the implementation of the FNAV system.

In summary, our liquidity analysis confirms the positive effect of the 2014 SEC reform on prime funds' aggregate portfolio liquidity in terms of both aggregate portfolio maturity and aggregate portfolio liquidity. Importantly, we show that the improvement in asset maturity and liquidity is not simply driven by safe assets, but it also applies primarily to risky asset classes. The shortened maturity and increased liquidity ratios indicate PIFs' response to increasing concerns about the potential mismatch of their short-term assets and liabilities resulting from heightened adverse selection. This led PIFs to boost their aggregate liquidity during the transition period. Importantly, this increase in liquidity holdings was subsequently readjusted after the adoption of the FNAV system by PIFs.

2.5.4 SEC Reform and Fund Performance

In this section, we complement our analysis using different proxies of fund performance in an attempt to quantify the extent of post-reform "search for yield" by PIFs. We first consider the raw spread between the fund's annualized yield and the FED target rate, *Spread*, computed as in Di Maggio & Kacperczyk (2017). As discussed in 2.3, this estimate of prime fund performance controls for market expectations of future FED policy rates, and hence limits the confounding effect of any anticipated policy rate changes on fund portfolio maturity risk. Our second yield proxy is the portfolio-based maturity-matched annualized spread of prime funds, *SpreadWAM*. This variable is computed as the difference between the annualized yield of a fund and the average portfolio yield of all other prime funds with similar portfolio *WAM*. Therefore, this proxy removes the indirect effect on the fund portfolio yield of changes in the FED policy rate, which is captured by the average yield of peer funds with similar maturity risks. We also derive a similar market-expectation-adjusted yield spread by focusing on funds' holdings risks. We define *SpreadHR* as the excess fund yield over the average portfolio yield of all other funds with similar *HR*. We argue that our maturity- and holdings-matched annualized spreads represent superior performance proxies of actual fund risk-taking behavior.

Table 2.6 reports the estimated loadings of the gross performance proxies on our main independent variables of interest, *POST2014* and *POST2016*, while controlling for a set of lagged fund and fund sponsor characteristics. The dependent variable in model (i) is the raw annualized spread variable *Spread*. The positive coefficients of the dummies *POST2014* and *POST2016* seem to suggest that prime funds intensified their search for yield in response to the new regulatory regime. This result is inconsistent with our previous findings on portfolio maturity risk and liquidity risk. However, we argue that the multiple rounds of FED policy rate hikes during our sample period are the likely source of such inconsistency. The evidence in models (ii) and (iii) confirms the confounding effect of the policy rate of fund performance using the maturity- and holdings-matched yield spreads, *SpreadWAM* and *SpreadHR*, as our dependent variable. On average, the *WAM*-adjusted yield spread decreased by 1 basis point in the two-year transition period followed by an increase of 1.2 basis points after the implementation of the FNAV regime. In model (iii), the average fund performance captured by *SpreadHR* decreased by 2 basis points after the reform announcement and dropped by 1.7 basis points (0.02 – 0.003) after the implementation date compared with the pre-reform period of 2012 to 2014.

Overall, the evidence in Table 2.6 suggests that prime institutional investors enjoyed a lower annualized spread as a result of prime funds' changes in the aggregate portfolio liquidity and maturity risk following the implementation of the new reform.

2.5.5 Changes in Portfolio-holdings Risk Profile before and after the SEC Reform

Our previous analysis of PIFs' risk-taking was conducted at the daily level using several proxies of portfolio risk-taking. In this section, we use detailed information on the weekly composition of prime fund portfolio holdings from iMoneyNet to examine whether the new regulation caused any change in the percentage of prime fund holdings in eligible risky assets (e.g., BNKOB and CP) and eligible safe assets (e.g., US treasury securities, US agency securities, and repo contracts collateralized by US treasury and agency securities).[20]

Table 2.7 reports the results of a battery of tests with sponsor and time-fixed effects. In model (i), our dependent variable is the holdings risk proxy, *HR*. Following Di Maggio & Kacperczyk (2017), we compute the holdings risk variable *HR* as the difference in fund weights in the riskiest asset classes (BNKOB) and the safest asset classes (US treasury and agency securities and repo contracts). In models (ii) to (ix) we consider a more granular decomposition of prime fund portfolios by examining the percentage change in portfolio holdings of each category of risky assets and safe assets around the time of the two implementation dates (23 July 2014 and 14 October 2016).

The evidence of model (i) confirms our previous conclusion on the change in prime funds' risk-taking behavior following the two rounds of regulatory changes. Specifically, the coefficient of the dummy variable *POST2016* in model (i) indicates that prime funds have markedly reduced their net exposure to risky assets (in excess of the percentage holdings of safe assets) by 34% in the two-year transition period from 2014 to 2016 and by 10% (i.e., 34 – 24) in the *POST2016* period. Importantly, these changes are mostly attributable to the reduction in prime fund holdings of foreign bank obligations (−18%). Interestingly, PIFs slightly altered the rebalancing of their portfolio holdings back to risky assets after the implementation date of the FNAV system, as indicated by the positive coefficients of 24% attached to the dummy variable *POST2016* in model (i) of Table 2.7. These sizable changes in the portfolio composition of prime funds during the two implementation periods

[20] MMFs can only invest in eligible securities which are those with credit ratings falling within the two investment grade categories of first-tier security and second-tier security. For instance, a commercial paper would be deemed a first-tier (second-tier) security if it attracts any credit rating from Standard & Poor's within the (conservative) range of AAA to A+ (A to BBB). MMFs cannot invest in speculative grade securities (from BBB– to D).

are not only statistically significant but also economically meaningful to both regulators and investors alike.

The coefficients in models (iii) and (iv) suggest that prime funds have shifted their portfolio holdings toward safer assets such as USOT (1.4%), REPO (14.7%), and non-negotiable time deposits[21] (10.4%). Additionally, PIFs have also increased their holdings of floating-rate notes (FRNS) by 5.9% in the transition period between 2014 and 2016. FRNS are securities with a coupon that is indexed to a benchmark interest rate such as the LIBOR rate. Prime funds hold FRNS which are commonly issued by US agencies. Since US agency securities are backed by the moral obligation of the US government, the default risk associated with these instruments is considered very low—though higher than that directly associated with US treasury securities.

Overall, PIFs tilted their holdings away from risky assets and towards relatively safe assets after the implementation date of 14 October 2016, with the reduction peaking during the two-year transition period between 2014 and 2016 which comprises the enhance disclosure event.

2.6 SEC Reform and Fund Survivorship

A possible caveat regarding our previous findings on weaker post-reform risk-taking incentives of PIFs is that these findings could also be the outcome of the decision of riskier funds to exit the prime segment. In our sample, of the 377 PIFs populating the money market segment before 14 Oct 2016, only 138 PIFs were still in existence after the implementation date. Among those funds that disappeared, 45 changed their label from prime to government funds, 41 changed their label from prime institutional to prime retail funds, and the remaining 153 exited the industry because of closure. To examine whether our previous findings were driven by a positive pre-reform selection that reduced the number of riskier funds in the prime segment, we perform a survival analysis by examining whether the pre-reform probability of fund exit is significantly higher among riskier funds.

[21] Non-negotiable time deposits (TD) are deposits maintained in a banking institution for a specified period of time less than five business days. This asset category comprises very liquid securities collateralized by cash deposits, and regularly enters the calculation of *DLA* and *WLA* of PIFs.

Table 2.8 reports the estimated coefficients of a probit model of PIFs' probability to exit the industry:

$$Pr(Exit_{i,t} = 1) = \alpha + \beta_1 RiskProxy_{i,t-1} + \beta_2 Event * RiskProxy_{i,t-1} \quad (2.3)$$
$$+ \Gamma_1' X_{i,t-1} + \Gamma_2' Event * X_{i,t-1} + \epsilon_{i,t} \quad (2.4)$$

where *Exit* is an indicator variable of a fund's decision to exit the prime institutional segment. Since a fund's exit could result from either fund closure or label change (i.e., from prime to government or from institutional to retail), we estimate equation 2.3 separately for fund closure events in models (i) and (ii), and for label change events in models (iii) and (iv). Our main independent variables of interest are lagged fund portfolio *WAM* and *WAL* to proxy for the extent of funds risk taking (*RiskProxy*). Other lagged control variables include the fund and fund sponsor characteristics described previously in Table 2.3. We also control for fund portfolio gross annualized yield (*GYIELD*) because fund exit decisions are likely to be related to fund performance. Since we are interested in exit decisions associated with the SEC reform, in models (i) and (ii) we also introduce the indicator variable, *Event*, which equals 1 if the fund closure precedes the compliance date of 23 July 2014. We account for unobservable changes in economic trends and time-invariant sponsor business characteristics by introducing time and sponsor-fixed effects. We cluster standard errors at the day level to account for any cross-sectional dependence of residuals.

Focusing first on fund closure events, the loading in model (i) of Table 2.8 on the variable *WAM* shows that riskier funds are not those more likely to exit the industry after the compliance date, while larger funds, poor performing funds, and those suffering from greater net cash outflows have a higher probability of closure. By contrast, we do find strong evidence that prior to July 2014 safer funds were more likely to exit the industry. This finding is consistent with the evidence obtained on a much earlier sample by Di Maggio & Kacperczyk (2017). Results are similar when we repeat this estimation using the independent variable *WAL* in model (ii).

In the last two columns of Table 2.8, we consider the risk profile of prime funds prior to their exit decision via label changes. In models (iii) and (iv), we use the indicator variable, *Event*, which is equal to 1 if the fund changed its label from institutional to retail, and 0 if it changed its label from prime to government (baseline model). The significant positive coefficient of the variable *WAM* in model (iii), indicates that the portfolio maturity risk of a PIF increases the likelihood of it being reclassified as a government institutional product.[22] Among the other independent variables, prime funds offered by larger fund sponsors (*LFAMTNA*) are more likely to be reclassified as government funds. This decision is not a response to lagged net cash outflows (*NFLOW*) since prime label change events are more likely among those funds experiencing greater net cash inflows.

The SEC reform required all institutional prime funds to"know their customers" and transfer all retail investor accounts—namely natural person accounts and omnibus accounts—to separate retail prime fund portfolios by the implementation date of 14 October 2016. Since this decision to change the institutional label of retail funds is a regulatory requirement based on the existing nature of the investor clientele, we should not expect the risk profile of PIFs necessarily to be associated with their probability of being reclassified as prime retail funds. The coefficient of the interaction variable *Event*WAM* (0.108 – 0.082) in model (iii) and that of *Event*WAL* (0.060 – 0.042) in model (iv) are both consistent with this argument.

Overall, the findings of Table 2.8 provide only weak evidence that PIFs' exit decision explains the change in the risk-taking profile of these funds. In an unreported test, we examined the validity of such conclusion by repeating the analysis of Table 2.3 for the sample of surviving funds only. Conditioning on surviving funds would render the survivorship bias explanation obsolete. The findings of this test indicate clearly that the reduction in maturity risk and liquidity risk also applies to funds that were present in periods before and after the implementation date.

2.7 Conclusion

This study explores, for the first time, the implications of mark-to-market pricing of PIFs for their risk-taking incentives. Using the 2014 MMF reform as an exogenous shock to the information sensitivity of PIFs' pricing regime, we show

[22] Cipriani *et al.* (2017) show that between November 2014 and October 2016 a large fraction of investors' money in PIFs shifted to the segment of government agency institutional funds.

that the disclosure of mark-to-market daily prices of PIFs has contributed to improving the overall risk profile of PIFs and thus the overall resiliency of the prime segment.

Using daily information on PIFs' characteristics from January 2012 to March 2018, we find that, following the announcement of the 2014 reform, PIFs have targeted greater portfolio liquidity, lower maturity risk, and lower annualized excess yield, on average. In addition, our results highlight an improvement in the risk profile of PIFs as indicated by a lower percentage holding of risky assets relative to safe assets. We confirm the positive effect of the lower portfolio risk on the post-reform search-for-yield behavior of PIFs. Importantly, we show that the decision to exit the prime market during the transition period is not limited to riskier funds, which suggests that fund's positive selection is unlikely to explain our findings on the change in PIFs' strategic behavior. Our results are robust to several controls for fund- and family-specific characteristics and are not driven by the heterogeneity of fund investors' risk preferences.

Overall, our findings shed new light on the beneficial effect of the disclosure and implementation of the mark-to-market pricing on the risk-taking behavior of PIFs. This is the first empirical study to examine the implication of more informationally sensitive debt for the risk-taking incentives and financial stability of the MMF segment. We document that in response to investors' greater scrutiny of PIFs' portfolio holdings and maturity risk exposure, PIFs have weaker incentives to take excessive risk. This study also contributes to the recent debate on the implication of the FNAV regime by showing its contribution to reducing investors' adverse selection. Overall, our study provides strong evidence to support the 2014 MMF reform against the recent US Congress bill, which aims to roll back the MMF reform and reinstate a less informationally sensitive NAV regime.

Table 2.1
Summary Statistics of the Sample of Prime Money Market Funds.

Table 2.1 presents summary statistics for our sample of US prime institutional money market mutual funds during the period January 2012 to March 2018. The following fund and affiliated fund family characteristics are summarized in Panel A: funds' assets under management (*FNDTNA*), in $ billion; the number of years since funds' inception (*FNDAGE*); funds' affiliated fund sponsors' assets under management (*FAMTNA*), in $ billion; funds' weighted average maturity (*WAM*); funds' weighted average life (*WAL*); funds daily net annualized yield (*NYIELD*); funds' daily gross annualized yield (*GYIELD*); investors' net investment flow as a percentage of funds' total assets under management (*NFLOWS*); and funds' annual charged expense ratio (*FEERATIO*). In Panel B, we report the composition of funds' holdings as percentages of their total assets management including: US treasury obligations (USTR), US agency obligations (USOT), tri-party repurchase agreements (REPO), total bank obligations(BNKOB), floating-rate notes(FRNS), asset-back commercial papers (ABCP), and financial and nonfinancial commercial papers (CP). In Panel C, we also report funds' daily liquid assets (*DLA*) as a percentage of their total assets under management; funds' weekly liquid assets (*WLA*) as a percentage of their total assets under management; and the decomposed *WAM* and *DLA* at the level of various asset classes.

	Panel A—Daily Fund and Sponsor Characteristics									
	N	Mean	SD	Min	Max	p5	p25	p50	p75	p95
FNDTNA	341,974	3.349	8.357	0.000	80.21	0.001	0.053	0.383	2.087	20.93
FNDAGE	340,638	15.03	8.266	0.003	44.56	2.649	8.893	13.89	20.68	29.96
FAMTNA	277,813	354.5	479.9	0.009	3359	7.866	106.5	230	332.6	1795
WAM	340,280	36.72	13.58	1	60	12	27	39	48	55
WAL	314,786	62.36	23.24	1	119	14	49	66	80	94
NYIELD	341,825	0.177	0.331	0	2.02	0	0.01	0.03	0.15	1.04
GYIELD	341,825	0.406	0.366	0.04	2.1	0.15	0.21	0.26	0.4	1.35
NFLOW	341,773	0.186	22.63	-1	5580	-0.05	-0.01	0.000	0.006	0.050
FEERATIO	338,577	0.226	0.115	0	1.22	0.1	0.16	0.2	0.26	0.45
	Panel B—Weekly Percentage Portfolio Holdings									
	N	Mean	SD	Min	Max	p5	p25	p50	p75	p95
%USTR	341,917	3.111	5.477	0	91	0	0	0	5	14
%USOT	341,917	3.749	7.783	0	89	0	0	1	4	18
%REPO	341,917	15.92	12.67	0	100	0	6	13	22	39
%BNKOB	341,917	20.86	12.18	0	60	0	11	21	30	40
%FRNS	341,917	14.06	12.06	0	88	0	5	12	20	37
%ABCP	341,917	10.32	9.669	0	66	0	1	8	17	28
%CP	341,917	31.32	15.37	0	100	8	20	30	42	58
	Panel C—Monthly Fund Maturity and Liquidity by Instrument									
	N	Mean	SD	Min	Max	p5	p25	p50	p75	p95
WAM	3,448	36.75	13.74	1	60	12	27	39	48	55
WAM_BNKOB	3,254	41.76	22.73	1	282.6	10.41	25.67	40.95	53.89	76.69
WAM_ABCP	2,913	46.9	23.92	1	196.6	12.8	29.69	44.84	60.71	88.6
WAM_CP	3,327	48.16	21.65	1	180.1	13.8	33.65	47.58	61.05	85.47
DLA	3,400	32.79	13.02	8.108	100	16.39	24	30.57	38.31	57.86
WLA	3,400	50.37	14.06	21.36	100	34.32	41.15	46.86	56.27	79.53
DLA_BNKOB	3,391	5.603	7.744	0	65.91	0	0.708	2.662	6.76	22.93
DLA_ABCP	3,391	1.089	1.952	0	19.73	0	0	0.153	1.349	5.242
DLA_CP	3,391	2.189	2.964	0	34.05	0	0	1.262	3.145	7.664

Table 2.2
Summary Statistics of Money Market Funds before and after the SEC Regulatory Event .

Table 2.2 presents the descriptive statistics of fund and fund family characteristics around the announcement date (23 July 2014) of the new money market fund reform adopted by the US Securities and Exchange Commission. The daily descriptive statistics of our sample of money market funds are separated for both the *Pre-2014* period (1 January 2012 – 22 July 2014) and the *Post-2014* period (23 July 2014 – 31 March 2018). The following daily fund and affiliated fund family characteristics are summarized in Panel A: funds' assets under management (*FNDTNA*), in $ billion; the number of years since funds' inception (*FNDAGE*); funds' affiliated fund sponsors' assets under management (*FAMTNA*), in $ billion; funds' weighted average maturity (*WAM*); funds' weighted average life (*WAL*); funds' daily net annualized yield (*NYIELD*); funds' daily gross annualized yield (*GYIELD*); investors' net investment flow as a percentage of funds' total assets under management (*NFLOW*); funds' annual charged expense ratio (*FEERATIO*). In Panel B, we also report funds' daily liquid assets (*DLA*) as a percentage of funds' total assets under management; funds' weekly liquid assets (*WLA*) as a percentage of funds' total assets under management; and the decomposed *WAM* and *DLA* at the level of various asset classes, including total bank obligations(BNKOB), asset-back commercial papers (ABCP), and financial and nonfinancial commercial papers (CP). Standard errors are presented in parentheses. t-statistics of the difference in these characteristics between the *Pre-2014* and the *Post-2014* periods, are clustered at the fund sponsor groupings.

	Panel A—Daily Fund and Sponsor Characteristics							
	Whole Sample				Subsample—Survivors			
	Pre-2014	Post-2014	Diff	t-Stat	Pre-2014	Post-2014	Diff	t-Stat
FNDTNA	3.598	3.108	-0.490	(-1.606)	5.218	3.490	-1.728***	(-3.593)
FNDAGE	14.11	15.93	1.82***	(3.958)	14.38	16.5	2.12***	(4.299)
FAMTNA	308.2	398.4	90.2**	(2.387)	336.4	439.6	103.2*	(1.800)
WAM	42.55	31.10	-11.45***	(-8.292)	41.35	27.20	-14.15***	(-6.628)
WAL	69.38	56.08	-13.30***	(-5.034)	72.27	52.90	-19.37***	(-6.371)
NYIELD	0.044	0.306	0.262***	(14.981)	0.050	0.449	0.400***	(19.415)
GYIELD	0.246	0.559	0.313***	(14.278)	0.258	0.728	0.470***	(23.496)
NFLOW	0.026	0.340	0.314	(1.014)	0.031	0.545	0.515	(1.031)
FEERATIO	0.202	0.250	0.048***	(5.825)	0.208	0.274	0.066***	(5.453)
	Panel B—Monthly Fund Maturity and Liquidity by Instrument							
	Whole Sample				Subsample—Survivors			
	Pre-2014	Post-2014	Diff	t-Stat	Pre-2014	Post-2014	Diff	t-Stat
WAM	43.07	31.54	-11.53***	(-6.622)	43.13	29.17	-13.96***	(-7.432)
WAM_BNKOB	50.69	34.29	-16.40***	(-7.287)	50.13	31.69	-18.44***	(-6.392)
WAM_ABCP	50.04	44.32	-5.72**	(-2.626)	51.02	42.71	-8.31***	(-3.890)
WAM_CP	55.40	42.08	-13.32***	(-6.320)	57.31	42.07	-15.24***	(-6.853)
DLA	31.98	33.45	1.47	(0.953)	30.07	33.77	3.719**	(2.191)
WLA	49.63	50.99	1.36	(0.891)	47.89	50.85	2.96	(1.568)
DLA_BNKOB	3.183	7.622	4.439***	(5.980)	3.188	8.862	5.674***	(5.613)
DLA_ABCP	0.788	1.339	0.551**	(2.369)	0.602	1.406	0.803***	(3.214)
DLA_CP	1.864	2.461	0.597*	(2.012)	1.272	2.177	0.905***	(4.158)

Table 2.3
Risk-taking Incentives of Prime Money Market Funds.

Table 2.3 presents the estimated coefficients of multivariate regressions of PIFs' risk-taking around the time of the announcement of the new reform as well as the time of the implementation of the FNAV trading rule. The dependent variables include funds' weighted average maturity (*WAM*), funds' weighted average life (*WAL*), and excess *WAM* (*EXCWAM*) and excess *WAL* (*EXCWAL*) over the average fund in the government institutional segment. *POST2014* is a dummy variable, which equals 1 for the period from 23 July 2014 to 31 March 2018, and 0 otherwise. *POST2016* is an indicator variable, which identifies the period from 14 October 2016. Lagged control variables include the logarithm of funds' total assets under management (*LFNDTNA*); the level of annual expense ratio charged by funds (*FEERATIO*); the logarithm of funds' number of years since inception (*LFNDAGE*); the logarithm of fund sponsors' total assets under management (*LFAMTNA*); the percentage change in fund assets accounted for capital appreciation (*NFLOW*); and funds' 30-day standard deviation of fund net cash flows (*FLOWVOL*). We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also apply a time-fixed effect to control for any unobservable economic trends. We cluster standard errors at the day dimension to account for any cross-sectional dependence of residuals. t-statistics are reported in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(i) WAM	(ii) WAL	(iii) WAM	(iv) WAL	(v) EXCWAM	(vi) EXCWAL
POST2014	-37.161***	-54.963***	-36.501***	-51.115***	-33.181***	-89.318***
	(-1079.534)	(-1142.546)	(-997.675)	(-1027.069)	(-963.918)	(-1856.686)
POST2016	5.352***	39.051***	17.900***	40.388***	5.103***	45.442***
	(176.962)	(1060.903)	(869.081)	(1075.223)	(168.735)	(1234.506)
LFNDTNA	0.440***	0.726***	0.469***	0.712***	0.440***	0.726***
	(45.888)	(38.170)	(41.854)	(35.296)	(45.888)	(38.170)
FEERATIO	11.981***	22.262***	11.636***	21.590***	11.981***	22.262***
	(31.022)	(29.737)	(30.574)	(29.267)	(31.022)	(29.737)
LFNDAGE	0.528***	1.152***	0.577***	1.271***	0.528***	1.152***
	(22.320)	(20.200)	(26.449)	(21.621)	(22.320)	(20.200)
LFAMTNA	-0.275***	-0.196***	-0.253***	-0.161**	-0.275***	-0.196***
	(-6.277)	(-2.585)	(-5.820)	(-2.130)	(-6.277)	(-2.585)
NFLOW	0.003***	0.000	0.003***	0.000	0.003***	0.000
	(8.382)	(1.404)	(8.368)	(1.180)	(8.382)	(1.404)
FLOWVOL			-0.001***	-0.000		
			(-13.827)	(-0.405)		
Sponsor FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.645	0.613	0.644	0.612	0.565	0.799
N	272,617	257,450	271,414	256,351	272,617	257,450

Table 2.4
Risk-taking Incentives of Institutional Prime Money Market Funds by Instruments.

Table 2.4 presents the estimated coefficients of monthly regressions of PIFs' weighted average asset maturity of different asset classes over the period from 2012 to 2018. The dependent variables include funds' weighted average maturity/life calculated with different instruments, including the dollar-weighted maturity/life of: (i) total portfolio holdings (Total), (ii) US Treasury securities (USTR), (iii) repurchase agreements (REPO), (iv) total bank obligations (BNKOB), (v) asset-backed commercial papers (ABCP), and (vi) financial and nonfinancial commercial papers (CP). We use estimated weighted average maturity by instrument as our dependent variable in Panel A of Table 4 and weighted average life in Panel B. *POST2014* is a dummy variable, which equals 1 for the period from 23 July 2014 to 31 March 2018, and 0 otherwise. *POST2016* is an indicator variable, which identifies the period from 14 October 2016. Lagged control variables include the logarithm of funds' total assets under management (*LFNDTNA*); the level of annual expense ratio charged by funds (*FEERATIO*); the logarithm of funds' number of years since inception (*LFNDAGE*); the logarithm of fund sponsors' total assets under management (*LFAMTNA*); and the percentage change in fund assets accounted for capital appreciation (*NFLOW*), which are not reported for brevity. We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also apply a time-fixed effect to control for any unobservable economic trends. We cluster standard errors at the day dimension to account for any cross-sectional dependence of residuals. t-statistics are reported in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A—WAM by Instrument					
	(i) Total	(ii) USTR	(iii) REPO	(iv) BNKOB	(v) ABCP	(vi) CP
POST2014	-27.975***	-67.153***	-0.837***	-30.504***	-34.394***	-31.658***
	(-90.611)	(-26.811)	(-3.433)	(-52.765)	(-41.955)	(-62.044)
POST2016	7.240***	-1.140	3.988***	12.081***	15.244***	12.042***
	(20.027)	(-0.219)	(19.465)	(38.363)	(16.269)	(19.808)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sponsor FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.715	0.487	0.406	0.586	0.407	0.405
N	2,339	1,838	2,196	2,285	2,094	2,297
	Panel B—WAL by Instrument					
	(i) Total	(ii) USTR	(iii) REPO	(iv) BNKOB	(v) ABCP	(vi) CP
POST2014	-44.643***	-617.011***	105.795***	-63.217***	-53.377***	-36.443***
	(-85.605)	(-31.320)	(4.207)	(-54.009)	(-74.559)	(-24.586)
POST2016	11.249***	13.946	-93.014***	24.372***	20.177***	40.396***
	(21.050)	(0.930)	(-2.984)	(23.989)	(40.369)	(36.326)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sponsor FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.658	0.197	0.464	0.311	0.420	0.403
N	2,175	1,836	2,194	2,285	2,093	2,296

Table 2.5
SEC Reform and the Percentage of Daily and Weekly Liquid Assets of Prime Funds.

Table 2.5 presents the estimated coefficients of monthly regressions of PIFs' daily liquid asset for different asset classes over the period from 2012 to 2018. The dependent variables include (i) funds' daily liquid asset (*DLA*); (ii) funds' weekly liquid asset (*WLA*) and funds' *DLA* calculated based on different instruments, including those of: (iii) securities that have one-day remaining of maturity time (*1DAY*); (iv) US Treasury securities (USTR); (v) total bank obligations (BNKOB); (vi) asset-backed commercial papers (ABCP); (vii) financial and nonfinancial commercial papers (CP). *POST2014* is a dummy variable, which equals 1 for the period from 23 July 2014 to 31 March 2018, and 0 otherwise. *POST2016* is an indicator variable, which identifies the period from 14 October 2016. Lagged control variables include the logarithm of funds' total assets under management (*LFNDTNA*); the level of annual expense ratio charged by funds (*FEERATIO*); the logarithm of funds' number of years since inception (*LFNDAGE*); the logarithm of fund sponsors' total assets under management (*LFAMTNA*); the percentage change in fund assets accounted for capital appreciation (*NFLOW*). We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also apply a time-fixed effect to control for any unobservable economic trends. We cluster standard errors at the day dimension to account for any cross-sectional dependence of residuals. t-statistics are reported in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

			DLA by Instrument				
	(i) DLA	(ii) WLA	(iii) 1DAY	(iv) USTR	(v) BNKOB	(vi) ABCP	(vii) CP
POST2014	3.350***	3.447***	17.695***	1.488***	15.206***	1.254***	0.613***
	(17.904)	(18.912)	(69.564)	(8.326)	(86.186)	(19.810)	(9.155)
POST2016	7.891***	13.714***	-2.017***	-1.864***	-5.983***	-0.084	-1.567***
	(21.850)	(31.060)	(-5.999)	(-5.892)	(-24.112)	(-0.981)	(-16.210)
LFNDTNA	-0.341*	-0.800***	0.019	0.090	0.266**	-0.155***	-0.078*
	(-1.701)	(-3.086)	(0.648)	(0.624)	(2.496)	(-4.211)	(-1.928)
FEERATIO	-53.800***	-42.702***	-2.983**	-7.640	-17.844***	0.421	7.076***
	(-7.014)	(-6.545)	(-2.347)	(-1.111)	(-3.032)	(0.382)	(4.539)
LFNDAGE	0.911*	0.573	-0.247	-0.504	2.319***	-0.264***	-0.587***
	(1.939)	(1.191)	(-1.390)	(-1.451)	(8.356)	(-3.112)	(-5.127)
LFAMTNA	-6.295***	-11.094***	1.372***	-2.654***	4.151***	-1.359***	0.638**
	(-5.955)	(-11.474)	(3.384)	(-4.012)	(6.233)	(-5.989)	(2.512)
NFLOW	0.002	0.008	-60.300***	0.025	-0.009	0.003	0.001
	(0.082)	(0.224)	(-8.238)	(0.943)	(-0.267)	(0.367)	(0.051)
Sponsor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.537	0.527	0.586	0.442	0.586	0.399	0.358
N	2,338	2,338	2,334	2,334	2,334	2,334	2,334

Table 2.6
SEC Reform and Funds' Tendency to Search for Yield.

Table presents 2.6 the estimated coefficients of daily regressions of PIFs' annualized yield spread over the period from January 2012 to March 2018. The dependent variables include (i) funds' annualized yield over federal policy rate (*Spread*); (ii) the portfolio-based maturity-matched annualized spread of prime funds, *SpreadWAM* computed as the difference between the annualized yield of a fund and the average portfolio yield of all other prime funds with similar portfolio *WAM*; and (iii) the portfolio-based holdings-risk-matched annualized spread of prime funds, *SpreadHR* computed as the difference between the annualized yield of a fund and the average portfolio yield of all other PIFs with a similar portfolio *HR*. *POST2014* is a dummy variable, which equals 1 for the period from 23 July 2014 to 31 March 2018, and 0 otherwise. *POST2016* is an indicator variable, which identifies the period from 14 October 2016. Lagged control variables include the logarithm of funds' total assets under management (*LFNDTNA*); the level of annual expense ratio charged by funds (*FEERATIO*); the logarithm of funds' number of years since inception (*LFNDAGE*); the logarithm of fund sponsors' total assets under management (*LFAMTNA*); and the percentage change in fund assets accounted for capital appreciation (*NFLOW*). We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also apply a time-fixed effect to control for any unobservable economic trends. We cluster standard errors at the day dimension to account for any cross-sectional dependence of residuals. t-statistics are reported in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(i) Spread	(ii) SpreadWAM	(iii) SpreadHR
POST2014	0.023***	-0.008***	-0.020***
	(145.189)	(-73.884)	(-152.630)
POST2016	0.101***	0.012***	0.003***
	(1160.764)	(129.324)	(36.447)
LFNDTNA	0.002***	0.001***	0.001***
	(32.000)	(28.053)	(13.688)
FEERATIO	0.095***	0.067***	0.042***
	(32.050)	(27.852)	(20.588)
LFNDAGE	0.003***	0.002***	0.001***
	(17.926)	(14.858)	(6.093)
LFAMTNA	0.009***	0.009***	0.007***
	(48.244)	(50.584)	(47.247)
NFLOW	0.000***	-0.000	0.000***
	(3.148)	(-0.376)	(4.100)
Sponsor FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
R^2	0.796	0.516	0.477
N	273,245	271,238	272,689

Table 2.7
SEC Reform and Portfolio Holdings Risk of Prime Funds.

Table 2.7 presents the estimated weekly regression coefficients of PIFs' portfolio holdings of different asset classes from 2012 to 2018. The dependent variables include: (i) holdings risk (*HR*), defined by Di Maggio & Kacperczyk (2017) as the difference in funds' risky versus safe assets holdings, and funds' percentage of assets invested in of (ii) US Treasury securities (USTR), (iii) US agency securities (USOT), (iv) tri-party repurchase agreements (REPO), (v) time deposits (TD), (vi) floating-rate notes (FRNS), (vii) total bank obligations (BNKOB), (viii) domestic bank obligations (DBNKOB), (ix) foreign bank obligations (FBNKOB), (x) asset-backed commercial papers (ABCP), and (xi) financial and nonfinancial commercial papers (CP). *POST2014* is a dummy variable, which equals 1 for the period from 23 July 2014 to 31 March 2018, and 0 otherwise; *POST2016* is an indicator variable, which identifies the period from 14 October 2016. Lagged control variables include the logarithm of funds' total assets under management (*LFNDTNA*); the level of annual expense ratio charged by funds (*FEERATIO*); the logarithm of funds' number of years since inception (*LFNDAGE*); the logarithm of fund sponsors' total assets under management (*LFAMTNA*); the percentage change in fund assets accounted for capital appreciation (*NFLOW*). We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also apply a time-fixed effect to control for any unobservable economic trends. We cluster standard errors at the day dimension to account for any cross-sectional dependence of residuals. t-statistics are reported in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		%Holdings by Instrument									
	(i) HR	(ii) USTR	(iii) USOT	(iv) REPO	(v) TD	(vi) FRNS	(vii) BNKOB	(viii) DBNKOB	(ix) FBNKOB	(x) ABCP	(xi) CP
POST2014	-33.959***	-1.019***	1.419***	14.689***	10.384***	5.937***	-18.870***	-1.024***	-17.846***	-3.536***	-12.538***
	(-82.463)	(-10.534)	(9.520)	(51.743)	(62.761)	(25.337)	(-119.890)	(-27.602)	(-114.150)	(-31.333)	(-57.588)
POST2016	23.854***	-0.198**	-2.438***	-14.798***	-10.901***	-4.397***	6.420***	1.785***	4.635***	6.178***	26.312***
	(39.379)	(-1.969)	(-11.039)	(-39.154)	(-50.164)	(-13.864)	(30.237)	(35.223)	(22.585)	(44.501)	(99.505)
LFNDTNA	2.116***	0.108***	0.424***	-1.173***	-0.574***	0.125***	1.474***	-0.014**	1.488***	-0.415***	-0.384***
	(22.994)	(5.811)	(11.127)	(-18.708)	(-11.113)	(3.234)	(30.201)	(-2.276)	(31.657)	(-14.761)	(-8.127)
FEERATIO	104.109***	1.617	-22.027***	-44.462***	-40.023***	35.324***	39.236***	-2.371***	41.607***	-8.803***	30.335***
	(14.844)	(1.324)	(-10.713)	(-16.479)	(-22.154)	(13.347)	(16.801)	(-7.363)	(17.873)	(-8.171)	(18.929)
LFNDAGE	-0.391	0.139***	-0.364***	-0.979***	1.544***	2.492***	-1.595***	0.019	-1.614***	0.083	-1.237***
	(-1.614)	(2.787)	(-3.158)	(-7.685)	(13.101)	(18.843)	(-16.113)	(0.699)	(-17.205)	(1.044)	(-6.069)
LFAMTNA	3.332***	-0.772***	-2.026***	-0.600***	2.238***	-0.332***	-0.065	0.029***	-0.094	2.702***	1.557***
	(18.311)	(-6.213)	(-16.444)	(-5.637)	(33.972)	(-3.216)	(-0.875)	(4.061)	(-1.324)	(57.212)	(21.314)
NFLOW	-1.399	-0.767	-0.793	2.492	3.330**	-2.998*	-0.467	0.281	-0.748	-0.237	-0.797
	(-0.412)	(-1.377)	(-0.671)	(1.090)	(2.529)	(-1.653)	(-0.372)	(0.931)	(-0.607)	(-0.284)	(-0.482)
Sponsor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.670	0.574	0.649	0.648	0.659	0.682	0.717	0.503	0.722	0.700	0.744
N	16,191	16,191	16,191	16,191	16,191	16,191	16,191	16,191	16,191	16,191	16,191

Table 2.8
SEC Reform and Fund Survivorship.

Table 2.8 presents the estimated coefficients of daily probit regressions on MMFs' likelihood of fund closure or changes of label. We consider two forms of exiting the market: fund closure in columns (i) and (ii), and change of label in columns (iii) and (iv). Lagged control variables include the daily annualized gross yield (GYIELD); the logarithm of funds' total assets under management (*LFNDTNA*); the level of annual expense ratio charged by funds (*FEERATIO*); the logarithm of funds' number of years since inception (*LFNDAGE*); the logarithm of fund sponsors' total assets under management (*LFAMTNA*); and the percentage change in fund assets accounted for capital appreciation (*NFLOW*). The *Event* variable equals 1 for any fund closure events occurred before the announcement of the reform (i.e. 23 July 2014) and zero otherwise in columns (i) and (ii). In columns (iii) and (iv), the *Event* variable is set to 1 for PIFs that have been reclassified as prime retail funds, and 0 for those that have been reclassified as government institutional funds. We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also apply a time-fixed effect to control for any unobservable economic trends. We cluster standard errors at the day dimension to account for any cross-sectional dependence of residuals. t-statistics are reported in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1%levels, respectively.

	(i) Closure	(ii) Closure	(iii) ChgLabel	(iv) ChgLabel
WAM	0.003		0.108***	
	(0.175)		(3.661)	
WAL		-0.001		0.060***
		(-0.141)		(5.898)
EVENT*WAM	-0.163**		-0.082**	
	(-2.102)		(-2.067)	
EVENT*WAL		-0.073*		-0.042
		(-1.906)		(-1.498)
GYIELD	-4.854**	-3.313*	-22.963***	-26.905***
	(-2.303)	(-1.742)	(-5.408)	(-4.482)
LFNDTNA	-0.205***	-0.236***	-0.021	-0.080
	(-4.316)	(-4.675)	(-0.318)	(-1.540)
FEERATIO	-0.072	-0.088	-0.041	0.105
	(-0.497)	(-0.627)	(-0.518)	(0.801)
LFNDAGE	-1.160*	-1.347*	-1.735	-0.775
	(-1.818)	(-1.916)	(-1.248)	(-0.395)
LFAMTNA	0.176**	0.063	0.072	-0.014
	(1.964)	(0.562)	(0.617)	(-0.105)
NFLOW	-0.756**	-0.713	0.670***	0.816***
	(-2.023)	(-1.631)	(3.910)	(3.629)
EVENT*GYIELD	-133.530	-33.264	13.023***	18.226***
	(-1.464)	(-1.560)	(3.543)	(3.466)
EVENT*LFNDTNA	0.423***	0.338***	0.390***	0.509***
	(2.660)	(4.127)	(3.068)	(4.598)
EVENT*FEERATIO	1.898***	0.973***	-0.155	-0.351*
	(2.651)	(3.843)	(-1.308)	(-1.828)
EVENT*LFNDAGE	212.253	77.400***	3.831*	3.040
	(1.390)	(2.740)	(1.917)	(1.219)
EVENT*LFAMTNA	-1.202	0.253	-0.208	-0.160
	(-0.924)	(0.445)	(-1.592)	(-0.848)
EVENT*NFLOW	22.398	26.068*	-2.228	-2.278
	(1.270)	(1.702)	(-1.258)	(-1.409)
Sponsor FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
$PseudoR^2$	0.430	0.426	0.633	0.673
N	5,978	4,848	1,510	1,263

Chapter 3

Floating NAV Pricing under Single- versus Multi-strike Prime Institutional Money Market Funds

Chanyuan Ge (contribution 80%), Lorenzo Casavecchia (contribution 20%)

3.1 Introduction

On 14 October 2016, the Securities and Exchange Commission (SEC) adopted an amendment to Rule 2a-7 under the Investment Company Act of 1940, to reform the money market fund (MMF) industry. A fundamental change introduced by the new regulation is the requirement that all prime institutional funds (PIFs) abandon the existing amortized-cost accounting and adopt a market-based or floating net asset value (FNAV), priced to the fourth decimal place (i.e., \$1.0000).

Historically, PIFs have offered investors a means to achieve high portfolio yields without having to sacrifice rapid access to cash at stable net asset value (NAV). The new FNAV system has altered the traditional money-likeness of PIFs, from hourly-liquidity vehicles to "plan-ahead" vehicles since prime institutional investors are no longer able to access liquidity on an hourly basis. Indeed, PIFs must now wait to receive mark-to-market security quotations from (external) pricing vendors; before, their transfer agents could wire all investor redemptions. This worsened institutional investors' trade-off between frequent intraday access to cash at constant NAV (CNAV) still offered by government MMFs and historically higher yields of prime MMFs, now trading at FNAV. Cipriani *et al.* (2017) show that the new reform resulted in a $1 trillion net cash outflows—largely within the same fund family—from high-yield prime MMFs to low-yield government MMFs, and quantify the premium investors are willing to pay for rapid access to cash at stable NAV. We find that in an attempt to cater to investors with different liquidity needs, PIFs started offering either multiple intraday redemption windows (multi-strike pricing) or a single daily redemption window (single-strike pricing).

The provision of multiple intraday liquidity access can pose significant operational challenges to the daily asset-liquidity management of PIFs because the NAV variability increases the uncertainty surrounding the estimation of next day net cash outflows. An inaccurate calibration of daily liquid holdings against next day mark-to-market liabilities would heighten funds' liquidity risk. A fund could face an even higher liquidity risk if its portfolio was more geared towards longer maturity assets, such as commercial paper and bank obligations, since, as Covitz & Downing (2007) and Hanson *et al.* (2015) argue, the market for these securities tend to be illiquid, in general. In this context, a sudden asset–liability mismatch would force the PIF to sell, ahead of time, its most liquid assets first (Manconi *et al.*, 2012), thus worsening portfolio illiquidity and heightening its liquidity risk. Of course, a PIF could limit investor redemption risk by resorting to emergency plans such as liquidity fees and redemption gates. However Cipriani *et al.* (2017), Hanson *et al.* (2015), and Lake (2013) show that the announcement of redemption restrictions by one MMF could set a system-wide run by panic-stricken investors who are anxious to redeem their shares before other funds follow suit.

The multi-strike NAV pricing of PIFs represents an innovation in the mutual fund industry. Undoubtedly, a multi-strike FNAV system comprising multiple intraday redemption windows provides institutional investors with more frequent access to cash during the day and better portfolio holdings monitoring than the alternative single-strike FNAV system. However, it is important to note that under the multi-strike pricing system, the costs associated with a flow-related liquidity shock could cascade over subsequent redemption windows within the same day. In turn, this could heighten the exposure of multi-strike funds (MSFNDs) to unanticipated asset–liability mismatches throughout the day. Indeed, while the costs of redemption-motivated trades of a single-strike fund (SSFND) are not reflected in daily NAV because trades happen only after the day of the redemptions, they are instead reflected multiple times during the day if a fund offers a sequence of intraday redemption windows. Thus, the role of fund portfolio liquidity and overall liquidity management becomes even more important among MSFNDs in the light of previous evidence on severe payoff complementarities in this industry segment. Schmidt *et al.* (2016) provide convincing evidence on the extent of strategic complementarities among PIFs. They show that funding (liability side) liquidity is a significantly more important driver of investor redemption behavior than market (asset side) liquidity for these funds. Chen *et al.* (2010) show that investor outflows impose greater liquidation costs on illiquid funds when readjusting their portfolio, which leads to negative externalities for other investors who remain invested in the fund. This creates a first-mover advantage in the redemption decision, even among FNAV funds.

To limit their exposure to heightened flow-related liquidity risk, it is plausible to posit that after the implementation of the new reform, MSFNDs have targeted greater portfolio liquidity and lower maturity risk than have SSFNDs. Using daily data on PIFs, we first show that prime institutional investors expressed a clear preference for multiple redemption windows by allocating significantly more money to MSFNDs than to SSFNDs. This is confirmed by the fact that MSFNDs manage on average 57% of the total assets in the prime segment, with the remaining 42% of these assets being managed by SSFNDs. Further, we find that MSFNDs face greater cash flow volatility and higher cumulative net cash outflows such that they are more likely to have an investor clientele with higher liquidity demand, thus indicating a greater difficulty for these funds to formulate cash flow projections.

Next, we examine whether the different intraday pricing system of PIFs explains the heterogeneity in their aggregate portfolio liquidity and maturity risks. We document that the dollar-weighted average maturity (WAM) of the average MSFND is three days shorter than that of the average SSFND, and the value-weighted average life (WAL) is nearly four days lower. Using the SEC's liquidity measures of PIFs, we find that MSFNDs, on average, hold 3% more daily liquid assets (DLA) and 1% more weekly liquid assets (WLA) than SSFNDs. Consistent with their heightened exposure to flow-related liquidity risk, our cross-sectional findings confirm the positive relation between a PIF's aggregate liquidity and the number of redemption windows that the fund offers.

To enhance our cross-sectional analysis, we use weekly information on fund portfolio holdings, and we separate holdings into safe assets (e.g., treasury and agency securities, and repurchase agreements collateralized by treasury securities) and risky assets (e.g., bank obligations, financial and nonfinancial commercial paper, and asset-backed commercial paper). Our results highlight a clear and better aggregate risk profile of MSFNDs, which we find to be primarily driven by a lower level of holdings risk. Notably, we document a greater likelihood for MSFNDs to tilt their portfolio holdings away from risky asset categories relative to safe securities.

Further, we show that our previous evidence is consistent with weaker economic incentives of MSFNDs to reach for yield. Chordia (1996) shows that high-redemption-risk funds underperform low-redemption-risk funds. If the differentiation in the NAV striking system allows funds to discriminate investors' liquidity needs by inducing self-selection of different types of investors into different funds, we would then expect SSFNDs to return higher yields than MSFNDs. Consistent with this argument, we show that SSFNDs generate 18 basis point higher gross and net annualized yields than MSFNDs, on average. We also consider several yield spread measures controlling for government MMFs' performance, Federal Reserve (FED) policy rate, portfolio maturity, or portfolio-holdings risk. Our results are consistent across various spread measures.

Finally, we explore the performance-chasing behavior of institutional investors as a robustness test to examine whether the weaker risk-taking incentives of MSFNDs are simply driven by their investors' higher sensitivity to performance rather than their heightened flow-related liquidity risk. While we document a positive flow-performance relation among the average PIF, we do not observe any cross-sectional difference in investors' performance-chasing behavior between SSFNDs and MSFNDs, which rules out the possibility that our previous findings on the weaker risk-taking incentives of funds offering multiple redemption windows are driven by differences in investors' risk appetite.

This is the first study to investigate the implication of the intraday pricing system on the risk-taking incentives of PIFs and their investors' capital allocation decisions. We contribute to the existing literature on the risk-taking incentives of MMFs (see e.g., Hanson *et al.*, 2015; Di Maggio & Kacperczyk, 2017) by showing the cross-sectional difference in single- versus multi-strike funds' risk-taking behavior. We argue that MSFNDs' weaker incentives to pursue risk are driven by their greater exposure to unanticipated asset–liability mismatches.

Additionally, our results contribute to the previous literature on fund liquidity. Chordia (1996) argues that mutual funds hold more cash to protect against the uncertainty about redemptions. Similarly, Liu & Mello (2011), using their sample of hedge funds, find that managers behave conservatively when investors' liquidity need is high. Further, Nanda *et al.* (2000) show that mutual funds that constrain liquidity withdrawals may have to share some profits in the form of higher investor returns, when there is a relative scarcity of investors with low liquidity needs. We contribute to this strand of the literature by showing that MSFNDs react to the greater cash flow volatility of their investors by targeting lower aggregate portfolio maturity, greater percentage of daily (and weekly) liquid assets, and thus return lower yields to their investors.

3.2 The Intraday FNAV System

Historically, institutional and retail investors used MMFs as deposit-like accounts for their short-term cash management needs. The money-likeness of MMF products allows investors to purchase and redeem MMF shares at a constant $1.00 per share on an hourly basis. Figure 3.1a. illustrates the redemption timeline of a typical institutional investor, Client A, who invested in a PIF before 14 October 2016 when the fund still operated under the CNAV system. For instance, if Client A places a redemption order of $30 million at 8:45 a.m., she will receive a wire for $30 million redemption proceeds roughly one hour after the redemption order is placed, namely 9:45 a.m.

Since 14 October 2016, all PIFs have adopted the FNAV pricing system. The transition from the CNAV to the FNAV system significantly reduces the money-likeness nature of prime fund products by significantly increasing investors' waiting period before receiving their redemption proceeds. For instance, if we consider the case of a single-strike fund offering only one redemption deadline at 3 p.m., as illustrated in Figure 3.1b., a redemption request lodged by Client A at 8:45 a.m. would not be finalized before 5 p.m. because the fund would now need to receive first the latest available market prices of their holdings as of the strike time from internal or third-party pricing vendor(s) and then await checks and

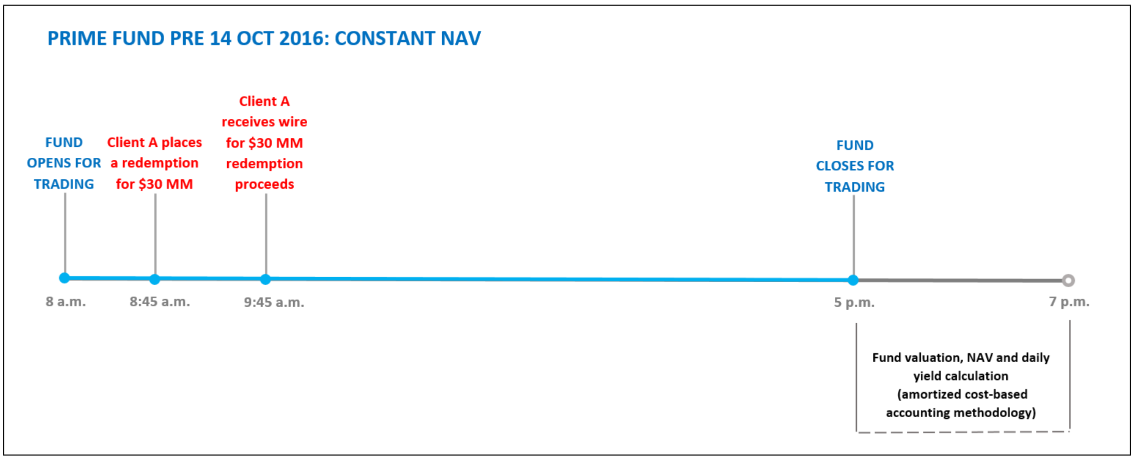

Figure 3.1a. Constant NAV Redemption Timeline.

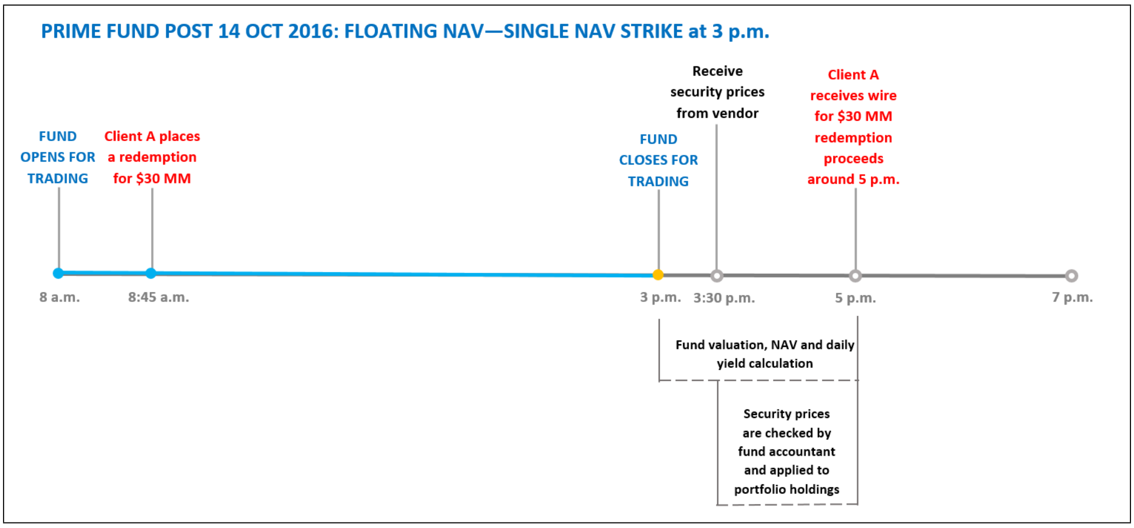

Figure 3.1b. Single-strike FNAV Redemption Timeline.

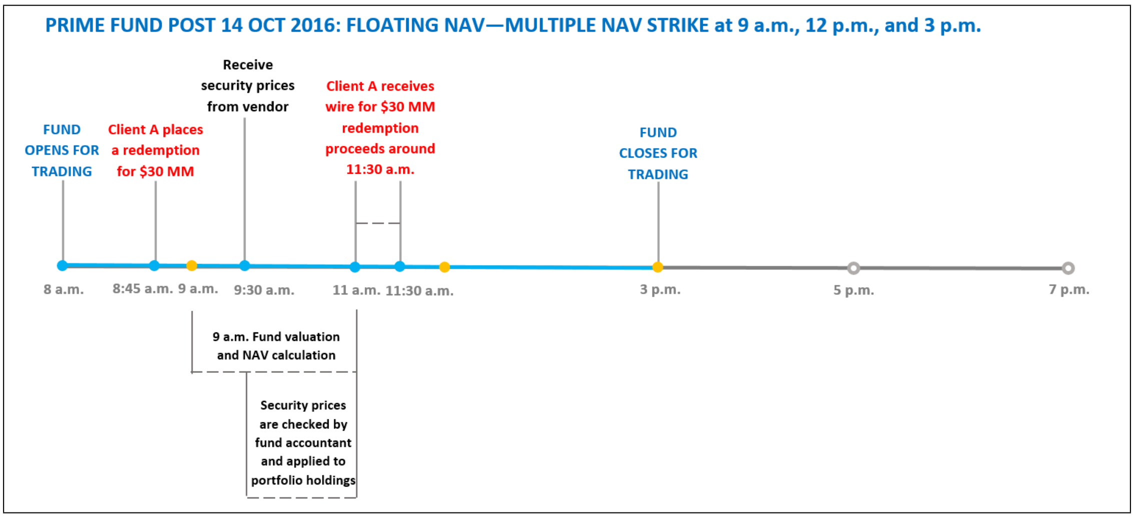

Figure 3.1c. Three-strike FNAV Redemption Timeline.

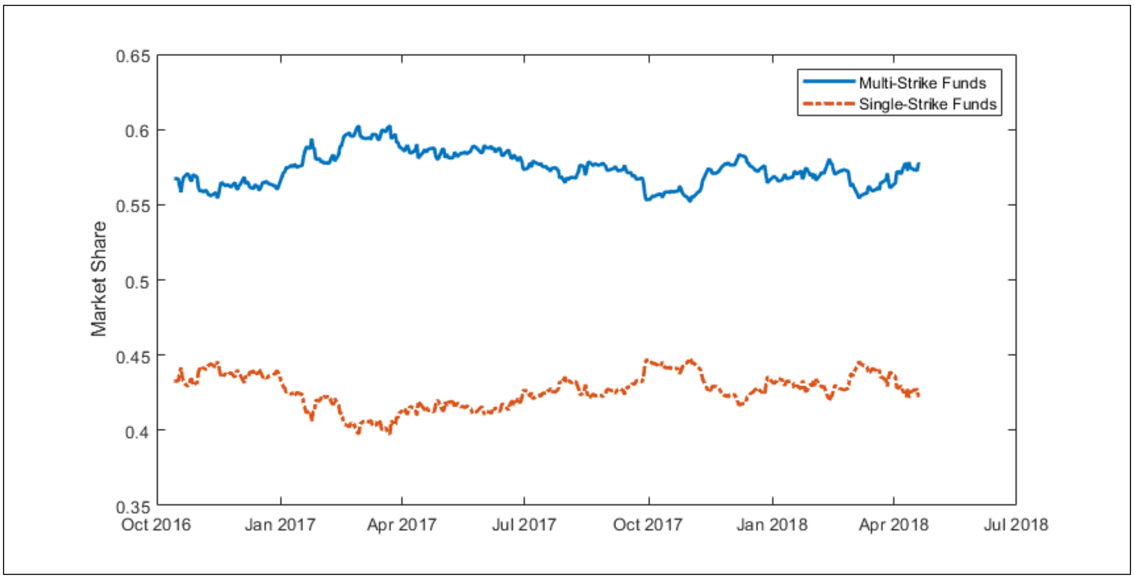

Figure 3.2. Prime Market Share: Single- vs. Multi-strike Funds.

application of these prices to the fund's portfolio holdings by the fund accountant. This process will generally take at least two hours from the redemption deadline. If an institutional investor urgently needs cash to support its operating activities, such as same-day salary payments, she will most likely need to plan and place the request at least one day ahead. This simple example illustrates how the transition from CNAV to FNAV has transformed PIFs from hourly-liquidity vehicles to "plan-ahead" vehicles because prime institutional investors are no longer able to access their capital on an hourly basis at a constant $1.00 per share.

To cater to investors with greater liquidity needs, PIFs innovated the intraday NAV striking system by offering investors multiple redemption windows and thus more frequent access to cash, which also shortened significantly the waiting period for investors to access their cash under the FNAV system. If we consider a typical MSFND with three strike times at 9 a.m., 12 p.m., and 3 p.m., as shown in Figure 3.1c., Client A, who lodges a redemption request before the first strike time of 9 a.m. will be able to receive the cash wires only by 11 a.m. Even if the investor misses the 9 a.m. redemption deadline, as long as the order is placed before 12 p.m., the investor can still receive the cash by 2 p.m., thus leaving enough time for daily operating activities.

The innovation of the MSFND products represents an effort by PIFs to preserve their money-likeness nature as much as possible by providing high-liquidity-demand investors with more-frequent access to cash. We observe a clear preference of prime institutional investors for multiple redemption windows by allocating significantly more money to MSFNDs than to SSFNDs, as illustrated in Figure 3.2. The blue line shows the time series of the total percentage of market share owned by MSFNDs in the prime institutional segment after the implementation date of the FNAV system, while the orange dotted line represents that of SSFNDs. This figure confirms the fact that MSFNDs manage on average 57% of the total assets in the prime segment, with the remaining 43% of these assets being managed by SSFNDs.

3.3 Data and Methodology

Our sample includes the universe of United States (US) institutional taxable prime money market mutual funds over the period of 14 October 2016 to 20 April 2018. We use the same data sources as discussed in Chapter 2. We obtain daily information on fund characteristics from iMoneyNet, and complement the sample with data from the CRSP Mutual Fund Database and the Form N-MFP. Importantly, our study is also the first to use novel data from iMoneyNet on intraday NAV pricing of MMFs. By distinguishing between prime funds with daily single NAV strike (single-strike MMFs) and those with daily multiple NAV strikes (multi-strike MMFs), we can test for the presence of cross-sectional differences in the risk-taking incentives of prime funds.

Panel A of Table 3.1 provides the descriptive statistics of our sample of PIFs from 14 October 2016 to 20 April 2018. The mark-to-market trading prices of prime fund shares average at $1.0002 with very little variation: FNAV only fluctuates between $0.9992 and $1.0012 during our sample period. We observe 50 of the total 138 PIFs offer a single redemption window to their investors and 88 MSFNDs. Further, the average prime fund strikes its NAV price more than twice (2.3 times) each day, with a maximum of four strike times during a day. The average prime fund class has $1.4 billion in assets under management, has been in operation for at least 17 years, and manages a portfolio of securities with a *WAM* of 23 days, and a *WAL* of 54 days. Importantly, *DLA* and *WLA* in the prime fund portfolio average at 34% and 51%, respectively. It is also interesting to note that the 5th percentile of funds' *DLA* (*WLA*) distribution of 16% (34%) is well above the minimum regulatory thresholds of 10% (30%), which would put pressure on the PIF board to impose liquidity fees or suspend institutional investor redemptions for up to 10 days. Panel A of Table 3.1 shows that the average prime fund experiences net cash inflows of 0.7%, varying between –4% (5th percentile) and +4% (95th percentile), and offers a daily net annualized yield of 90 basis points which reflects a daily gross annualized yield of 1.24% and an annualized expense ratio of 33 basis points.

In Panel B of Table 3.1, we report the descriptive statistics of weekly PIF portfolio holdings. Typically, prime funds invest in an array of asset categories, including US treasury and agency debt and repo contracts, domestic and foreign bank obligations (BNKOB), floating-rate notes (FRNS), asset-backed commercial papers (ABCP), and financial and nonfinancial commercial papers (CP). Over the sample period, the average prime funds invested 14% in BNKOB, 14% in ABCP, and an additional 35% of its assets in CP. These securities are typically referred to as risky assets, though an appropriate evaluation of their risk profile would require an analysis of their *WAM*. About 15% of prime fund portfolio is allocated to US treasury debt and repo (0.7%), government and agency repo contracts (0.5%) and tri-party repo contracts (13.6%). Repo contracts are among the safest assets prime funds could invest in because of their daily collateral and overnight maturity.[1]

3.4 Fund Characteristics and the FNAV Striking System

We begin this section with a preliminary analysis of the heterogeneous characteristics of funds offering single versus multiple redemption windows to their investors under the FNAV system. To this end, we first separate our sample into SSFNDs and MSFNDs. We then compute the descriptive statistics of various fund and sponsor characteristics of these two fund groups. The evidence in Panel A of Table 3.2 suggests that the average MSFND is smaller in size (*FNDTNA*) and older (*FNDAGE*) than the average SSFND. Additionally, MSFNDs are more likely to be affiliated to smaller fund sponsors (*FAMTNA*). However, the heterogeneity in the aggregate liquidity level of single- and MSFNDs seems to be unclear under the

[1] MMFs invest primarily in tri-party repo contracts intermediated by two repo clearing banks, J.P. Morgan Chase and the Bank of New York Mellon. The majority of these repo contracts comprise overnight investments, in which securities are repurchased by the seller on the next business day. Only a minority of tri-party repo contracts mature later than the next business day (term repos), with the clearing banks readjusting daily the collateral value of these contracts. Given the overnight nature of these collateralized repo contracts, they are typically deemed safe investments.

univariate setting. While MSFNDs, on average, hold securities with shorter *WAM*, they tend to hold similar proportion of daily and weekly liquid assets compared with SSFNDs.

A closer inspection of PIFs' portfolio composition in Panel B suggests that MSFNDs, on average, exhibit lower exposure to risky securities than do SSFNDs. For instance, the average MSFND tilts its portfolio holdings less towards: foreign bank obligations (FBNKBO), ABCP and CP than the average SSFND. Additionally, MSFNDs hold more US treasury securities (USTR) and FRNS but less US agency debt (USOT) and third-party repurchase agreements (REPO). Table 3.2 provides preliminary evidence concerning the heterogeneous risk-taking incentives of PIFs that offer different FNAV striking systems to their investors.

3.5 Investors' Liquidity Demand and FNAV Striking System

The intraday striking system might benefit MMF investors by providing them with more frequent access to cash compared with SSFNDs. However, from PIF managers' perspective, the presence of multiple redemption windows could lead to higher volatility in both the frequency and magnitude of redemption requests, thus heightening the probability of an asset–liability mismatch. We use three proxies to capture investors' liquidity demand. We follow the definition of the SEC and define the flow-related liquidity risk, as the volatility of investors' net cash flows. Funds facing a faster pace of investors' purchases and redemptions are more likely to face a higher liquidity risk. As such, our first proxy is the standard deviation of fund net cash flows estimated over the previous 30 days (*FLOWVOL*). Our second measure is computed as the 90-day standard deviation of fund net cash flows (*FLOWVOL90*) to capture the volatility of daily fund flows over a longer time window. An investor clientele with higher liquidity demand would lead to greater exposure of PIFs to the flow-related liquidity risk as reflected by a higher likelihood of unanticipated investor redemptions. Our third proxy is the 30-day cumulative net fund flows (*CUMUFLOW*), which quantifies the severity of investors' net cash outflows. PIFs experiencing larger cumulative net fund outflows are likely to face more binding liquidity constraints.

To capture the heterogeneity of investors' liquidity demand of SSFNDs versus MSFNDs, we adopt the following regression specification:

$$LiquidityDemand_{i,t} = \quad \alpha + \beta Strike + \Gamma' X_{i,t-1} + \epsilon_{i,t} \tag{3.1}$$

where the dependent variable $LiquidityDemand_{i,t}$ is our fund liquidity demand proxy of fund i at time t, *Strike* is a generic variable reflecting the striking system of fund i, $X_{i,t-1}$ is a set of lagged control variables at time $t-1$, and $\epsilon_{i,t}$ is the residual term. The coefficient of interest is β, which captures the difference in the fund investors' cross-sectional liquidity demand. In our regression specifications, we control for a host of fund and fund family characteristics including the logarithm of funds' total net assets ($LFNDTNA$), the logarithm of funds' age since inception ($LFNDAGE$), the funds' expense ratio ($FEERATIO$), the logarithm of fund sponsors' total net assets ($LFAMTNA$), and the percentage change in funds' assets adjusted for capital appreciation ($NFLOW$). We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also include a time-fixed effect to control for any changes in the unobservable economic trends. We cluster standard errors at the daily level to account for any cross-sectional dependence of residuals.

Table 3.3 reports the estimated findings of the regression model illustrated in equation 3.1 using alternative measures of investors' liquidity demand. We consider two measures of a fund's striking system. The first variable, *D_Strike*, is an indicator variable, which equals 1 if a fund offers multiple redemption windows to its investors, and 0 otherwise. Our second variable, *N_Strike*, quantifies the exact number of strike times offered by a fund. In columns (i) to (iv) of Table 3.3, we observe a positive relation between the *Strike* variables and the volatility of fund net cash flows over both a 30-day rolling window in columns (i) and (ii) and a 90-day rolling window, in columns (iii) and (iv). This indicates that MSFNDs are more likely to attract investors with higher liquidity needs than SSFNDs. Interestingly, the positive coefficients of *N_Strike* in columns (ii) and (iv) suggests that the greater the number of redemption windows a fund offers, the more volatile its net cash flows. In columns (v) and (vi), we document a negative relation between the *Strike* variables and the cumulative fund flows. Consistent with our expectation, MSFNDs are more likely to suffer from greater cumulative net fund outflows compared with SSFNDs.

Our results also show that bigger and older funds are likely to experience more volatile fund flows and greater cumulative net cash outflows. Additionally, we find a negative relationship between *FEERATIO* and investors' liquidity needs, indicating that funds that charge higher expense ratios suffer less from flow instability. This resonates strongly with the evidence of Christoffersen & Musto (2002) who show that MMFs experiencing less asset attrition rates tend to charge higher fees to their investors, on average. Similarly, it confirms the findings of Schmidt *et al.* (2016) who find weaker coordination motives among less sophisticated investors.

Overall, our results document a positive relation between investors' liquidity demand and the number of redemption windows that a fund provides to its investors. MSFNDs offer intraday pricing to their customers at the cost of stronger exposure to flow-related liquidity risk than is the case with SSFNDs, which in turn suggests their greater need for higher asset liquidity to face unanticipated redemption liabilities.

3.6 Risk-taking of PIFs and the Intraday Striking System

PIFs offer fund products with different striking systems to cater to investors with different levels of liquidity demand. The findings discussed in the previous section confirm that MSFNDs offering investors frequent access to capital during the day face greater flow-related liquidity risk. In this section, we examine how different intraday striking systems affect the risk-taking incentives of PIFs.

3.6.1 Fund Liquidity and the FNAV Striking System

Flow-related liquidity management is critical to the functioning of MMFs because they need to meet daily net cash outflows with maturing short-term assets without risking falling below the mandated liquidity thresholds. Its role is even more prominent for funds offering multiple redemption windows since the cost of redemption-motivated trades are reflected multiple times during the day. It is therefore reasonable to expect that the new intraday pricing system has strengthened the incentives of MSFNDs to minimize their exposure to liquidity risk by shortening the average portfolio maturity or, equivalently, raising the percentage of daily liquid assets.

We consider four risk proxies for overall portfolio risk-taking of PIFs. The first two risk proxies are funds' dollar-weighted average maturity (WAM) and the dollar-weighted average life[2] (WAL). These two measures focus on funds' portfolio maturity risk. Shorter aggregated portfolio maturity implies lower maturity risk and higher portfolio liquidity because a faster asset turnover would increase the cash available to the fund to meet next day unexpected daily redemptions. We also use daily reported liquidity ratios such as funds' DLA and WLA[3] as two additional risk-taking proxies. These two liquidity measures are defined by the SEC under the amended Rule 2a-7, and are a critical factor of a fund's board decision to impose a liquidity fee or a redemption gate to preserve the overall portfolio liquidity. Contrary to the WLA, the DLA directly quantifies directly the amount of cash that will be available on the next business day to meet investors' redemption requests.

To quantify the heterogeneity of funds' risk-taking incentives for funds with different intraday striking times, we adopt the following regression specification:

$$RiskProxy_{i,t} = \quad \alpha + \beta Strike + \Gamma' X_{i,t-1} + \epsilon_{i,t} \tag{3.2}$$

where the dependent variable $RiskProxy_{i,t}$ is our risk proxy of fund i at time t, $Strike$ is a variable reflecting the striking system of fund$i$, $X_{i,t-1}$ is a set of lagged control variables at time $t-1$, and $\epsilon_{i,t}$ is the residual term. The coefficient of interest is β, which captures cross-sectional differences in funds' risk-taking. We also control for the same set of fund- and sponsor-level characteristics, previously described in Table 3.3. We employ sponsor- and time-fixed effects to control for any unobservable changes in the sponsor's characteristics and economic trends.

[2] When calculating WAM (WAL) under Rule 2a-7, a fund adviser is permitted to use the interest-rate reset date (security's stated final maturity) for variable- and floating- rate securities. Therefore, the number of days to maturity for the WAM of a security is the interest rate reset date, while that for the WAL of a security is the lower of the stated final maturity date or next demand feature date.

[3] According to SEC's definition, DLA and WLA include any (i) cash, (ii) direct obligations of the US government, (iii) securities that will mature or are subject to a demand feature that is exercisable and payable within one (five) business day(s), and (iv) amounts receivable and due unconditionally within one (five) business day(s) pending sales of portfolio securities. All definitions are sourced from the amended Rule 2a-7 published on the SEC website.

We also cluster standard errors at the daily level to account for any cross-sectional dependence of residuals.

Table 3.4 reports the estimated regression results of equation 3.2 by using various liquidity risk proxies as our dependent variables. In columns (i) to (iv), we use the two maturity measures, *WAM* and *WAL*, as the dependent variables. We document a negative relation between our *Strike* variables and funds' aggregate portfolio maturity; this relation is both statistically and economically significant. For instance, the results in column (i) and (iii) suggest that the average *WAM* of MSFNDs is three days shorter than that of SSFNDs, while the average *WAL* is nearly four days shorter. The coefficients of *N_Strike* in models (ii) and (iv) indicate that to offer one additional redemption window to investors, a fund would need to decrease its *WAM* by two days and its *WAL* by three days. In columns (v) to (viii) of Table 3.4, we use *DLA* and *WLA* as our liquidity risk proxies. Our *Strike* variables are positively associated with *DLA* and *WLA*. The coefficients in columns (v) and (vii) suggest that MSFNDs, on average, hold 3% higher *DLA* and 1% higher *WLA* than SSFNDs. We document qualitatively similar results in (vi) and (vii) when using the continuous variable measuring the number of redemption windows (*N_Strike*) as our *Strike* variable.

In summary, our liquidity analysis suggests that MSFNDs managed their flow-related liquidity risk by shortening their aggregate portfolio maturity and boosting their daily and weekly liquid holdings to minimize the risk of unanticipated asset–liability mismatches during the day.

3.6.2 Fund Holdings Risk and the FNAV Striking System

Next, we use detailed information on the weekly composition of prime fund portfolio holdings from iMoneyNet to examine whether the difference in the intraday striking system affects prime funds' holdings in eligible risky assets (e.g., bank obligations and commercial papers) and eligible safe assets (e.g., US treasury securities, US agency securities, and repo contracts collateralized by US treasury and agency securities). If, indeed, multiple redemption windows heighten a fund's flow-related liquidity risk, one should then expect MSFNDs to hold a lower percentage of risky assets.

Table 3.5 reports the results of an analysis of PIFs' portfolio composition with sponsor- and time-fixed effects. In column (i), we follow Di Maggio & Kacperczyk (2017) and define *HR* as funds' holdings risk which is computed as the difference in fund weights between risky asset classes (domestic and foreign bank obligations) and safe asset classes (US treasury and agency securities and repo contracts). In column (ii), we focus on the aggregate risky holdings of PIFs (*RISKY*), which include bank obligations, asset-backed commercial papers, and financial and nonfinancial commercial papers. In columns (iii) to (xii) we consider a more granular decomposition of prime fund portfolios by examining the heterogeneity in fund's holdings of different categories of risky and safe asset classes including (iii) USTR, (iv) USOT, (v) REPO, (vi) time deposits (TD), (vii) BNKOB, (viii) domestic bank obligations (DBNKOB), (ix) FBNKOB, (x) CP, (xi) ABCP, and (xii) FRNS. The dependent variable of the regression model reported in Panel A of Table 3.5 is *D_Strike*. In Panel B, we repeat this analysis of Panel A using an alternative dependent variable for the number of strikes, *N_Strike*. Other fund and sponsor characteristics are those described previously in Table 3.3 and are unreported for brevity in Table 3.5.

The evidence of column (i) in Panel A of Table 3.5 confirms our expectation of the weaker risk-taking incentives of MSFNDs. Specifically, the coefficient of the dummy variable *D_Strike* in model (i) indicates that the average MSFND shows 9% lower net exposure to risky assets (in excess of the percentage holdings of safe assets) than the average SSFND. Importantly, this difference is mostly attributable to a lower percentage holding of FBNKOB (–3.3%) and a higher percentage holding of REPO (5.4%). Moreover, column (ii) shows that MSFNDs, on average, tilt their portfolio holdings away from risky asset categories more than do SSFNDs. The 10% lower risky holdings of the average MSFND is attributable to all risky asset categories of BNKOB (–3.1%), ABCP (–3.3%), and CP (–3.4%). Our results are qualitatively similar when using *N_Strike* as the alternative proxy for fund's striking system, as shown in Panel B of Table 3.5.

By exploring PIFs' portfolio holdings composition, we find that the difference in the intraday pricing system of PIFs explains the cross-sectional difference in funds' holding decisions regarding risky versus safe assets. Largely, our findings confirm that funds offering multiple strike times to investors are more likely to tilt their portfolio holdings away from (towards) risky (safe) asset holdings as a response to their heightened exposure to unanticipated daily cash redemptions.

3.6.3 Fund Performance and the FNAV Striking System

Our previous findings show clearly that multi-strike prime funds responded to their heightened flow-related liquidity risk by improving their portfolio risk profile. In this section, we complement our analysis using different proxies of fund performance to investigate the heterogeneity of "search for yield" by PIFs with different intraday striking times. Chordia (1996) shows that high-redemption-risk funds underperform low-redemption-risk funds. To be consistent with our previous evidence on PIFs' risk-taking incentives, we would expect weaker economic incentives of MSFNDs to reach for yield such that SSFNDs outperform MSFNDs.

In addition to the funds' reported annualized daily yield, we also consider four additional yield spread measures including (ii) the spread between funds' annualized yield and the FED target rate, *Spread*, computed as in Di Maggio & Kacperczyk (2017); (iii) funds' annualized yield spread in excess of the average government institutional fund, *SpreadGov*; (iv) the portfolio-based maturity-matched annualized spread of prime funds, *SpreadWAM*, computed as the difference between the annualized yield of a fund and the average portfolio yield of all other prime funds in the same quintile portfolio of sorted *WAM*; and (v) the portfolio-based holdings-risk-matched annualized spread of prime funds, *SpreadHR*, computed as the difference between the annualized yield of a fund and the average portfolio yield of all other prime funds in the same quintile portfolio of sorted *HR*. The later two proxies are designed to remove the indirect effect on fund portfolio yield of changes in the FED policy rate, which are captured by the average yield of peer funds with similar maturity or holdings risk. We argue that our maturity-matched and holdings-matched annualized yield spread represent a superior performance-based proxy for fund risk-taking behavior.

Table 3.6 reports the estimated loadings of our gross (net) performance proxies on our main independent variables of interest, *D_Strike* in Panel A (Panel B), while controlling for a set of lagged fund and fund sponsor characteristics, described previously in Table 3.3.[4] The negative coefficient of the dummy *D_Strike* in Panel A of Table 3.6 suggests that prime funds with multiple strike times show lower incentives to search for yield. This result is consistent across various yield spread measures. We reach similar conclusions when using net performance proxies as our dependent variables in Panel B of Table 3.6. The coefficient of *D_Strike* in model

[4] We obtain qualitatively similar results when using *N_Strike* as our independent variable of interest, which are not reported here for brevity.

(i) of Panel B of Table 3.6 suggests that MSFNDs also return lower after-fee performance (*NYIELD*) to their investors. In economic terms, the significant coefficient of –0.018 of the variable *D_Strike* in model (i) of Panel B in Table 3.6 indicates that investors pay a premium of 1.8 basis points to MSFNDs for their more frequent access to cash.

Overall, the evidence in Table 3.6 highlights the trade-off between liquidity demand and (gross or net) performance faced by institutional investors in MSFNDs.

3.7 Investors' Risk Appetite and the FNAV Striking System

The fee revenue generated by a fund (or its fund sponsor) depends on the fund size, and ultimately on investors' net money flows. When incentives between funds and investors are aligned, net flows and fee incomes increase with fund performance, thus incentivizing funds to search for yield. A potential concern with our findings is that MSFNDs might exhibit lower risk-taking incentives because of the lower performance sensitivity of their investor clientele base rather than their strategic decision to reduce the risk of an asset–liability mismatch during multiple striking sessions throughout the day. To address this concern, we investigate whether there exists any cross-sectional difference in SSFND versus MSFND investors' risk appetites. To this end, we first compute the percentage net cash flows of prime MMFs as: $(TNA_t - TNA_{t-1} * (1 + r_t))/TNT_{t-1}$. We also filter out the top and bottom 0.5% tails of the distribution of net cash flows to guard against possible errors that are due to fund restructuring (see e.g. Huang *et al.*, 2007). Next, we estimate pooled ordinary least squares regressions with day- and fund sponsor-fixed effects to control for the possibility that our findings might in fact reflect unobservable economic trends or changes in fund sponsor characteristics. We cluster standard errors at the daily level to account for any cross-sectional dependence of residuals. We include the same set of lagged control variables as described in Table 3.3.

Table 3.7 presents the findings of the estimated sensitivity of investor flows to net yield (*NYIELD*). The loadings of fund flows on the annualized yield in models (i) and (ii) confirm that institutional investors chase, on average, past performance among prime money funds. In models (iii) and (iv), we add the interaction term between *NYIELD* and *D_Strike* to capture any cross-sectional difference in investors' flow-sensitivity to past performance that is due to funds' striking times. The insignificant coefficients of the interaction term, *NYIELD*D_Strike*, suggest that the performance-chasing behavior of investors does not vary significantly between SSFNDs and MSFNDs.

On the whole, the lack of any evidence for weaker flow–performance sensitivity of investors among MSFNDs rules out the alternative explanation based on investor risk appetite for our previous findings of weaker risk-taking incentives among funds offering multiple intraday striking times.

3.8 Conclusion

This study explores, for the first time, the intraday FNAV strike system of PIFs, which represents an innovation in the MMF industry. We show that following the 2016 SEC reform, prime funds decided to offer either single or multiple redemption windows to cater to investors with different liquidity needs.

Using unique information on the striking system of PIFs, we find that, to limit their exposure to heightened flow-related liquidity risk, MSFNDs, on average, have targeted greater portfolio liquidity and lower maturity risk than have SSFNDs. In addition, our results highlight an improvement in the risk profile of MSFNDs as indicated by a lower percentage holding of risky assets relative to safe assets. We show that these findings are confirmed by weaker economic incentives of MSFNDs to reach for yield, which suggests that their investors are prepared to pay a premium to access their daily liquidity more frequently. Our results are robust to several controls for fund- and family-specific characteristics and are not driven by the heterogeneity of fund investors' risk preferences.

Overall, our findings shed new light on the cross-sectional differences in the risk-taking behavior of PIFs under the new FNAV system, and its association with funds' flow-related liquidity risk. This study emphasizes for the first time that the intraday striking system, designed to segment investors according to their liquidity needs, allows prime funds to preserve their money-likeness at the cost of marginally lower shareholder annualized yield.

Table 3.1
Summary Statistics of the Sample of Prime Money Market Funds.

Table 3.1 presents summary statistics for our sample of US prime institutional money market mutual funds after the implementation date of the 2014 SEC reform (i.e. 14 October 2016). The following fund and affiliated fund family characteristics are summarized in Panel A: funds' reported floating net asset value (*FNAV*); an indicator variable equals one for funds offering more than one strike times (*D_Strike*); funds' exact number of strike times (*N_Strike*); funds' assets under management (*FNDTNA*), in $ billion; the number of years since funds' inception (*FNDAGE*); fund sponsors' assets under management (*FAMTNA*), in $ billion; funds' weighted average maturity (*WAM*); funds' weighted average life (*WAL*); funds' daily liquid assets (*DLA*) as percentages of funds' total assets under management; funds' weekly liquid assets (*WLA*); funds' daily net annualized yield (*NYIELD*); funds' daily gross annualized yield (*GYIELD*); investors' net investment flow as a percentage of funds' total assets under management (*NFLOW*); funds' annual charged expense ratio (*FEERATIO*); the 30-day standard deviation of fund net cash flows (*FLOWVOL*); the 90-day standard deviation of fund net cash flows (*FLOWVOL90*)and the 30-day cumulative fund net cash flows (*CUMUFLOW*). In Panel B, we report the composition of funds' holdings as percentages of funds' total asset management, including US treasury obligations (USTR); US agency obligations (USOT); tri-party repurchase agreements (REPO); total bank obligations(BNKOB); floating-rate notes(FRNS); asset-back commercial papers (ABCP); and and financial and nonfinancial commercial papers (CP).

	Panel A—Daily Fund and Sponsor Characteristics									
	N	Mean	SD	Min	Max	p5	p25	p50	p75	p95
FNAV	44,167	1.0002	0.0002	0.9992	1.0012	1	1	1.0002	1.0003	1.0005
D_Strike	45,074	0.623	0.485	0	1	0	0	1	1	1
N_Strike	45,074	2.263	1.048	1	4	1	1	3	3	4
FNDTNA	45,070	1.381	5.300	0.000	59.04	0.000	0.002	0.041	0.687	6.390
FNDAGE	44,312	16.72	9.544	0.019	44.56	0.893	9.974	15.81	23.39	32.85
FAMTNA	38,001	495.8	609.9	12.07	2376	49.7	192.9	253.3	577.9	2158
WAM	45,067	23.35	9.664	1	59	10	17	22	29	40
WAL	45,005	53.53	21.63	1	93	10	42	58	70	82
DLA	43,805	34.06	15.22	8.220	100	19.31	25.18	30.16	37.26	65.53
WLA	43,805	51.18	14.51	30.61	100	38.99	41.87	45.73	54.95	90.10
NYIELD	45,050	0.897	0.406	0	2.02	0.21	0.60	0.91	1.18	1.56
GYIELD	45,050	1.235	0.356	0.12	2.10	0.64	0.99	1.28	1.40	1.86
NFLOW	44,912	0.00721	0.497	-0.998	66.00	-0.040	-0.001	0.000	0.001	0.042
FEERATIO	42,034	0.331	0.205	0	1.22	0.1	0.18	0.28	0.43	0.73
FLOWVOL	44,642	37.08	100.7	0	1575	0.000	0.031	1.968	22.10	207.5
FLOWVOL90	43,449	51.97	131.8	0	1792	0.000	0.097	5.122	40.37	263.6
CUMUFLOW	44,642	-71.61	1298	-34531	10690	-359.8	-5.017	0.000	6.905	410.3
	Panel B—Weekly Percentage Portfolio Holdings									
	N	Mean	SD	Min	Max	p5	p25	p50	p75	p95
%USTR	45,071	0.665	2.15	0	20	0	0	0	0	5
%USOT	45,071	0.447	2.185	0	52	0	0	0	0	2
%REPO	45,071	13.55	13.27	0	100	0	4	10	19	38
%BNKBO	45,071	14.21	9.065	0	46	0	8	13	20	33
%FRNS	45,071	19.19	15.49	0	75	0	6	16	30	47
%ABCP	45,071	13.81	11.27	0	46	0	3	12	24	33
%CP	45,071	35.46	16.93	0	92	9	24	36	45	66

Table 3.2
Summary Statistics of Single- versus Multi-strike Money Market Funds.

Table 3.2 presents the descriptive statistics of fund and fund family characteristics after the implementation date of the 2014 SEC reform (i.e. 14 October 2016) for funds offering single or multiple redemption windows to their investors. The daily descriptive statistics of our sample of money market funds are separated for both single-strike funds (SSFND) and multi-strike funds (MSFND). The following daily fund and affiliated fund family characteristics are summarized in Panel A: funds' assets under management (*FNDTNA*), in $ billion; the number of years since funds' inception (*FNDAGE*); fund sponsors' assets under management (*FAMTNA*), in $ billion; funds' weighted average maturity (*WAM*); funds' weighted average life (*WAL*); funds' daily liquid assets (*DLA*) as percentages of funds' total assets under management; funds' weekly liquid assets (*WLA*); funds' daily net annualized yield (*NYIELD*); funds' daily gross annualized yield (*GYIELD*); investors' net investment flow as a percentage of funds' total assets under management (*NFLOW*); funds' annual charged expense ratio (*FEERATIO*); and the 30-day standard deviation of fund net cash flows (*FLOWVOL*). In Panel B, we report the composition of funds' holdings as percentages of funds' total asset management including: US treasury obligations (USTR); US agency obligations (USOT); tri-party repurchase agreements (REPO); total bank obligations(BNKOB); domestic bank obligations(DBNKOB); foreign bank obligations(FBNKOB); floating-rate notes(FRNS); asset-back commercial papers (ABCP) and financial and nonfinancial commercial papers (CP). Standard errors are presented in parentheses. t-statistics of the difference in these characteristics between SSFND and MSFND are clustered at the day dimension.

	Panel A—Daily Fund and Sponsor Characteristics			
	SSFND	MSFND	MSFND – SSFND	t-stat
FNDTNA	1.562	1.271	-0.291***	(-67.205)
FNDAGE	16.25	17.00	0.75***	(134.308)
FAMTNA	505.6	490.3	-15.3***	(-16.860)
WAM	25.22	22.21	-3.01***	(-37.957)
WAL	51.77	54.6	2.83***	(11.841)
DLA	34.26	33.95	-0.31	(-1.381)
WLA	53.26	49.93	-3.33***	(-27.780)
NYIELD	0.907	0.891	-0.016***	(-16.135)
GYIELD	1.233	1.236	0.003***	(3.052)
NFLOW	0.012	0.004	-0.008	(-1.323)
FEERATIO	0.326	0.334	0.008***	(18.736)
FLOWVOL	25.84	43.95	18.11***	(17.576)
	Panel B—Weekly Percentage Portfolio Holdings			
	SSFND	MSFND	MSFND – SSFND	t-stat
%USTR	0.215	0.937	0.722***	(17.826)
%USOT	0.533	0.394	-0.139***	(-7.629)
%REPO	14.66	12.88	-1.78***	(-16.536)
%BNKBO	14.09	14.29	0.20***	(3.651)
%DBNKBO	0.641	1.199	0.558***	(17.607)
%FBNKBO	13.45	13.09	-0.36***	(-4.986)
%FRNS	17.17	20.41	3.24***	(30.119)
%ABCP	15.41	12.84	-2.57***	(-38.797)
%CP	39.10	33.26	-5.84***	(-74.459)

Table 3.3
Investors' Liquidity Demand and Prime Funds' Striking System.

Table 3.3 presents the estimated daily regression coefficients of the cross-sectional investors' liquidity demand of single- and multi-strike PIFs after 14 October 2016, the implementation date of the 2014 SEC reform. We consider four proxies for investors' liquidity demand, including: funds' 30-day standard deviation of fund net cash flows (*FLOWVOL*) in columns (i) and (ii); funds' 90-day standard deviation of fund net cash flows (*FLOWVOL90*) in columns (iii) and (iv); and funds' 30-day cumulative net cash flows (*CUMUFLOW*) in columns (v) and (vi). The independent variables of interest are *D_Strike*, an indicator variable equaling 1 if a fund offers more than one strike times, and *N_Strike*, which represents funds' exact number of strike times. Lagged control variables include: the logarithm of funds' total assets under management (*LFNDTNA*); the level of annual expense ratio charged by funds (*FEERATIO*); the logarithm of funds' number of years since inception (*LFNDAGE*); the logarithm of fund sponsors' total assets under management (*LFAMTNA*); the percentage change in fund assets accounted for capital appreciation (*NFLOW*). We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also apply a time-fixed effect to control for any unobservable economic trends. We cluster standard errors at the day dimension to account for any cross-sectional dependence of residuals. t-statistics are reported in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(i) FLOWVOL	(ii) FLOWVOL	(iii) FLOWVOL90	(iv) FLOWVOL90	(v) CUMUFLOW	(vi) CUMUFLOW
D_Strike	13.022***		17.776***		-91.446***	
	(17.865)		(33.126)		(-4.576)	
N_Strike		6.364***		8.014***		-47.151***
		(17.504)		(38.933)		(-4.510)
LFNDTNA	12.390***	12.362***	16.250***	16.207***	-16.639**	-16.454**
	(33.828)	(33.826)	(27.682)	(27.662)	(-2.164)	(-2.149)
FEERATIO	-16.121***	-15.648***	-33.540***	-32.903***	42.232**	38.718**
	(-11.781)	(-11.595)	(-12.501)	(-12.259)	(2.461)	(2.357)
LFNDAGE	6.768***	7.586***	8.885***	10.151***	-54.485***	-60.304***
	(15.803)	(16.220)	(21.147)	(22.587)	(-5.099)	(-5.062)
LFAMTNA	27.435***	27.819***	47.596***	48.201***	240.657***	237.319***
	(9.023)	(9.167)	(14.309)	(14.439)	(4.119)	(4.117)
NFLOW	-0.608**	-0.614**	-0.902*	-0.919*	2.245	2.253
	(-2.224)	(-2.246)	(-1.728)	(-1.767)	(0.926)	(0.925)
Sponsor FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.367	0.366	0.388	0.387	0.151	0.151
N	34,053	34,053	33,174	33,174	34,053	34,053

Table 3.4
Fund Liquidity and Prime Funds' Striking System.

Table 3.4 presents the estimated daily regressions coefficients of the portfolio aggregate liquidity of single- and multi-strike PIFs after 14 October 2016, the implementation date of the 2014 SEC reform. We consider four proxies for funds' liquidity level, including funds' weighted average maturity (*WAM*) in columns (i) and (ii), funds' weighted average life (*WAL*) in columns (iii) and (iv), funds' daily liquid asset as a percentage of funds' total assets under management (*DLA*) in columns (v) and (vi), and funds' weekly liquid asset as a percentage of funds' total assets under management (*WLA*) in columns (vii) and (viii). The independent variables of interest are *D_Strike*, an indicator variable equaling 1 if a fund offers more than one strike times, and *N_Strike*, which represents funds' exact number of strike times. Lagged control variables include: the logarithm of funds' total assets under management (*LFNDTNA*); the level of annual expense ratio charged by funds (*FEERATIO*); the logarithm of funds' number of years since inception (*LFNDAGE*); the logarithm of a fund sponsor's total assets under management (*LFAMTNA*); the percentage change in fund assets accounted for capital appreciation (*NFLOW*). We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also apply a time-fixed effect to control for any unobservable economic trends. We cluster standard errors at the day dimension to account for any cross-sectional dependence of residuals. t-statistics are reported in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(i) WAM	(ii) WAM	(iii) WAL	(iv) WAL	(v) DLA	(vi) DLA	(vii) WLA	(viii) WLA
D_Strike	-3.257***		-3.866***		2.835***		1.329***	
	(-31.060)		(-18.102)		(8.682)		(6.197)	
N_Strike		-1.675***		-2.527***		1.397***		0.649***
		(-28.969)		(-23.154)		(7.949)		(5.685)
LFNDTNA	0.251***	0.257***	0.441***	0.446***	-0.003	-0.009	0.015	0.012
	(17.558)	(17.895)	(15.060)	(15.325)	(-0.065)	(-0.188)	(0.345)	(0.276)
FEERATIO	4.260***	4.140***	11.499***	11.317***	-6.249***	-6.151***	-4.795***	-4.750***
	(16.680)	(16.291)	(19.235)	(18.962)	(-8.706)	(-8.682)	(-7.409)	(-7.393)
LFNDAGE	0.289***	0.093***	3.279***	3.027***	0.184**	0.351***	-0.328***	-0.250***
	(7.906)	(2.644)	(47.728)	(42.345)	(2.131)	(4.797)	(-3.861)	(-3.291)
LFAMTNA	-7.699***	-7.807***	-15.033***	-15.307***	14.225***	14.304***	12.640***	12.676***
	(-13.063)	(-13.177)	(-11.070)	(-11.251)	(11.346)	(11.380)	(11.395)	(11.389)
NFLOW	0.012	0.012	-0.013	-0.019	0.017	0.016	-0.030	-0.030
	(0.204)	(0.208)	(-0.103)	(-0.147)	(0.224)	(0.213)	(-0.436)	(-0.443)
Sponsor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.501	0.499	0.501	0.504	0.335	0.334	0.403	0.403
N	34,353	34,353	34,294	34,294	33,142	33,142	33,142	33,142

Table 3.5

Fund Holdings Risk and Prime Funds' Striking System.

This table presents the estimated weekly regression coefficients of the portfolio holdings risk of single- and multi-strike PIFs after 14 October 2016, the implementation date of the 2014 SEC reform. The dependent variables include (i) holdings risk (*HR*), defined by Di Maggio & Kacperczyk (2017) as the difference in funds' risky versus safe asset holdings and funds' percentage of assets invested in of: (ii) risky asset classes, including domestic and foreign bank obligations, financial and nonfinancial commercial papers, and asset-backed commercial papers (*RISKY*); (iii) US treasury securities (USTR); (iv) US agency securities (USOT); (v) repurchase agreements (REPO); (vi) time deposits (TD); (vii) total bank obligations (BNKOB); (viii) domestic bank obligations (DBNKOB); (ix) foreign bank obligations (FBNKOB); (x) financial and nonfinancial commercial papers (CP); (xi) asset-backed commercial papers (ABCP); (xii) floating-rate notes (FRNS). The independent variables of interest are *D_Strike* in Panel A, an indicator variable equaling 1 if a fund offers more than one strike times, and *N_Strike* in Panel B, which represents funds' exact number of strike times. Lagged control variables include the logarithm of funds' total assets under management (*LFNDTNA*); the level of annual expense ratio charged by funds (*FEERATIO*); the logarithm of funds' number of years since inception (*LFNDAGE*); the logarithm of a fund sponsor's total assets under management (*LFAMTNA*); the percentage change in fund assets accounted for capital appreciation (*NFLOW*). The lagged control variables are not reported for brevity. We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also apply a time-fixed effect to control for any unobservable economic trends. We cluster standard errors at the day dimension to account for any cross-sectional dependence of residuals. t-statistics are reported in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A - Dummy Strike

	(i) HR	(ii) RISKY	(iii) USTR	(iv) USOT	(v) REPO	(vi) TD	(vii) BO	(viii) DBO	(ix) FBO	(x) CP	(xi) ABCP	(xii) FRNS
D_Strike	-8.555***	-9.807***	0.059	0.059	5.350***	2.190***	-3.088***	0.233***	-3.321***	-3.462***	-3.257***	-1.107***
	(-9.395)	(-12.056)	(1.312)	(0.780)	(8.889)	(7.726)	(-9.520)	(6.615)	(-10.046)	(-9.174)	(-11.220)	(-4.428)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sponsor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.610	0.682	0.505	0.305	0.669	0.666	0.768	0.703	0.723	0.770	0.763	0.631
N	1,773	1,773	1,773	1,773	1,773	1,773	1,773	1,773	1,773	1,773	1,773	1,773

Panel B - Number of Strike Times

	(i) HR	(ii) RISKY	(iii) USTR	(iv) USOT	(v) REPO	(vi) TD	(vii) BO	(viii) DBO	(ix) FBO	(x) CP	(xi) ABCP	(xii) FRNS
N_Strike	-4.676***	-5.566***	0.054**	-0.002	2.836***	1.043***	-1.789***	0.083***	-1.872***	-1.902***	-1.876***	-0.241*
	(-9.918)	(-12.422)	(2.212)	(-0.059)	(9.050)	(6.737)	(-10.398)	(5.384)	(-10.684)	(-9.159)	(-11.712)	(-1.757)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sponsor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.613	0.686	0.505	0.305	0.670	0.665	0.771	0.702	0.726	0.771	0.766	0.631
N	1,773	1,773	1,773	1,773	1,773	1,773	1,773	1,773	1,773	1,773	1,773	1,773

Table 3.6
Fund Performance and Prime Funds' Striking System.

Table 3.6 presents the estimated daily regression coefficients of funds' before-fee and after-fee performance of single- and multi-strike PIFs after 14 October 2016, the implementation date of the 2014 SEC reform. The dependent variables include (i) funds' reported annualized daily gross performance (*GYIELD*) or funds' reported annualized daily net performance (*NYIELD*); (ii) the spread between funds' annualized yield and the federal target rate (*Spread*); (iii) US treasury securities (*SpreadGov*); (iv) the spread between funds' annualized yield and the average yield of a portfolio of funds with matched portfolio *WAM* (*SpreadWAM*); (v) spread between funds' annualized yield and the average yield of a portfolio of funds with matched portfolio-holdings risk (*SpreadHR*). We consider different spread measures computed based on funds' gross performance in Panel A and those estimated using funds' net yield in Panel B. The independent variable of interest is *D_Strike*, an indicator variable equaling 1 if a fund offers more than one strike times. Lagged control variables include: the logarithm of funds' total assets under management (*LFNDTNA*); the level of annual expense ratio charged by funds (*FEERATIO*); the logarithm of funds' number of years since inception (*LFNDAGE*); the logarithm of fund sponsors' total assets under management (*LFAMTNA*); the percentage change in fund assets accounted for capital appreciation (*NFLOW*). The lagged control variables are not reported for brevity. We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also apply a time-fixed effect to control for any unobservable economic trends. We cluster standard errors at the day dimension to account for any cross-sectional dependence of residuals. t-statistics are reported in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(i) GYIELD	(ii) Spread	(iii) SpreadGov	(iv) SpreadWAM	(v) SpreadHR	(vi) NYIELD	(vii) Spread	(viii) SpreadGov	(ix) SpreadWAM	(x) SpreadHR
D_Strike	-0.018***	-0.018***	-0.018***	-0.004***	-0.003***	-0.018***	-0.018***	-0.018***	-0.006***	-0.002*
	(-15.845)	(-15.737)	(-15.737)	(-4.201)	(-2.865)	(-15.737)	(-15.845)	(-15.845)	(-4.863)	(-1.713)
LFNDTNA	0.003***	0.003***	0.003***	0.001***	0.002***	0.003***	0.003***	0.003***	0.002***	0.002***
	(13.769)	(13.688)	(13.688)	(9.879)	(14.238)	(13.688)	(13.769)	(13.769)	(14.759)	(12.811)
FEERATIO	-0.944***	0.056***	0.056***	0.028***	0.047***	0.056***	-0.944***	-0.944***	-0.943***	-0.944***
	(-266.862)	(15.689)	(15.689)	(11.839)	(15.709)	(15.689)	(-266.862)	(-266.862)	(-354.043)	(-285.724)
LFNDAGE	0.004***	0.004***	0.004***	0.002***	0.003***	0.004***	0.004***	0.004***	0.006***	0.004***
	(13.653)	(13.622)	(13.622)	(6.552)	(7.506)	(13.622)	(13.653)	(13.653)	(13.373)	(7.582)
LFAMTNA	-0.087***	-0.087***	-0.087***	-0.047***	-0.049***	-0.087***	-0.087***	-0.087***	-0.077***	-0.082***
	(-9.661)	(-9.651)	(-9.651)	(-7.424)	(-7.244)	(-9.651)	(-9.661)	(-9.661)	(-10.677)	(-9.995)
NFLOW	-0.001**	-0.001**	-0.001**	-0.000	-0.001*	-0.001**	-0.001**	-0.001**	-0.000	-0.001
	(-2.260)	(-2.268)	(-2.268)	(-0.345)	(-1.948)	(-2.268)	(-2.260)	(-2.260)	(-1.349)	(-1.353)
Performance	Gross	Gross	Gross	Gross	Gross	Net	Net	Net	Net	Net
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sponsor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.975	0.495	0.424	0.259	0.259	0.968	0.906	0.902	0.913	0.903
N	34,346	34,346	34,346	34,178	34,211	34,346	34,346	34,346	34,178	34,211

Table 3.7
Investor Risk Appetite and Prime Funds' Striking System.

Table 3.7 presents the estimated daily flow–performance sensitivity for our sample of PIFs over the sample period of 14 October to 20 April 2018. Our dependent variable is the funds' net cash flow (*NFLOW*), which is winsorized at top and bottom 0.5% tails of the flow distribution. The main independent variables of interest are the daily annualized net yield (*NYIELD*), and the interaction term with *D_Strike*, which equals 1 if a fund offers multiple redemption windows to its investors. Lagged control variables include the logarithm of funds' total assets under management (*LFNDTNA*); the level of annual expense ratio charged by funds (*FEERATIO*); the logarithm of funds' number of years since inception (*LFNDAGE*); the logarithm of fund sponsors' total assets under management (*LFAMTNA*); the percentage change in fund assets accounted for capital appreciation (*NFLOW*). We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also apply a time-fixed effect to control for any unobservable economic trends. We cluster standard errors at the day dimension to account for any cross-sectional dependence of residuals. t-statistics are reported in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	NFLOW			
	(i)	(ii)	(iii)	(iv)
NYIELD	0.008**	0.008**	0.008**	0.008**
	(2.095)	(2.054)	(2.108)	(2.067)
NYIELD*D_Strike			-0.001	-0.001
			(-1.422)	(-1.492)
LFNDTNA	-0.000*	-0.000	-0.000*	-0.000
	(-1.733)	(-1.495)	(-1.765)	(-1.528)
FEERATIO	0.000	0.000	0.000	-0.000
	(0.111)	(0.074)	(0.004)	(-0.039)
LFNDAGE	-0.001***	-0.001***	-0.001***	-0.001***
	(-3.259)	(-3.509)	(-3.093)	(-3.334)
LFAMTNA	-0.003	-0.003	-0.003	-0.004
	(-1.381)	(-1.449)	(-1.422)	(-1.492)
NFLOW		-0.045***		-0.045***
		(-4.316)		(-4.322)
Winzorisation	Yes	Yes	Yes	Yes
Sponsor FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R^2	0.017	0.019	0.017	0.019
N	34,465	34,465	34,465	34,465

Chapter 4

Jack of All Trades versus Specialists: Fund Family Specialization and Mutual Fund Performance

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4.1 Introduction

A key issue faced by many firms concerns the choice of the scope of their operations, with some firms opting for a high degree of operational specialization, or focus, while others preferring to broaden their scope into unrelated businesses. This issue is particularly relevant in the mutual fund industry given the remarkable heterogeneity in the degree to which firms (i.e., fund families) diversify across the two unrelated segments of active and passive fund management.[1] Generally, a fund

[1] There is a vast literature on the effect of firm's related diversification on performance which reconciles the conflicting views on the effect of firm's operational focus on firm value (see among others, Bettis, 1981; Markides & Williamson, 1994; Gary, 2006). According to Rumelt (1974), two businesses are said to be related when they share a common SIC code, market, resource, or investment goal. According to this literature, firms that strictly confine their operations within their core skills and competencies enjoy better performance by leveraging the knowledge gained in similar product areas. In this study we do not measure relatedness, though the degree of firm's operational scope across the unrelated segments of active and passive investing resonates strongly with the literature on related diversification.

family's decision to restrict its assets to, and specialize the product offering in, the active management segment depends on many factors including its belief about the overall managerial ability to outperform the market. This belief is not only revealed by the investment philosophy and marketing efforts of the fund family but also, and more importantly, by its fund product mix offered to investors. Indeed, while some firms prefer to diversify their fund product offering across the active-passive "divide" to minimize investors' redemption risk and maximize fee revenue (see e.g., Elton *et al.*, 2007), other firms opt for a high degree of operational specialization whereby they specialize their product offering in one of these segments. For instance, T. Rowe Price is well-known for its distinctive asset concentration (in excess of 94%) in the active segment, and for its army of fund managers, buy-side analysts, and data scientists who support the fundamental research and security selection of active funds.

An interesting question to both academics and investors alike is whether the choice of operational scope of a fund family bears implications for investors' wealth. Does fund performance benefit from an affiliation to a fund family with a more active "pedigree" as reflected by its decision to concentrate most of the assets and fund product offering in the active management segment? Our study is the first to address this question. This issue is important as investors often first identify a fund family and then choose from among the mutual funds offered by that family (Massa, 2003; Elton *et al.*, 2006). As such, a fund family's choice of asset-based specialization in the active or passive management segments could affect investors' wealth across family funds, and their exposure to family-level liquidity risk.

It is unclear whether the decision of a fund family to concentrate its product offering in the active management segment would necessarily benefit the performance of constituent mutual funds. There are reasons to believe however that this is the case.[2] The resource-based theory of the firm (see e.g. Silverman, 1999) would suggest that firms with greater focus on the active segment should possess better skills at running active funds due to institutional advantages from expertise and learning economies in that segment, or simply a research infrastructure which is better geared towards the goal of outperforming the index. Siggelkow (2003) finds that active funds belonging to more style-focused fund

[2] In this study, we refer to actively-focused fund families as those with higher asset-based concentration in the active equity mutual fund segment. We acknowledge that the definition of active mutual funds could also include closet-indexing fund products, and control for this possibility in the study.

families perform better, on average, due to superior internal capabilities and expertise from specialization. Van Nieuwerburgh & Veldkamp (2010) develop a model where specialization arises because of increasing returns to scale in learning. They argue that private information acquisition through specialized learning can rationalize a higher degree of asset concentration.[3] Milgrom & Roberts (1995) show that a better alignment between a firm's system of activities and its product portfolio affects positively its performance. Cheng *et al.* (2006), Frey & Herbst (2014), and Irvine *et al.* (2004) quantify the significant performance benefits accruing to active equity mutual funds affiliated to fund families with well-developed internal research departments. As such, we posit that equity mutual funds of more actively-focused fund families outperform peer funds of less actively-focused fund families because of superior private information production from better family-level resources and expertise in the active management segment.[4]

On the other hand, there are also reasons to believe that mutual funds might not necessarily benefit from greater asset-based specialization of the fund family in the active management segment. First, de Figueiredo Jr & Rawley (2011) argue that fund families are able to diversify across different products when they possess greater investment skill as market forces would constraint the horizontal expansion options of unskilled fund families. Using a sample of hedge funds, they find that funds of diversified fund families outperform those of more focused fund families by in excess of 2% per annum. Thus, it could be argued that fund families, which are able to broaden their operational scope into unrelated segments, face weaker constraints to horizontal expansion because of superior investment skills. Second, active funds offered by more passively-focused fund families could face greater incentives from within-family competition to produce superior

[3] At the fund level, Kacperczyk *et al.* (2005) show that a higher degree of industry concentration is a measure of informational advantages, and is associated with superior fund performance. Among hedge funds, Shawky *et al.* (2012) find that higher diversification across styles and geographies is associated with worse performance due to lower task specialization.

[4] One could argue that although a less actively-focused fund family might not have the necessary resources, or even the expertise, to operate in the active management segment, it could resume to outsourcing contracts with external advisors to overcome such limitations. This decision however, comes at a significant cost as Chen *et al.* (2013) and Chuprinin *et al.* (2015) show that fund families that strategically outsource their funds so as to expand firm boundaries, experience poor fund performance due to contractual externalities and conflict of interest. In our context, this implies that the performance of funds of less actively-focused families could be explained by outsourcing decisions. Our findings do not support however this explanation.

performance. Cremers *et al.* (2016) show that the growth in the demand for index funds has forced mutual funds to increase their active share so as to differentiate themselves from passive product offerings, hence delivering better performance to investors. This raises the possibility that active funds of more passively-focused families might have stronger incentives to generate better performance, all else equal.

In this study, we examine whether the degree of fund family' specialization in the active management segment affects the performance and capital allocation of its constituent equity mutual funds. Using the percentage of fund family's assets invested in the active segment (ACF) as a proxy of its expertise in that segment, we show that mutual funds of more actively-focused fund families (i.e., high ACF) outperform peer funds of less actively-focused fund families (i.e., low ACF) over the period 1993 to 2015. In economic terms, a one-standard deviation increase in ACF boosts fund's gross risk-adjusted returns by about 70 basis points per year, on average. Our findings remain qualitatively unchanged when we use holding-based performance measures such as Kacperczyk *et al.*'s (2008) mutual fund return gap, or the measure of stock picking skills of Daniel *et al.* (1997). They also survive after controlling for fund family size, the number of distinct funds and styles of the fund family, the percentage of institutional investors, the degree of active share of the fund itself, an indicator variable for single-fund families, and the inclusion of family, time and fund-manager fixed effects.

Next, we investigate the information content of fund family's ACF, and its ability to capture managerial skills, by relating this variable to proxies of activeness of the investment process of mutual funds (see Cremers & Petajisto, 2009; Amihud & Goyenko, 2013), fund manager's reliance on public information (Kacperczyk & Seru, 2007), and extent of private information production (Kacperczyk *et al.*, 2016). Our findings suggest that mutual funds of high-ACF fund families are associated with significantly higher portfolio selectivity, lower sensitivity to changes in information in the public domain, and greater reliance on private information production, a clear signal of managerial skill. Importantly, we show that mutual funds affiliated to high-ACF fund families are rewarded with significant higher investor flows, suggesting that this proxy captures attributes of managerial skill that are not already measured by past fund performance.

Fund families are characterized by high heterogeneity in the degree to which they pursue an active management strategy, with some fund families experiencing different exposure to closet-indexing–and thus different propensity towards active management–for any given level of *ACF*. To address this issue, we use three measures of cross-sectional heterogeneity in fund family's active specialization to refine the information signal of our proxy of *ACF*. Our evidence shows that the positive association between *ACF* and performance is particularly pronounced among funds of active fund families characterized by greater reliance on private information, more aggressive departures from market risk, and higher intensity of portfolio turnover.

A possible caveat with these findings is that omitted factors could impact both fund family's decision to choose a certain degree of active concentration and the performance of its constituent funds. To rule out this possibility, we conduct a quasi-experiment using fund families' sponsorship acquisition events of intact target mutual funds.[5] Taking those fund family acquisitions as exogenous shocks to the characteristics of target active funds, we estimate the change in fund performance around the sponsorship acquisition event. Our findings show that lower active specialization of the acquiring fund family relative to the selling fund family, contributes to worse post-acquisition performance outcomes of intact target funds. Collectively, these findings confirm that a better alignment between the investment strategy of intact target funds and the active segment focus of the acquiring fund family benefits target fund shareholders.

Importantly, we show that funds of high-*ACF* fund families enjoy significant institutional advantages from better allocation of resources to information production as proxied by the presence within the fund family of a brokerage division in the same physical location of the fund management division, or by the greater number of active fund managers, buy-side research analysts, and registered broker-dealers employed by the fund family in its research department. This result confirms previous evidence on the benefits enjoyed by mutual funds of fund families with a well-developed research infrastructure (see Cheng *et al.*, 2006; Irvine *et al.*, 2004).

Finally, we take a number of steps to mitigate the scope for alternative interpretations of our evidence by showing that our findings are not driven by cross sectional differences in contractual externalities of outsourcing agreements. They

[5] Contrary to mergers where target funds disappear after being absorbed by incumbent funds of the acquiring fund families, target funds of sponsorship acquisitions survive as independent entities.

are also not explained by differences in fund cost structure across fund families. Index investing is naturally geared towards reducing costs rather than improving performance. If more passive fund families impose binding constraints on the level of portfolio turnover and tracking error to contain operating costs, then that could also explain the underperformance of active funds offered by less actively-focused fund families. We show however that this argument is not supported by our empirical findings.

Overall, we provide strong evidence that funds of fund families specialized in the active segment perform better, and are more likely to trade on private information. In equilibrium, such a result would be hard to justify as we also observe active funds of fund families with greater passive focus. We argue however that the downside of higher active concentration of a fund family as compared to greater diversification across both the active and passive segments, is the heightened exposure of the fund family (and its investors) to flow-related liquidity risk. Our findings show that high-ACF fund families are indeed more likely to experience greater correlation of net cash *outflows* across their active funds.[6]

Our study contributes to the growing literature on the effect a fund family's product diversity on investor wealth and capital allocation (see e.g., Mamaysky & Spiegel, 2002; Khorana & Servaes, 2012; Massa, 2003). We contribute to this literature by highlighting the performance implications of fund families' product diversity across the unrelated segments of active and passive investing. In this light, we also contribute to the extant literature on the effect of side-by-side management of different fund products of a fund family on fund performance (see e.g., Chen & Chen, 2009; Nohel *et al.*, 2010; Cici *et al.*, 2010; Del Guercio *et al.*, 2018). Finally, by emphasizing the performance benefits of fund family's decision to pursue segment specialization, this study contributes also to the debate on the value of active management in the mutual fund industry.[7]

6 An example of hightened flow-related liquidity risk of specialized fund families is provided by the market-money specialist, Reserve. Contrary to diversified fund family giants, this family was unable to draw resources to bail out its Reserve Primary Fund on September 2008 due to its extreme money-market concentration.

7 Ferson (2010) provides an excellent review of the current state of the literature on mutual fund performance.

4.2 Data and Methodology

4.2.1 Sample Data

Our mutual fund sample is obtained from the CRSP Survivorship Bias Free Mutual Fund database (CRSP MFDB). The following steps are followed to identify mutual fund families and link them to their mutual fund(s). First, fund family names are checked carefully to account for minor variations of such names (e.g., Deutsche Asset Mgmt versus Deutsche Asset Management, Inc.), and to account for different divisions of the same company (e.g., BNY Mellon Asset Management versus Dreyfus Corp). Following Chen *et al.* (2013), we then search each fund family name on the Investment Adviser Public Disclosure (IAPD) website administrated by the Securities and Exchange Commission (SEC), and collect all previously-registered names of that fund family.[8] Third, we record all the names of the control entities of a fund family using the information contained in Item 10 and in Schedule D of the Form ADV, which allows us to account for the possibility that entities with different names may represent the same ownership structure of the fund family.[9] Next, we use the management company codes available in the CRSP MFDB after 2000 to augment the link between the fund family and its fund(s). Thus, two distinct fund family names attached to a particular fund portfolio reflect the same fund family if the following criteria are met: (i) the two family names belong to the same family according to the IAPD historical information and, (ii) the CRSP management code has remained unchanged. Lastly, we also searched through all fund family names using various sources to improve the accuracy of the fund family identification procedure, which include SEC action letters, FACTIVA, and general information available on fund families' website.[10]

The result of this matching is a sample of 2,137 distinct fund families over the entire sample period from 1993 (the start date of fund family names in CRSP) to 2015. The sample of constituent mutual funds includes all United States (US) domestic diversified equity mutual funds with the following investment objectives: large-cap funds (*EDCL*), mid-cap funds (*EDCM*), small-cap funds (*EDCS*), micro-cap funds

[8] The IAPD website provides accurate historical information on all previously registered names.

[9] Item 10 and Schedule D of the Form ADV contain information on the name of the entity where books and records are kept.

[10] SEC action letters provide information on fund family re-organizations following merger events.

(*EDCI*), growth funds (*EDYG*), growth and income funds (*EDYB*), and equity income funds (*EDYI*). Fund investment objectives are identified using CRSP ICDI codes which combine information from three different sources, including Weisenberger (1962-1993), Strategic Insight (1993-1998), and Lipper (1998-2015) over our sample period.

To compute holding-based measures of fund performance, we merge the CRSP MFDB with Thomson Financial. We also use stock-level information from the CRSP/Compustat database and analysts' past recommendations (of up to five quarters) from IBES, to compute proxies of fund's reliance on public and private information (see e.g., Kacperczyk & Seru, 2007; Kacperczyk *et al.*, 2016). Since mutual fund performance, total net assets (TNA), and net cash flows are available on a monthly basis while fund fees are available on an annual basis (although they are accrued daily), we perform our analysis at both monthly and yearly frequencies. All mutual fund share class characteristics are aggregated (TNA-weighted) at the level of the fund portfolio.

4.2.2 Empirical Methodology

Our proxy for fund family's asset concentration in the active equity mutual fund segment, *ACF*, is computed as one minus the percentage of fund family's assets under management (AUM) invested in index mutual funds and exchange-traded fund (ETF) products[11]. We exclude from this calculation all fund family's assets invested in fixed income funds and hybrid funds as our study is concerned exclusively with diversified domestic equity mutual funds. To accurately identify index and ETF products, we use the two flags $index\_fund\_flag$ and et_flag available in CRSP MFDB.[12] We also augment these flags by conducting a detailed fund-name search for any of the following text matches: *"Index"*, *"Idx"*, *"Ix"*, *"Indx"*, *"Nasdaq"*, *"Dow"*, *"Jones"*, *"DJ"*, *"Mkt"*, *"Market"*,

11 We compute a fund family's non-active assets as the sum of assets of its funds categorized as index mutual funds or ETF products within the fund family.

12 The flag $index\_fund\_flag$ identifies three different categories of index funds: A "pure" index fund, if the investment mandate requires the fund to hold virtually all the securities of the noted index with weightings equal to those in the index; an "index-based" fund, if the investment mandate allows the fund to invest a portion of fund assets outside the securities held by the index; and an "enhanced" index fund, if the investment mandate allows the fund to invest in derivatives based on the index itself and/or the securities within the index, or by utilizing different weightings for the securities held by the index. The et_flag identifies instead whether a family fund is an ETF.

"Composite", *"S&P"*, *"Barra"*, *"Russell"*, *"Wilshire"*, *"100"*, *"400"*, *"500"*, *"600"*, *"1000"*, *"1500"*, *"2000"*, *"3000"*, *"5000"*, *"SPDR"*, *"ishares"*, *"StreetTRACKS"*, *"HOLDRs"*, *"ETF"*, and *"Exchange"*.

We estimate fund performance using various benchmarks. In addition to the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966), we benchmark fund returns using the Carhart's (1997) four-factor model ($4-FACTOR$), our representative model in this study:

$$\begin{aligned} R_{i,t} - R_{F,t} =& \alpha_i + \beta_{i,M}(R_{M,t} - R_{F,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t \\ &+ \beta_{i,MOM}MOM_t + e_{i,t} \end{aligned} \tag{4.1}$$

where the dependent variable is the monthly gross return on portfolio i in month t minus the risk-free rate, and the independent variables are given by the excess return of the market portfolio and the returns of the three zero-investment factor portfolios. The expression $R_{M,t} - R_{F,t}$ denotes the excess return of the market portfolio over the risk-free rate; *SMB* is the return difference between small and large capitalization stocks; *HML* is the return difference between high and low book-to-market stocks; and *MOM* is the return difference between stocks with high and low past returns. Following Jensen (1968), we use the intercept of the four-factor model, α_i, as a measure of abnormal performance.

Since funds could follow balanced portfolio policies or invest in international securities, we also employ a six-factor model (*6-FACTOR*) that includes the excess returns on the Morgan Stanley Capital International (MSCI) index covering Europe, Australia, and the Far East, and the Barclays US Aggregate Bond Index (ex-Lehman US Aggregate Bond Index). To mitigate concerns about possible look-ahead bias in the estimation of fund performance, we estimate risk-adjusted returns as the monthly abnormal returns based on the various factor models, where the factor loadings are estimated over the previous 36 months (with a minimum of 30 months of available observations).

Finally, we use fund portfolio holdings to compute Kacperczyk *et al.*'s (2008) mutual fund return gap, *RETGAP*, calculated as the difference between fund i's gross returns and the gross returns predicted based on its lagged holdings. Our aim is to show that fund families's asset concentration in active fund products benefits their mutual fund performance by creating significantly more value through fund's "unobservable actions". We verify the robustness of our results on mutual fund performance using Daniel *et al.*'s (1997) measure of stock picking skills (*CS*).

4.2.3 Descriptive Statistics and Information Content of Fund Family's *ACF*

Table 4.1 contains the summary statistics of our sample of mutual funds and their fund families over the period 1993 to 2015. The average mutual fund manages assets of \$603 million (*FNDTNA*), and has been in operation for about 9 years (*LFNDAGE*). The average fund turnover (*TURNR*) of 0.72 translates into total operating expenses of 1.24% (*OPEX*), and advisory fees of 0.91% (*ADVFEE*). We also report the statistics of mutual fund net performance which is estimated using the Carhart (1997) four-factor model (*4-FACTOR*), the representative model in this study. Consistent with previous studies, mutual funds underpeform (after fees) the market by about the amount of their advisory fees, on average. The average mutual fund family has an industry market share of 0.16% (*FAMMKTS*), and offers about 9 fund portfolios (*NPFOLIO*) across 5 distinct investment objectives (*NINVOBJ*). Importantly, an average of 61% of fund families' assets tend to be invested in active mutual fund products (*ACF*), with this percentage varying noticeably in the cross section between 27% (5th percentile) and 90% (95th percentile). Thus, fund families tend to have a relatively high degree of related product diversification across the passive and active segments.

In Table 4.2 we present the descriptive statistics of the sample of fund families over different time intervals to assess the time series variation in both fund and fund family characteristics. Mutual fund industry assets (*INDUSTRYSIZE*) have grown from \$1.9 trillion in 1993 to about \$17.3 trillion in 2015. Over the same period, the average fund's total asset under management (*FNDTNA*) has grown from \$456 million in 1993 to \$1.1 billion in 2015, while the (equally-weighted) fee structure (*OPEX*) has remained relatively stable over time in the narrow range of 1.1% and 1.2%. The average fund family's total asset under management (*FAMTNA*) has increased from about \$4 billion to more than \$21 billion. While the average market share of fund families has not changed over this period (*FAMMKTS*), the degree of industry concentration has increased dramatically, with the 5 largest (by TNA) fund families controlling an average market share (*TOP5FAMMKTS*) of about 44% in 2015 (an almost 10% increase since 1993).

Further, the number of fund families in our sample has increased from 452 in 1993 to about 780 in 2015. These summary statistics of fund families are very close to those documented by Khorana & Servaes (2012) over their earlier sample period from 1976 to 2009.

4.3 Empirical Results

Our empirical strategy uses both cross-sectional and panel variations to evaluate the relationship between the performance of equity mutual funds and the degree of asset-based concentration of their fund families in the active management segment. Our analysis in Section 4.3.1 suggests that fund family's active concentration benefits the performance of its constituent funds. This result is robust to the use of manager-level panel data with manager, family and time fixed effects in Section 4.3.4. We examine the heterogeneity of family specialization using different proxies of fund activeness in Section 4.3.3. In Section 4.3.2, we provide evidence on the economic mechanism that drives this result by showing that managers of funds affiliated with more active fund families produce superior performance on account of more private information. In Section 4.3.5, we show that our proxy of family specialization captures attributes of managerial skill that are not already reflected by fund performance. We also conduct a series of tests in Section 4.3.7 that confirm that the superior performance is related to the amount of resources dedicated by the fund family to information production. In Section 4.3.6, we exploit a quasi-experiment involving fund families' sponsorship acquisitions of intact target funds to test the robustness of our findings to exogenous variation in family-level active specialization. We conclude with an evaluation of the economic trade-off faced by fund families with high active concentration in Section 4.3.10.

4.3.1 Cross-Sectional Performance Regressions

We begin with an examination of the cross sectional relationship between fund performance and the degree of fund family's asset concentration in the active management segment. To address concerns related to the correlation of fund performance with other fund characteristics, we control for a host of fund and fund family characteristics. Since our predictions are cross sectional in nature we estimate Fama & MacBeth's (1973) cross-sectional regressions with heteroscedasticity- and autocorrelation-consistent (HAC) standard errors, with a lag of order 3. We test however the robustness of our findings to the inclusion of fixed effects in Section 4.3.4. Specifically, we estimate the following cross sectional regression:

$$PERF_{i,t} = \beta_0 + \beta_1 ACF_{i,t-1} + \Gamma' X_{i,t-1} + \epsilon_{i,t} \tag{4.2}$$

where $PERF_{i,t}$ is a generic variable (expressed in percentage terms) for the performance variables discussed in Section 4.2; $ACF_{i,t-1}$ is the percentage of assets invested in the active segment by the fund family of fund i in month t; and $X_{i,t-1}$ is a set of control variables in month $t-1$ which includes: the logarithm of fund's asset under management (*LFNDTNA*), the logarithm of the number of years since fund's inception (*LFNDAGE*); fund's portfolio turnover (*TURNR*); fund's annual operating expense (*OPEX*); investors' net cash flows (*NFLOW*); fund's cumulative returns over the past 12 months (*PRET*); the logarithm of fund family's total net assets (*LFAMTNA*); the logarithm of fund family's total number of investment objectives (*LNINVOBJ*); the logarithm of fund family's total number of portfolios (*LNPFOLIO*); the fund-level exit fees (*EXITFEE*); and a dummy variable, which equals 1 if more than 75% of fund family's assets are issued to institutional investors (*DUMMY_INST*), as proposed by Chen *et al.* (2010). The term Γ is the vector of estimated coefficients of the control variables. Our main coefficient of interest is β_1, which quantifies the sensitivity of mutual fund performance to fund family's *ACF*.

In Table 4.3, we report the findings of the regression specification illustrated in equation 4.2 using fund's gross risk-adjusted returns. The estimated loading (0.294) of *CAPM* in model (i) on the independent variable *ACF* is both economically and statistically significant (t-statistic of 2.65). To give an idea of the economic magnitude of such relationship, a one standard deviation (19%) increase in *ACF* would translate into a 70 basis points (0.19*0.294*12) increase in yearly fund performance of the average funds. This economic magnitude remains relatively stable when we turn to alternative factor model specifications in other columns of Table 4.3. Importantly, our results remain significant when we use the two holdings-based performance measures of return gap (*RETGAP*) and characteristic selectivity (*CS*). The coefficients of these variables are illustrated in models (v) and (vi), respectively. Consistent with our prediction, mutual funds benefit significantly from their affiliation to fund families with greater assets concentration in the active segment.

Our evidence that fund performance declines with the fund's own size but increases with the size of the other funds in the fund family resonates with the findings of Chen *et al.* (2004). Further, lagged fund performance, *PRET*, affects positively both net and gross current risk-adjusted returns (see also Chen *et al.*, 2013). Among the other control variables, the number of investment objectives offered by the fund family has a negative effect on fund performance. This is congruent with the evidence of Siggelkow (2003) who shows that the less style-focused the fund family's product offering the worse the performance of its constituent funds.

In model (iii) we also control for the degree of active share of the fund itself, *ACTSHR*.[13] The aim is to account for the possibility that the positive loading of fund performance on *ACF* might in fact reflect the impact of *ACTSHR* on the performance of a fund which also accounts for a large percentage of the fund family's overall mutual fund business. Consistent with Cremers & Petajisto (2009), *ACTSHR* (for below-median TNA funds) boosts fund performance but does not explain the estimated coefficient of *ACF*.

Further, since our measure of *ACF* could be equal to either 0 or 100% in the case of single-fund families, we interacted our variable *ACF* with the dummy variable *SINGLEFND* which equals one for single-fund families. We also repeated the analysis in Table 4.3 by re-estimating the model in equation 4.2 for the restricted sample of multi-fund families, and reached qualitatively similar conclusions.

4.3.2 Fund Family's Reliance on Private Information, Market Deviations, and *ACF*

In this section, we provide preliminary evidence on the information content of *ACF* and, more importantly, its ability to capture managerial skills by relating this measure to the degree to which fund managers rely on private information, or trade on this information by taking positions that deviate from the market. Our aim is to explore the economic mechanism that drives the findings of Table 4.3. We use different measures of fund's return deviation from common factor benchmarks from previous literature (see e.g., Cremers & Petajisto, 2009; Amihud & Goyenko, 2013),

[13] Due to the significant reduction in the number of quarterly observations, we limit this test to our representative performance measure of *4-FACTOR* in Table 4.3.

and quantify directly the degree of activeness and selectivity in the investment process of mutual funds of actively-focused fund families.

Our proxies of activeness and selectivity of a fund portfolio strategy comprise the following dependent variables: the fund's R^2 (*R-SQUARED*), estimated as in Amihud & Goyenko (2013); the fund's monthly tracking error (*TRKERR*), computed as the standard deviation of the residual of the Carhart (1997) four-factor model, and the degree of fund's active share (*ACTSHR*) which is available over the much shorter sample period from 1993 to 2009.[14]

Several studies have questioned more recently whether such measures of portfolio activeness and selectivity really capture managerial skills, given existing alternative explanations, such as luck, model misspecification, and survivorship bias. For this reason, we complement our analysis using two state-of-the-art measures of fund's reliance on private information. Our first proxy is the *RPI* measure proposed by Kacperczyk & Seru (2007). This measure quantifies the degree to which a fund manager relies on *public* information. The second proxy (*RSI*) quantifies instead the degree of *private* information production, and is computed as the cross-sectional covariance of a fund's portfolio weights of each stock, relative to the market, with subsequent stock-specific earnings surprises (see e.g., Kacperczyk *et al.*, 2016). These two information-based proxies are less likely to be affected by potential misspecification issues commonly credited to existing activeness measures.

Table 4.4 illustrates the findings of multiple cross sectional regressions with HAC standard errors. The estimated coefficients of the main independent variable, *ACF*, across different model specifications are consistent with the prediction of superior managerial skills among funds of high-*ACF* fund families. Compared to peer funds, mutual funds of fund families with greater asset-based specialization in the active segment are characterized, on average, by: (1) significant lower (–0.069) reliance on public information (*RPI*); greater covariance (0.095) of portfolio holdings with private information (*RSI*); (2) negative loading on the activeness proxy of *R-SQUARED* (–0.018) proposed by Amihud & Goyenko (2013); (3) and significant higher fund's tracking error (0.002) and active share (0.077).

In keeping with our expectation, mutual funds of high-*ACF* fund families thus exhibit a remarkable divergence of their portfolio returns from those of the market,

[14] We thank Antti Petajisto for making active share data available through his website.

are more actively tilted, and tend to rely more (less) on private (publicly-available) information.

4.3.3 Heterogeneity of Family-level Active Specialization and Fund Performance

In this study, we define an actively-focused fund family as one with a high asset concentration in the active management business. However, fund families are likely to have a very heterogenous mix of active funds in their product offering. For instance, Cremers & Petajisto (2009) find that many actively managed US equity mutual funds have holdings that are similar to those of their benchmarks, and argue that among active funds it is important to distinguish those that are truly active from those that are closet-indexing funds. In their international study, Cremers *et al.* (2016) find a relatively large amount of closet indexing among mutual funds, and show that a significant fraction of actively managed funds do not deviate considerably from their benchmarks. In our context this implies that if two actively-concentrated fund families have the same level of *ACF*, it might very well be that one fund family has a higher proportion of closet-indexing products (i.e., lower propensity towards active management) than the other fund family.

Previously, we showed that funds offered by high-*ACF* fund families outperform peer funds of low-*ACF* fund families. If this outperformance does indeed reflect better managerial skills and greater reliance on private information, it should be more pronounced among those families whose products are truly more active in nature, and less likely to follow closet-indexing strategies. Thus, we predict that the positive relationship between fund performance and fund family's *ACF* documented in Table 4.3 is likely to be significantly understated.

We address this concern using three proxies that better capture the cross-sectional variation in active funds of a fund family, and interact these proxies with our main variable of *ACF*. Our first proxy, *FAMRPI*, quantifies the reliance on public information of the average fund product of a fund family (Kacperczyk & Seru, 2007). Our expectation is that funds offered by fund families with higher *ACF* but lower *FAMRPI* would stand to benefit from superior information flow among all active funds offered by the fund family.[15] Our second proxy is the average

[15] We reached very similar conclusions using the alternative proxy of private information *RSI* in an unreported test.

monthly volatility of fund excess returns offered by a fund family (*FAMDEV*). We believe that an interaction term between *FAMDEV* and *ACF* will provide a clearer signal of the propensity of the fund family to move away from an indexing strategy, equal conditions. Our last proxy is the intensity of portfolio turnover of the average fund of a fund family (*FAMTURNR*). Fund families with a higher concentration in active fund products which are also characterized by more aggressive aggregate purchases or sales of securities (*ACF***FAMTURNR*), are likely to be more active in the portfolio management of their funds (see e.g. Khorana & Servaes, 2012).

Table 4.5 presents the findings of several cross sectional regressions. In Panel A of Table 4.5 we control for *FAMRPI* and the interaction term *ACF*FAMRPI*. In Panel B (Panel C) of Table 4.5 we consider the alternative proxy of *FAMDEV* (*FAMTURNR*), and its interaction with *ACF*. All regression specifications include the set of fund and fund family characteristics (unreported for brevity) described in Table 4.3. The loading of the dependent variables on the interaction term *ACF*FAMRPI* confirms our expectation that mutual funds belonging to fund families with greater average reliance on private information are associated, on average, with better performance. To give an idea of the economic relevance of this finding, a one standard deviation (0.17) increase in the family-level *FAMRPI* variable would weaken the sensitivity of performance (*4-FACTOR*) to *ACF* in column (iii) of Panel A of Table 4.5 from 0.992 to 0.512, or equivalently a 48% decrease. Our results remain unchanged when we consider the other two proxies of *FAMTURNR* and *FAMDEV* in Panels B and C of Table 4.5, respectively.

Overall, our performance tests in Tables 4.3 and 4.5 are congruent with the prediction that active mutual funds affiliated to fund families with higher *ACF* perform better than counterfactual peer funds offered by more passive fund families. This positive relationship is even more pronounced among those active families with greater reliance on private information, more aggressive departures from market risk, and higher intensity of average portfolio turnover.

4.3.4 Robustness to Managerial Self-selection and Fixed Effect Specifications

An obvious concern with interpreting our previous findings causally is that the cross sectional differences in performance conditional on fund family's active focus could arise from several other factors, such as managerial self-selection in fund families with more focused operational scope. In this section, we examine whether managers with ex-ante superior investment skills are more likely to gravitate towards these type of organizations, in equilibrium. [16]

To get a proxy of ex-ante managerial ability we use data from Morningstar on fund managers' biographical sketch over the period from 1993 to 2015. In particular, we construct two measures of ex-ante managerial skills: the dummy variable *IVYLEAGUE*, which is equal to one if the fund manager graduated from one of the Ivy League Universities; and the dummy variable *GRADSCHOOL* which equals 1 if the fund manager has any postgraduate qualifications (MA, MBA, or PhD). These variables have been shown to be associated with better investment returns to fund investors (see e.g., Chevalier & Ellison, 1999). We refine this signal of managerial quality using the interaction term *IVYLEAGUE*GRADSCHOOL* to identify those managers who have obtained a postgraduate qualification from one of the Ivy League Universities. We also control for the dummy variable *MGMTEAM*, which equals 1 if family funds are managed by a team of managers as Massa *et al.* (2010) have established the self-selection of better managers into single-manager funds.

The findings of this test are illustrated in Panel A of Table 4.6. The evidence there shows that fund families with greater active concentration are more likely to attract better managerial talent as measured by both the level (*GRADSCHOOL*) and prestige (*IVYLEAGUE*) of a fund manager's academic qualification.[17] In Section 4.3.7 we provide a possible explanation for this association between fund family's active focus and managerial quality by examining the amount of resources allocated by the fund family to soft information production.

To the extent that the differences in performance conditional on the operational scope of a fund family, are not driven by time-invariant manager characteristics, re-estimating the regression model in equation (4.2) using manager fixed effects would allow a more accurate estimation of the effect of *ACF* on mutual fund performance. To this end, we restructured the panel data at the fund manager level rather than at the fund level, and introduced family, time and manager fixed effects. The findings of these estimations are illustrated in Panel B of Table 4.6. The dependent variable there is one of our proxies of gross fund performance. For

[16] In Section 4.3.6, we report the results of a quasi-experiment that more generally accounts for selection bias due to possible omitted variables.

[17] Please notice that managerial self selection per se does not invalidate our empirical findings if the heterogeneity in fund managers' skill is induced by differences in fund family's *ACF*.

brevity, we omit the estimated coefficients on other lagged fund and fund family control variables described previously in Table 4.3.

The coefficient of ACF of 0.216 in model (i) of Panel B of Table 4.6 suggests that a one standard deviation (19%) increase in a fund family' ACF would improve the (gross) performance of its average active fund by almost 50 basis points, per year. Importantly, the positive relationship between performance and ACF remains significant even after controlling for manager fixed effects, which exploit the within manager-fund variation by tracking over time the performance of the same manager across families characterized by different levels of ACF. Despite such more stringent model specifications, the heterogeneity in fund family's active concentration continues to be a major determinant of the performance of its constituent funds.

4.3.5 Investor Response to Fund Family Active Concentration Index

A large body of literature has documented that mutual fund investors chase past fund performance when allocating their capital across funds (see e.g. Sapp & Tiwari, 2004). If the proxy of ACF measures aspects of managerial skill, which traditional performance measures may not capture, we should expect a significant positive relationship between ACF and future fund flows. We examine this prediction empirically by estimating the following regression:

$$NFLOW_{i,t} = \beta_0 + \beta_1 ACF_{i,t-1} + \Gamma' X_{i,t-1} + \epsilon_{i,t}. \qquad (4.3)$$

The dependent variable, $NFLOW_{i,t}$, is the percentage *net* cash flows experienced by fund i in month t, and $X_{i,t-1}$ is a vector of lagged control variables comprising the fund and fund family characteristics described in Table 4.3. We also include the past 1-year cumulative return of the fund ($PRET$); the after-fee four-factor risk-adjusted return ($\alpha_{4-FACTOR}$), and its squared value ($\alpha^2_{4-FACTOR}$) to account for possible non-linearities in the flow-performance sensitivity. All regressions include dummy variables of investment objectives. In columns (i) to (iv), we estimate panel regressions with time-fixed effects and standard errors clustered at the family groupings. In columns (v) to (vii), we illustrate the findings of Fama &

MacBeth (1973) cross sectional regressions with HAC standard errors estimated with a lag of order 3.

Since net cash flows are not available in CRSP, we follow the literature by estimating investment flows as follows:

$$NFLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}}, \tag{4.4}$$

where $TNA_{i,t}$ denotes the total net assets of fund i in month t, and $R_{i,t}$ denotes its after-fee return in the same month. This variable was then winsorised at the 1st and 99th percentiles, to reduce the impact of outliers resulting from mergers and splits of funds.

The coefficient of interest in the regression specified in equation (4.5) is β_1, namely the sensitivity of investor flows to fund family's *ACF*. Our expectation is that the loading on this variable is both positive and significant. The estimates of the coefficients in the basic flow regression are presented in Table 4.7. Specifically, in columns (i), (ii), and (iv) we reproduce two major findings documented in the literature, namely that (1) investor flows chase past performance, and that (2) this effect is driven primarily by past raw returns.

We present the findings on the relationship between *NFLOW* and *ACF* using both panel and cross-sectional regressions. The coefficient β_1 (0.007) in column (iii) is positive and significant, both statistically (t-statistics of 7.17) and economically: a one-standard deviation (19%) increase in *ACF* boosts subsequent *net* fund flows by 1.6% per year, even after controlling for fund's past performance since both past realized and risk-adjusted returns are included in column (iii). Although we cannot separate investors' inflows and outflows, our evidence suggests that *ACF* captures some attributes of managerial skill that are not measured by past returns. Our findings in this section are also robust to alternative model specifications which account for the convex flow-performance relationship identified by the positive coefficients of the variable $\alpha^2_{4-FACTOR}$, in columns (iv) and (vii).

4.3.6 A Quasi-Experiment: Fund Families' Sponsorship Acquisitions and the Effect of *ACF* on the Performance of Intact Target Funds

A concern with our previous findings of a positive relationship between fund performance and *ACF* is that this relationship could be driven by unobserved fund family characteristics affecting both fund performance and product offering focus. In this section, we use a natural experiment to establish robustness by considering the special case of fund families' sponsorship acquisition of intact target mutual funds held by other fund families. Contrary to mutual fund mergers where the target fund disappears completely following its absorption by incumbent fund(s) of the acquiring fund family, target funds of sponsorship acquisitions survive as independent entities. According to Luo & Qiao (2012), 33% of target funds are merged, on average, with incumbent funds of the acquiring fund family, while the remaining 66% of target funds are kept intact following family-level sponsorship acquisitions.[18]

We estimate the performance of active equity intact funds around the sponsorship acquisition event using objective-adjusted returns, CAPM, and four-factor model estimated over the previous –24 to –1 months (the month 0 of the sponsorship acquisition event is excluded from the performance analysis), and the 1 to 24 months following the event month. Consistent with the literature, we refer to these two intervals as –2 and 2, respectively. We also repeated the analysis using the longer pre-event window of –36 to –1 months and post-event window of 1 to 36 months, and referred to these two intervals as (–3, 3), respectively. We then allocate intact target funds to three portfolios (*LOW 30*, *MID 40*, and *HIGH 30*) of sorted changes in *ACF* between the acquiring fund family and the target fund family (ΔACF). The *LOW 30* (*HIGH 30*) portfolio comprises intact target funds experiencing the lowest (highest) change in *ACF* from the old to the new fund family.

Panel A of Table 4.8 illustrates the average annualized change in performance measures of intact target funds for each portfolio of sorted ΔACF over the event

[18] We follow the methodology proposed by Luo & Qiao (2012) to identify fund family's sponsorship acquisition (please refer to Luo & Qiao (2012) for more details on this identification strategy). Importantly, in order to estimate the performance of intact target funds, we require them to disclose return information over the 24 months in both the pre-acquisition period and the post-acquisition period.

window (–2, 2). Focusing on the four-factor model results in Panel A of Table 4.8, we find that the difference in the change in target fund performance between the *HIGH 30* and the *LOW 30* portfolios of ΔACF, is 2.65% on an annualized basis (t-statistic of 2.56). Interestingly, moving from the portfolio of *LOW 30* to the portfolio of *HIGH 30*, the change in post-acquisition performance for the intact target fund increases monotonically. The same trend, with similar significance, can be noted when we use the target fund's objective-adjusted returns and the 1-factor model returns over the same interval (–2, 2). Our conclusions become even stronger, both economically and statistically, when we consider the longer event window of (–3, 3).[19] The findings of Panel A of Table 4.8 indicate that an increase in the degree of asset-based focus of fund families in active management segment contributes to more positive post-acquisition performance outcomes from the perspective of target fund shareholders.

It is possible that the evidence of Panel A of Table 4.8 stems largely from some uncontrolled fund or fund family characteristics known to affect fund performance from previous literature. We seek to account for such factors in Panel B of Table 4.8 by estimating a multivariate regression where the dependent variable is the change in intact target fund performance between the intervals –2 and 2. The main independent variable of interest is ΔACF. Other lagged control variables include the change in fund and fund family characteristics around the sponsorship acquisition event. The findings of Panel B of Table 4.8 confirm in a multivariate setting that active target funds experience an improvement in performance in the post-acquisition period if the new fund family is more concentrated in the active management segment than the old fund family. The economic magnitude of this improvement is significant: a one standard deviation decrease in the mean ΔACF of the managing fund family relates to 0.91% (annualized) decrease in post-acquisition alphas of the intact target fund. Our findings are in line with those of Panel B of Table 4.8 when we consider the alternative interval of (–3, 3) in an unreported test. Collectively, these results suggest that greater commonality between investment strategies of target funds and segment focus of acquiring fund families benefits target fund shareholders.

[19] In an unreported test, we also evaluated the change in fund-level TNA, turnover, operating expenses, and advisory fees, and found no significant variation in these fund characteristics around sponsorship acquisition events.

4.3.7 Research Infrastructure, Information Production and Active Concentration of Fund Families

The greater reliance on private information and the superior performance of constituent funds of high-ACF families hints at the possibility that these funds might enjoy significant institutional advantages from better allocation of resources to information production by their fund family. Under our economic interpretation, high-ACF fund families provide fund managers with more dedicated resources for information production. In this section, we examine this conjecture using different proxies of the size of fund family's research infrastructure supporting their active funds' primary objective of generating superior performance. Our regression model is expressed as follows:

$$Reseach\_Infrastr_{i,t} = \alpha_0 + \alpha_1 ACF_{i,t} + \Delta' X_{i,t-1} + \epsilon. \tag{4.5}$$

We use several proxies of the size of fund family's research infrastructure as identified by the generic variable *Research_Infrastr*. In addition to an indicator variable which equals one if the fund family has a brokerage division in the same physical location of its asset management division (*BKR_DIVISION*), we also use the following proxies of family-level information production: the number of fund managers employed by the fund family across the other active mutual funds (*NUM_ACTMGRS*); the number of buy-side security analysts (*NUM_BUYANALYSTS*), the number of registered broker-dealers (*NUM_BKR-DEALERS*), and the number of security traders (*NUM_TRADERS*) employed by the brokerage division of the fund family.[20] Other family-level control variables include the logarithm of fund family's total net assets (*LFAMTNA*); the logarithm of fund family's total number of investment objectives (*LNINVOBJ*); the logarithm of fund family's total number of portfolios (*LNPFOLIO*); and a dummy variable, which equals 1 if more than 75% of fund family's assets are issued to institutional investors (*DUMMY_INST*), as proposed by Chen *et al.*

[20] The data on the existence of a brokerage division of the firm is obtained from a fund family's detailed response to Question 7.A of the annual ADV form available through the SEC EDGAR historical archives. From this annual form we also extract the number of registered broker-dealers of the fund family based on the firm's response to Question 5.B.2. The number of mutual fund managers is sourced from the Morningstar database. Last, we obtain the number of buy-side security analysts and that of security traders employed by the firm's brokerage division from the annual reports of Nelson's Directories of Investment Managers.

(2010). The term Δ is the vector of estimated coefficients of the control variables. Our prior is for high-*ACF* families to be better equipped with internal research personnel and infrastructure (i.e, $\alpha_1 > 0$). The findings of these family-level regressions are reported in Table 4.9. For brevity, we omit the coefficients on the other lagged fund family characteristics.

The loading of the dependent variable *BKR_DIVISION* in model (i) confirms that actively-focused fund families are more likely to have a brokerage division under their control. The loading of *NUM_ACTMGRS* in model (ii) of 15.43 implies that a one standard deviation (19%) increase in the independent variable *ACF* amounts to an increase of about 3 more managers (0.19*15.43) actively seeking to outperform the market. We obtain similar findings in model (iii) when we consider the number of buy-side analysts employed by the firm, *NUM_BUYANALYSTS*. In this case, a one standard deviation increase in fund family's *ACF* is associated with 4 more analysts employed by its brokerage division. The last two model specifications in columns (iv) and (v) yield qualitatively similar conclusion on the association between the variable *ACF* and the proxies of family-level information production.

In the whole, the evidence in Table 4.9 confirms that more actively-focused fund families are likely to devote more resources to private information production to help their fund managers generate superior performance.

4.3.8 An Alternative Explanation: Are More Passive Fund Families Simply Running their Active Funds on the Cheap?

Our previous evidence of a positive relationship between *ACF* and gross alpha casts doubts on alternative explanations based on cross sectional differences in the fee-setting policies of mutual funds or their fund families. However, it is still plausible to argue that active funds of more passive fund families underperform those of actively-concentrated fund families if passive families tend to run their active funds on the cheap to lower markedly ongoing total operating costs and management fees across the entire product spectrum (*cost-based explanation*). Since fund families could also vary cross-sectionally depending on their once-off load structure, we also consider a fund's front-end load (*FRONTLOAD*), and a fund's back-end load which is computed by excluding any contingent deferred sales charges accruing to fund brokers (*EXITFEE*).[21]

If a strong cross-sectional correlation between *ACF* and the structure of fund's (ongoing and once-off) charges is prevalent in our sample this could potentially invalidate the regression specification in equation (4.2) due to multi-collinearity. To assess the robustness of this specification, we inspect the sensitivity of different fund fees to fund family's *ACF* in Table 4.10. All models include dummy variables for investment objectives. Robust (HAC) t-statistics are illustrated in parentheses.

First, the loadings of fund fees on fund and fund family characteristics are consistent with previous studies. Specifically, the evidence of columns (i) and (iii) shows that total operating expenses and advisory fees exhibit a significant negative dependence on their assets under management (see e.g. Barber *et al.*, 2005). In addition, the negative dependence of such fees on fund family size (measured by assets under management or number of constituent funds) suggests that economies of scale and scope operate at the family level, with the costs of investment research, managerial expertise, and portfolio rebalancing spread more efficiently across larger families (see also Warner & Wu (2011)). Unsurprisingly, funds offered to an institutional clientele, and funds engaging in less portfolio turnover exhibit lower advisory fees and exit gates, on average.

Importantly, we find no evidence that *ACF* is correlated with a fund cost structure after controlling for fund- and family-specific variability. Thus, it is unlikely that the findings documented in previous sections are in fact an artifact of spurious correlation between our *ACF* proxy and the advisory fee-setting policies of a fund—or its fund family.

[21] Mutual funds charge a variety of fees depending on the nature of the service provided to investors. While annual 12b-1 fees are typically used to cover distribution and marketing expenses, annual management fees are paid out of fund assets to remunerate the fund's investment adviser. Total annual operating expenses comprises both these fees, together with other minor fees such as custodial, legal and accounting costs. We also consider the upfront fees of purchasing and selling fund shares such as front-end loads (typically used to compensate brokers) and redemption fees (charged to defray the dilution costs of investor redemptions).

4.3.9 Does Outsourcing Explain the Performance Sensitivity to ACF? An IV Approach

Recent studies have investigated the relationship between firm boundaries and fund performance. Chen *et al.* (2013) document that 40% of fund families outsource the management of their funds to external advisory firms, and that a typical fund family on average outsources the management of 26% of its funds. They argue that outsourcing mutual fund management represents a strategy for fund families to expand their boundaries though at the cost of poor fund performance due to contractual externalities. If passively-oriented fund families do not possess the necessary expertise – or even the track record – to manage their active funds, they could decide to expand their boundaries (product offerings) by outsourcing the management of (some of) their active mutual funds to external investment advisors (or sub-advisors). In this context, the underperformance of active funds of passive fund families could arise from contractual externalities of external advisors. In this section, we test the effect of outsourcing on the multivariate relationship between fund family's ACF and fund performance.[22]

We construct our outsourcing indicator variable based on the information about fund family names and fund advisor names provided by the CRSP Mutual Fund Database. For each month in our sample period, we compare the name of each fund's management company to that of its listed fund advisor. To be conservative, we identify a fund to be outsourced if the first three blocks of the fund family name do not match those of the fund advisor name. The descriptive statistics of our outsourcing variable are very similar to those illustrated by Chen *et al.* (2013). For instance, the average fraction in our sample of outsourced funds among the top 100 fund families is about 30% in 2015, with 36% of the fund families having at least one fund managed by external advisors in that year.

Following Chen *et al.* (2013), we apply an instrumental variable (IV) approach in our analysis, and instrument for a fund's outsourcing status based on the number of funds the family offers at its inception. We prefer the IV over the OLS approach for the following reasons: if a fund family is increasing the number of product offerings

[22] Notably, we consider front-office arrangements associated with the outsourcing of advisory services. We acknowledge that there are other types of (back-office) arrangements such as administrative, transfer-agent, custodian, trustee, and auditor services (see e.g. Cumming *et al.* (2015)). We do not have however access to data to isolate also the effect of these additional outsourcing agreements in our study.

relative to its asset base, it might run into capacity constraints and be more likely to outsource the creation of the fund. Further, in Chen *et al.*'s (2013) subsample of equity funds, the negative relationship between outsourcing and performance is only significant under the IV approach, but loses its explanatory power under the OLS approach.

For the first-stage analysis, we employ a logit model and obtained the first stage residual (*RESIDUAL_FIRST_STAGE*) and the estimated outsourcing variable (*OUTSOURCING*). Given that the first stage is a non-linear model, we use a two-stage inclusion as first proposed by Hausman (1978). The following second-stage regression specification is then employed:

$$\begin{aligned} PERF_{i,t} = \;& \beta_0 + \beta_1 ACF_{i,t-1} + \beta_2 ACF_{i,t-1} * OUTSOURCING_{i,t-1} \\ & + \beta_3 OUTSOURCING_{i,t-1} + \beta_4 RESIDUAL\_FIRST\_STAGE_{i,t} \\ & + \Gamma' X_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{4.6}$$

Table 4.11 reports the estimated coefficients for the second stage panel regression on fund's gross performance.[23] The evidence there shows a significant negative loading of gross performance on *OUTSOURCING*. This finding is consistent with Chen *et al.* (2013) who argue that contractual externalities lead to underperformance of outsourced funds as compared to in-house managed funds.

The main coefficient of interest, β_2, on the interacted term *ACF*OUTSOURCING* is economically and statistically insignificant across all our performance measures, which implies that the association between fund family active concentration and performance is not correlated with the outsourcing status of constituent funds of a fund family. At the same time, the statistical significance of the coefficient of *ACF* confirms the role of fund family's active concentration in generating superior information in both internally- and externally-managed mutual funds.

The findings of Table 4.11 provide reassuring evidence that outsourced funds do not face different sensitivity of performance to *ACF*. Thus, the positive association between family-level active concentration and fund performance does not seem to be explained by contractual externalities associated with endogenous fund family's outsourcing decisions.

[23] As in Chen *et al.* (2013), we estimate Equation (4.6) using time-fixed panel regressions with standard errors clustered by fund family.

4.3.10 Concentrated Fund Families and Flow-related Liquidity Risk

Our analysis suggests that funds of actively-focused fund families perform significantly better. However, in equilibrium, one also observes funds of fund families with lower *ACF*, which are diversified across both the active and the passive segments. We conjecture that the downside of a fund family's concentration in the active segment is its relatively lower diversification of investor redemption risk and hence higher correlation of net cash outflows following exogenous shocks to investor liquidity demand.[24] Further, according to the 2015 Investment Company Institute (ICI) Fact Book, almost $1 trillion in net cash flow and reinvested dividends has been shifted by investors between active funds and index funds and ETF products from 2007 to 2014. Thus, if investor demand for active and passive products is time-varying, a fund family could prefer lower asset concentration in the active segment and diversify its product offering across the active and passive segments to better hedge its flow-related income risk (see e.g., Massa, 1998).

We begin by providing anecdotal evidence on the flow-related redemption risk faced by fund families sorted by their level of *ACF*. To this end, we compute the yearly change in average style-adjusted net cash flows in the years before and the years after the flow-related liquidity shock of September 2008 for quintile portfolios of sorted *ACF*. The changes in the average style-adjusted net cash flows, $\Delta NFLOW$, are computed as the difference between the post-September 2008 averages and the pre-September 2008 averages over the 12-, 24-, and 36-month windows surrounding the September 2008 event. The findings of this analysis are illustrated in Panel A of Table 4.12. The evidence there shows clearly that fund families in the *High ACF* quintile portfolio experienced a 10% greater style-adjusted net cash outflows than fund families in the *Low ACF* quintile portfolio. This difference is statistically significant and economically meaningful. Importantly, we did not find any significant difference in style-adjusted net cash flows between these two extreme quintile portfolios in the periods before the 2008 shock.

[24] Consistently, in an unreported test we find that the within-family net cash flow correlation of fund families with above-median *ACF* is, on average, twice (0.60 versus 0.29) that of fund families with below-median *ACF*.

These findings are also confirmed by the multivariate analysis of Panel B of Table 4.12, where the dependent variable is the change in the annual style-adjusted net cash flow averages computed in the 12 months after September 2008 (inclusive) and the 12 months before September 2008, $\Delta NFLOW$. We also interact the main independent variable of interest, *ACF*, with the variable *PCT_INST* which is computed as the percentage of fund family assets in institutional share classes. Schmidt *et al.* (2016) show that investors' redemption risk and strategic complementarities are higher among these institutional classes.

After controlling for several fund and fund family characteristics (unreported for brevity), the evidence of Panel B of Table 4.12 show that fund families with greater asset concentration in the active management segment experienced significant greater net cash outflows. For instance, the coefficient in model (i) of –0.158 indicates that a one standard deviation (19%) increase in fund family's *ACF* is likely associated with a 3% (0.19*0.158) greater average net cash outflows of a fund family. This finding is mostly prevalent among those families which are more exposed to institutional redemption risk as confirmed by the loading (–0.369 = –0.084 – 0.285) on the interaction term between *ACF* and *PCT_INST* in model (ii).

In the whole, the evidence of Table 4.12 shows that actively-concentrated fund families experience significant diversification *losses* during periods of heightened flow-related liquidity risk. Thus, investors' tendency to confine their mutual fund purchases to one fund family (see e.g., Capon *et al.*, 1996; Elton *et al.*, 2006) could have a detrimental effect on their overall liquidity risk exposure, with this risk increasing among fund families with a higher percentage of institutional investor classes.

4.4 Conclusion

This study explores the performance benefits enjoyed by mutual funds offered by fund families whose product offering reflects greater specialization in the active management segment. Our study shows that fund families with greater asset-based focus on the active segment are more likely to possess better managerial skills at running their active funds. We show that this result derives in part from fund families' superior expertise from specialization and learning economies as measured by the size of their research infrastructure, and the amount of resources dedicated to private information production.

Using a large sample of US active equity mutual funds, we find that funds belonging to actively-focused fund families outperform (before fees) peer funds offered by other fund families by about 70 basis points, per year. In addition, we provide new evidence that our family-level active concentration measure contains information on the degree of activeness and selectivity of the investment process of family funds. Importantly, we show that mutual funds offered by actively-focused fund families are significantly more (less) likely to rely on private (public) information. Our results are robust to family, time and fund-manager fixed effects, and are confirmed by a natural experiment involving fund families' sponsorship acquisition events.

The findings of this study highlight the significant performance drag experienced by an average equity mutual fund investor if the operational scope and investment philosophy of her fund family are not aligned with the primary objective of active funds of outperforming the index. We also confirm the presence of a "dark side" of firm specialization by showing that actively-focused fund families are more likely to experience significant diversification losses during periods of severe market stress. This could in turn worsen the liquidity risk exposure of individual investors, in the light of the existence of significant flow-related payoff complementarities among open-ended mutual funds. Our study suggests that mutual fund investors would be better off purchasing active mutual funds across specialized fund families rather than concentrating their fund share purchases within a single specialized fund family.

Table 4.1
Descriptive Statistics.

Table 4.1 presents summary statistics for our sample of US diversified active equity mutual funds during the period January 1993 to March 2015. The following fund and affiliated fund family characteristics are summarized: funds' assets under management (*FNDTNA*), in $ million; the logarithm of the number of years since funds' inception(*FNDAGE*); funds' portfolio turnover (*TURNR*); funds' annual operating expense (*OPEX*); funds' annual advisory fees (*ADVFEE*), which are computed as the difference between funds' total operating expenses and 12b-1 fees; investors' net cash flow (*NFLOW*); funds' objective-adjusted returns (*OAR*); funds' redemption fees (*EXITFEE*); fund family's total number of mutual fund portfolios (*NPFOLIO*); fund family's total number of distinct investment objectives (*NINVOBJ*); and the percentage of fund family's total asset concentration in active mutual fund products (*ACF*). We also report the summary statistics of funds' after-fee returns adjusted using any of the following factor models: the CAPM model (*CAPM*); and the Carhart (1997) four-factor model (*4-FACTOR*), which we identify as our representative factor model.

			Percentiles		
	N	Mean	25%	50%	75%
FNDTNA	319,553	602.97	12.81	72.30	313.70
FNDAGE	319,553	8.83	3.50	7.04	11.67
TURNR	319,553	0.72	0.26	0.57	0.99
OPEX	319,553	1.24%	0.92%	1.24%	1.66%
ADVFEE	319,553	0.91%	0.77%	0.98%	1.16%
NFLOW	319,553	0.94%	-1.43%	-0.07%	1.75%
EXITFEE	319,553	0.20%	0.00%	0.00%	0.00%
NPFOLIO	231,352	8.73	1.00	3.00	8.00
NINVOBJ	231,169	4.50	1.00	2.00	6.00
ACF	230,757	61.17%	49.72%	63.77%	73.72%
OAR	319,553	0.02%	-0.74%	0.00%	0.78%
CAPM	317,596	-0.68%	-13.80%	-1.40%	11.56%
4-FACTOR	317,596	-1.17%	-14.38%	-1.43%	11.49%

Table 4.2

Descriptive Statistics by Time Intervals and by Quintile Portfolios of *ACF*.

Table 4.2 presents summary statistics for our sample of US diversified active equity mutual funds during the period January 1993 to March 2015. Panel A reports the time-series descriptive statistics of the mutual fund sample based on 2-year time intervals ending in T. The averages of the following fund and affiliated fund family characteristics are summarized: funds' assets under management (*FNDTNA*), in $ million; the logarithm of the number of years since funds' inception(*FNDAGE*); funds' portfolio turnover (*TURNR*); funds' annual operating expense (*OPEX*); funds' annual advisory fee (*ADVFEE*); total industry size (*INDUSTRYSIZE*) in $ million; total number of fund families (*NUMFAM*); fund family's assets under management (*FAMTNA*), in $ millions; the average percentage of fund family's market share (*FAMMKTS*); the total market share of the top 5 fund families (*TOP5FAMMKT*); the fund family's number of distinct fund portfolios (*NPFOLIO*); the fund family's number of distinct investment objectives (*NINVOBJ*); and the fund family's percentage of assets under management in active fund products (*ACF*).

	1993	1995	1997	1999	2001	2003	2005	2007	2009	2011	2013	2015
FNDTNA	456.45	423.12	493.09	590.45	640.41	441.30	559.92	689.52	594.61	695.85	834.00	1,109.54
FNDAGE	6.07	6.16	6.22	5.80	6.25	6.74	7.40	7.82	9.43	11.45	13.34	14.83
TURNR	0.58	0.67	0.53	0.61	0.80	0.81	0.68	0.64	0.78	0.75	0.61	0.56
OPEX	1.11%	1.15%	1.10%	1.09%	1.18%	1.23%	1.25%	1.16%	1.22%	1.22%	1.18%	1.14%
ADVFEE	0.87%	0.83%	0.86%	0.84%	0.87%	0.90%	0.91%	0.84%	0.90%	0.90%	0.86%	0.83%
INDUSTRYSIZE	1,947,152	2,617,427	3,981,198	5,932,215	6,287,439	6,823,417	8,434,996	11,691,852	10,952,027	12,139,583	16,089,222	17,258,435
NUMFAM	452	507	601	771	700	676	639	605	589	703	765	780
FAMTNA	4,308.0	5,162.6	5,888.6	6,834.1	7,332.4	9,009.7	11,534.6	15,992.0	17,312.9	18,301.8	18,640.9	21,278.8
FAMMKTS	0.22%	0.20%	0.18%	0.14%	0.13%	0.15%	0.16%	0.16%	0.16%	0.16%	0.13%	0.13%
TOP5FAMMKTS	32.78%	34.32%	35.20%	35.35%	32.05%	34.63%	38.33%	39.50%	41.32%	41.42%	42.77%	43.86%
NPFOLIO	5.39	6.29	6.71	6.90	7.30	8.06	8.70	9.88	10.58	10.52	10.26	10.83
NINVOBJ	5.74	6.08	5.01	4.67	4.53	4.97	4.84	4.78	5.27	5.06	4.65	4.57
ACF	62.9%	60.7%	64.2%	61.2%	66.0%	58.0%	65.0%	64.0%	67.0%	64.4%	62.7%	61.3%

Table 4.3
Relationship between Family Active Concentration and Fund Performance.

Table 4.3 presents the Fama & MacBeth (1973) estimates of monthly regressions of fund performance on selected fund and fund family characteristics over the period 1993 to 2015. The dependent variable is the funds' gross performance estimated using any of the following factor models: (a) the CAPM model (*CAPM*), in column (i); (b) the Carhart (1997) four-factor model (*4-FACTOR*), in columns (ii)-(iii); and (c) the four-factor model augmented with the excess returns of the MSCI (inclusive of Europe, Australia, and the Far East) and the Lehman US Aggregate Bond Index (*6-FACTOR*), in column (iv). We also use two alternative performance proxies: (d) the characteristic selectivity measure, *CS*, of Daniel *et al.* (1997), in column (v); and (e) the return gap measure, *RETGAP*, of Kacperczyk *et al.* (2008), in column (vi). This variable is computed as the difference between fund i's gross returns and the gross returns predicted based on its lagged holdings. The main independent variable of interest is the degree of asset concentration (in percentage) of the fund family business in active fund products (*ACF*). Lagged control variables include: the logarithm of funds' total assets under management (*LFNDTNA*); the logarithm of funds' age (*LFNDAGE*); funds' portfolio turnover (*TURNR*); funds' annual operating expense (*OPEX*); investors' net investment flow (*NFLOW*); the cumulative returns of the fund over the past 12 months (*PRET*); the logarithm of fund family's TNA (*LFAMTNA*); the logarithm of fund family's total number of investment objectives (*LNINVOBJ*); the logarithm of fund family's total number of portfolios (*LNPFOLIO*); funds' exit fee (*EXITFEE*); a dummy variable which equals 1 if more than 75% of fund family assets are issued to institutional share (*DUMMY_INST*); and a dummy variable for single-fund families (*SINGLEFND*). In model (iii) we also control for Cremers & Petajisto's (2009) active share measure, *ACTSHR*, and its interaction with a dummy variable which is equal to 1 if the fund TNA is below the cross sectional median fund TNA. The table reports estimated coefficients of Fama & MacBeth (1973) cross sectional regressions with heteroskedasticity and autocorrelation consistent (HAC) standard errors with a lag of order 3 (t-statistics are reported in parentheses). All regressions include dummy variables for fund investment objectives. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	CAPM	4-FACTOR	4-FACTOR	6-FACTOR	RETGAP	CS
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
ACF	0.294***	0.280**	0.292***	0.281**	0.167**	0.362**
	(2.649)	(2.542)	(2.635)	(2.537)	(1.909)	(2.351)
LFNDTNA	-0.024***	-0.027***	-0.030***	-0.027***	-0.018***	-0.013**
	(-2.606)	(-2.906)	(-3.066)	(-2.843)	(-3.685)	(-2.458)
LFNDAGE	0.036**	0.037**	0.029*	0.035**	0.023*	0.036**
	(2.246)	(2.228)	(1.726)	(2.146)	(1.769)	(2.111)
TURNR	0.051**	0.049**	0.041*	0.050**	0.016*	0.025
	(2.107)	(2.078)	(1.759)	(2.101)	(1.777)	(1.014)
OPEX	0.198	0.090	0.104	0.209	0.132	-0.248
	(0.083)	(0.038)	(0.044)	(0.089)	(0.097)	(-0.227)
NFLOW	-0.166	-0.179	-0.106	-0.180	-0.188	-0.097
	(-0.837)	(-0.900)	(-0.469)	(-0.919)	(-0.864)	(-1.362)
PRET	0.927***	0.915***	0.846***	0.922***	0.901***	2.102***
	(3.067)	(3.052)	(2.799)	(3.075)	(3.125)	(3.690)
LFAMTNA	0.061***	0.061***	0.065***	0.061***	0.026**	0.027***
	(5.361)	(5.316)	(5.048)	(5.214)	(2.363)	(3.422)
LNINVOBJ	-0.167***	-0.167***	-0.163***	-0.165***	-0.163***	-0.054*
	(-2.894)	(-2.889)	(-2.751)	(-2.870)	(-2.922)	(-1.955)
LNPFOLIO	0.037	0.037	0.034	0.037	0.021	-0.003
	(0.858)	(0.872)	(0.780)	(0.861)	(0.466)	(-0.109)
EXITFEE	-1.827	-2.077	-3.542	-1.968	-2.055	3.103
	(-0.665)	(-0.764)	(-1.191)	(-0.717)	(-0.087)	(1.199)
DUMMY_INST	0.013	0.016	0.026	0.017	0.012	0.039***
	(0.812)	(0.953)	(1.059)	(1.018)	(1.008)	(3.144)
*ACF*SINGLEFND*	-0.016	0.020	-0.017	0.020	-0.017	0.023
	(-0.982)	(0.830)	(-1.031)	(0.871)	(-1.003)	(0.961)
ACTSHR			1.097			
			(1.506)			
ACTSHR			1.012**			
(below-median TNA)			(2.506)			
R^2	10.1%	9.9%	18.4%	9.9%	11.4%	14.8%
N	175,411	175,411	37,682	175,411	139,710	138,985

Table 4.4
Fund Family's Reliance on Private Information, Activeness, and *ACF*.

Table 4.4 presents the estimated monthly regression coefficients of proxies for fund-level activeness and reliance on public information on selected fund and fund family characteristics over the period from 1993 to 2015. Our dependent variable is one of the following proxies of fund-level activeness and reliance on public information: (i) fund advisor's degree of reliance on public information (*RPI*), proposed by Kacperczyk & Seru (2007); (ii) fund advisor's degree of reliance on private information (*RSI*), computed as the cross-sectional covariance of a fund's portfolio weights of each stock, relative to the market, with subsequent stock-specific earnings surprises (see e.g. Kacperczyk *et al.*, 2016); (iii) funds' R^2 (*R-SQUARED*); (iv) portfolio tracking error (*TRKERR*), computed as the standard deviation of the residual of the 4-factor model; and (v) funds' active share (*ACTSHR*) available over the shorter sample period from 1993 to 2009 (see e.g. Cremers & Petajisto, 2009). The main independent variable of interest is a fund family's asset concentration in the active segment, *ACF*. Other lagged control variables are those described in Table 4.3. The funds' redemption fees (*EXITFEE*), and investors' net cash flow (*NFLOW*) are untabulated for brevity. All regressions include dummy variables to control for mutual fund investment styles. The table documents the estimated coefficients of Fama & MacBeth (1973) cross sectional regressions with heteroskedasticity and autocorrelation consistent (HAC) standard errors with a lag of order 3 (t-statistics are reported in parentheses). One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	RPI	RSI	R-SQUARED	TRKERR	ACTSHR
	(i)	(ii)	(iii)	(iv)	(v)
ACF	-0.069***	0.095***	-0.018***	0.002***	0.077**
	(-3.815)	(4.158)	(-7.811)	(9.589)	(2.158)
LFNDTNA	-0.005**	-0.157***	0.002***	-0.000***	-0.002
	(-2.480)	(-3.886)	(3.873)	(-4.374)	(-0.651)
LFNDAGE	-0.008**	0.372	-0.001	0.000***	-0.004
	(-2.385)	(0.483)	(-1.159)	(4.487)	(-0.200)
TURNR	0.041***	-0.193***	-0.012***	0.002***	-0.012
	(10.405)	(-4.271)	(-10.771)	(14.252)	(-1.515)
OPEX	6.521***	0.738	-0.062	0.055***	-0.365
	(13.746)	(0.772)	(-0.654)	(6.487)	(-0.648)
PRET	-0.209**	0.275**	0.054**	-0.003	0.060
	(-1.985)	(2.291)	(2.416)	(-1.419)	(0.745)
LFAMTNA	0.011***	-0.034**	0.002***	-0.000***	-0.028*
	(2.805)	(2.277)	(5.128)	(-6.633)	(-1.947)
LNINVOBJ	-0.050***	0.329	0.027***	-0.002***	-0.136
	(-4.551)	(0.623)	(18.077)	(-14.197)	(-1.636)
LNPFOLIO	-0.024***	0.099	-0.011***	0.001***	0.173*
	(-2.970)	(1.015)	(-10.859)	(15.931)	(1.658)
DUMMY_INST	-0.010*	0.065***	0.005***	-0.000***	-0.027*
	(-1.944)	(3.707)	(6.371)	(-5.798)	(-1.823)
N	37,196	155,664	148,537	148,537	37,682

Table 4.5
Fund Performance and *ACF* after Controlling for the Degree of Fund Family's Deviation from the Index.

Table 4.5 presents the estimated regression coefficients of fund performance on selected fund characteristics and fund family's active concentration (*ACF*), for the period from 1993 to 2015. The dependent variable is fund after-fee performance computed as (i) the funds' investment objective adjusted monthly return (*OAR*) or using any of the following four factor models: (ii) the CAPM model (*CAPM*); (iii) the Carhart (1997) four-factor model (*4-FACTOR*); and (iv) the four-factor model augmented with the excess returns of the MSCI (inclusive of Europe, Australia, and the Far East) and the Lehman US Aggregate Bond Index (*6-FACTOR*). To mitigate any look-ahead bias, we estimate fund portfolio risk-adjusted returns as a one-month abnormal return from the factor model, where the loadings on the various factors are estimated over the previous 36 months (with a minimum of 30 observations). In column (v) of each Panel of this table we consider the return gap measure, *RETGAP*, computed as the difference between fund i's gross returns and the gross returns predicted based on its lagged holdings, as calculated in Kacperczyk *et al.* (2008). The main independent variable of interest is the degree of concentration (in percentage) of fund family business in active fund products (*ACF*). To account for the heterogeneity in the degree of concentration in active products, we interacted *ACF* with the following variables: (A) the reliance on public information of the average fund product (see Kacperczyk & Seru, 2007) offered by the fund family (*FAMRPI*); (B) the degree of volatility of excess returns of the average fund within the fund family (*FAMDEV*); (C) the intensity of portfolio turnover of the average fund within the fund family (*FAMTURNR*). Lagged control variables for fund and fund family characteristics are discussed in Table 4.3, and are not reported here for brevity. We estimate Fama & MacBeth (1973) cross sectional regressions with heteroskedasticity and autocorrelation consistent (HAC) standard errors with a lag of order 3 (t-statistics are reported in parentheses). One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A—Controlling for family-level average correlation of fund returns with the benchmark

	OAR	CAPM	4-FACTOR	6-FACTOR	RETGAP
	(i)	(ii)	(iii)	(iv)	(v)
ACF	0.914***	1.076***	0.992***	1.006***	1.411***
	(4.997)	(5.020)	(4.716)	(4.762)	(3.599)
ACF FAMRPI*	-3.501***	-2.881*	-3.002*	-2.978*	-3.417***
	(-2.748)	(-1.830)	(-1.957)	(-1.930)	(-3.211)
FAMRPI	1.739**	1.235	1.321	1.292	2.016***
	(2.336)	(1.325)	(1.452)	(1.413)	(3.488)
Investment styles	Yes	Yes	Yes	Yes	Yes
Std Error	HAC3	HAC3	HAC3	HAC3	HAC3
R^2	5.7%	17.4%	10.9%	10.2%	19.8%
N	148,253	148,253	148,253	148,253	119,143

Panel B—Controlling for family-level average volatility of fund returns relative to the benchmark

	OAR	CAPM	4-FACTOR	6-FACTOR	RETGAP
	(i)	(ii)	(iii)	(iv)	(v)
ACF	0.020	-0.068	-0.082	-0.054	0.031
	(0.076)	(-0.221)	(-0.270)	(-0.175)	(0.166)
ACF FAMDEV*	8.079**	9.751**	8.834**	8.485**	7.582***
	(2.329)	(2.240)	(2.053)	(1.966)	(3.749)
FAMDEV	-2.968	-3.607	-3.172	-2.981	-1.163
	(-1.225)	(-1.162)	(-1.032)	(-0.971)	(-0.116)
Investment styles	Yes	Yes	Yes	Yes	Yes
Std Error	HAC3	HAC3	HAC3	HAC3	HAC3
R^2	8.0%	23.7%	14.5%	13.9%	18.1%
N	148,253	148,253	148,253	148,253	119,143

Panel C—Controlling for family-level average fund portfolio turnover

	OAR	CAPM	4-FACTOR	6-FACTOR	RETGAP
	(i)	(ii)	(iii)	(iv)	(v)
ACF	0.321***	0.313***	0.298***	0.296***	0.168***
	(4.023)	(3.276)	(3.127)	(3.110)	(3.357)
ACF FAMTURNR*	0.189**	0.234**	0.230**	0.234**	0.226***
	(2.165)	(2.244)	(2.253)	(2.276)	(2.999)
FAMTURNR	0.019	0.007	0.006	0.006	0.014
	(0.399)	(0.134)	(0.112)	(0.130)	(0.093)
Investment styles	Yes	Yes	Yes	Yes	Yes
Std Error	HAC3	HAC3	HAC3	HAC3	HAC3
R^2	3.0%	15.1%	8.6%	8.4%	17.7%
N	162,133	162,133	162,133	162,133	131,888

Table 4.6
Managerial Talent, Fund Family's Active Concentration and Fund Performance.

Panel A of Table 4.6 shows the results of different probit regression models of fund family's degree of active concentration on different proxies of fund managers' ex-ante characteristics over the period from 1993 to 2015. Our dependent variable is an indicator variable which is equal to 1 if the fund family has an above-median *ACF*, and zero otherwise. Our main independent variables of interests are two attributes which proxy for ex-ante fund managers' quality: the dummy variable *D.[GRADSCHOOL]* which is equal to one if the manager has a graduate diploma (MA, MBA, or PhD), and 0 otherwise; and the indicator variable *D.[IVYLEAGUE]* which is equal to one if the fund manager has any degree from one of the Ivy League academic institutions. We also interact these two variables with each other to strengthen the signal of ex-ante managerial quality. Further, we include the dummy variable *D.[MGMTEAM]* which equals 1 if the mutual fund is managed by a team of fund manager, and zero if the mutual fund is managed by a single manager. In Panel B we re-estimated the regression models of Table 4.3 using fund manager level panel data rather than fund level panel data. The aim is to facilitate the use of manager fixed effects and isolate the impact of managerial talent, time and family effects on the positve relationship between fund performance and *ACF*. In all models, we control for the lagged fund and fund family characteristics previously described in Table 4.3. In column (iii) we also include the (untabulated) active share measure, *ACTSHR*, proposed by Cremers & Petajisto (2009). Standard errors are clustered at the family groupings and t-statistics are reported in parentheses. One, two and three asterisks indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A—Managerial Talent and Fund Family's *ACF*

	(i)	(ii)	(iii)	(iv)	(v)
IVYLEAGUE	0.0374***	0.004	0.011***	1.173***	0.001
	(4.770)	(1.548)	(3.094)	(3.285)	(0.061)
GRADSCHOOL		0.015***	0.016***	0.023***	0.014***
		(5.536)	(5.448)	(8.142)	(5.296)
*IVYLEAGUE * GRADSCHOOL*			0.054***		0.061***
			(3.001)		(3.982)
MGMTEAM				-0.068***	-0.054
				(-2.938)	(-1.227)
Family Controls	Yes	Yes	Yes	Yes	Yes
R^2	7.02%	7.13%	7.12%	6.74%	7.04%
N	23,693	23,693	23,693	23,693	23,693

Panel B—Fund Performance with Fund Manager Fixed Effects in Manager-level Panel Data

	CAPM	4-FACTOR	4-FACTOR	6-FACTOR	RETGAP	CS
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
ACF	0.216**	0.232**	0.197**	0.284***	0.164*	0.278**
	(2.201)	(2.384)	(2.178)	(3.012)	(1.932)	(2.369)
Time Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Family Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Manager Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Family Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	247,549	247,549	57,311	247,549	193,414	191,665

Table 4.7
Relationship between Family Active Concentration and Fund Flows.

Table 4.7 presents the estimated coefficients for the monthly regression of fund net investment flows on selected fund characteristics and fund family's active concentration (*ACF*), for the period from 1993 to 2015. Lagged control variables include: the cumulative returns of the fund over the past 12 months (*PRET*); funds' net performance under the 4-factor model ($\alpha_{4-FACTOR}$);the logarithm of funds' total assets under management (*LFNDTNA*); the logarithm of funds' age (*LFNDAGE*); portfolio turnover (*TURNR*); funds' annual operating expense (*OPEX*); the logarithm of fund family's TNA (*LFAMTNA*); the logarithm of fund family's total number of investment objectives (*LNINVOBJ*); the logarithm of fund family's total number of portfolios (*LNPFOLIO*); funds' exit fee (*EXITFEE*); a dummy variable which equals 1 if more than 75% of fund family assets are issued to institutional share (*DUMMY_INST*). The table reports the estimated coefficients of time series cross sectional regressions with time fixed effects and standard errors clustered by fund and family in models (i) to (iii). In all other model specifications we estimate Fama & MacBeth (1973) cross sectional regressions with heteroskedasticity and autocorrelation consistent (HAC) standard errors with a lag of order 3 (t-statistics are reported in parentheses). All regressions include dummy variables to control for differences in mutual fund investment styles. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	NFLOW						
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
ACF			0.007***	0.006***		0.004***	0.004***
			(7.168)	(7.197)		(3.390)	(3.392)
PRET		0.114***	0.114***	0.114***	0.185***	0.185***	0.185***
		(16.949)	(16.957)	(17.340)	(17.139)	(17.260)	(17.208)
$\alpha_{4-FACTOR}$	0.183***	0.050***	0.051***	0.051***	-0.010	-0.009	0.007
	(8.788)	(4.252)	(4.292)	(3.987)	(-0.640)	(-0.560)	(0.447)
$\alpha^2_{4-FACTOR}$				1.165***			1.502***
				(2.894)			(2.643)
LFNDTNA	0.001***	-0.000	-0.000*	-0.000*	-0.001***	-0.001***	-0.001***
	(2.996)	(-1.354)	(-1.828)	(-1.830)	(-4.214)	(-4.505)	(-4.489)
LFNDAGE	-0.017***	-0.017***	-0.017***	-0.017***	-0.014***	-0.014***	-0.014***
	(-40.745)	(-40.375)	(-40.507)	(-40.500)	(-21.472)	(-21.706)	(-21.685)
TURNR	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-3.381)	(-4.436)	(-4.168)	(-4.286)	(-3.156)	(-3.051)	(-3.318)
OPEX	-0.361***	-0.475***	-0.505***	-0.505***	-0.505***	-0.527***	-0.512***
	(-8.394)	(-12.238)	(-12.793)	(-12.804)	(-7.484)	(-7.715)	(-7.550)
LFAMTNA	0.002***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(10.061)	(7.443)	(7.814)	(7.787)	(5.047)	(5.091)	(5.262)
LNINVOBJ	-0.006***	-0.005***	-0.004***	-0.004***	-0.004***	-0.003***	-0.003***
	(-8.284)	(-7.005)	(-5.830)	(-5.837)	(-4.117)	(-3.343)	(-3.233)
LNPFOLIO	0.001*	0.001***	0.001*	0.001*	0.001**	0.001	0.001
	(1.771)	(2.884)	(1.721)	(1.736)	(2.018)	(1.189)	(1.024)
DUMMY_INST	-0.002***	-0.001	-0.001	-0.001	-0.003***	-0.003***	-0.003***
	(-2.748)	(-1.050)	(-1.544)	(-1.545)	(-3.210)	(-3.487)	(-3.374)
EXITFEE	0.325***	0.279***	0.265***	0.265***	0.285***	0.270***	0.274***
	(10.818)	(9.587)	(8.916)	(8.920)	(3.985)	(3.722)	(3.760)
Investment styles	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes	No	No	No
Std Error	Family	Family	Family	Family	HAC3	HAC3	HAC3
R^2	10.9%	12.3%	12.4%	12.8%	13.6%	13.8%	14.0%
N	175,118	162,186	162,133	162,133	162,186	162,133	162,133

Table 4.8
Event Study: Across Fund Family Mergers and Fund Performance.

Table 4.8 evaluates the univariate and multivariate relationship between fund family active concentration and fund performance around the exogenous shock of fund family's sponsorship acquisitions of fund targets held by other fund families. In sponsorship acquisitions the selling fund families transfer their equity fund business completely to the acquiring fund family, and hence target funds of sponsorship acquisitions remain intact entities. The dependent variable in both panels is the change in the performance of intact target funds surrounding the sponsorship acquisitions. We estimate fund performance using the Fama-French 1- and 4-factor models estimated over the previous -24 to -1 months (the month 0 of the event is excluded from the performance analysis), and the 1 to 24 months following the event month. We refer to these two intervals as -2, and 2, respectively. For robustness, we also consider the longer periods from -36 to -1 months and from 1 to 36 months following the event, and refer to these two intervals as -3, and 3, respectively. Results are reported for annualized change in performance over the intervals (-2, +2) and (-3, +3). We also compute the difference in the percentage active concentration between the acquiring and the target fund families (ΔACF). We then sort ΔACF and allocate mutual funds to portfolios of bottom 30%, mid 40%, and top 30% of ΔACF. Panel A illustrates the average change in annual alpha and the difference in means between high (*HIGH 30*) and low (*LOW 30*) ΔACF, with associated t-statistics for the two-sample mean t-test. Panel B reports standardized regression coefficients (with *t*-statistics in parentheses). The independent variables in Panel B are described in Table 4.3. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A—Change in the characteristics of intact target funds following a across-family merger

	Window	LOW 30	MID 40	HIGH 30	HIGH - LOW
	(i)	(ii)	(iii)	(iv)	(v)
ΔACF	(-2, +2)	-14.3%	1.2%	13.8%	
ΔOAR	(-2, +2)	-1.81	0.13	0.72	2.53
		(-2.12)	(0.41)	(3.11)	(2.89)
$\Delta CAPM$	(-2, +2)	-2.12	0.11	0.56	2.68
		(-2.00)	(0.33)	(2.12)	(2.37)
Δ*4-Factor*	(-2, +2)	-1.63	0.29	1.02	2.65
		(-2.31)	(0.55)	(3.11)	(2.56)
ΔACF	(-3, +3)	-16.2%	2.6%	17.5%	
ΔOAR	(-3, +3)	-2.35	-0.08	0.99	3.34
		(-2.91)	(-0.58)	(3.22)	(3.75)
$\Delta CAPM$	(-3, +3)	-2.69	0.04	0.86	3.55
		(-2.45)	(0.98)	(2.91)	(3.43)
Δ*4-Factor*	(-3, +3)	-1.72	0.63	1.25	2.98
		(-1.67)	(0.61)	(3.33)	(3.11)
N (Intact Targets)		177	236	177	

Panel B—Multivariate regression of change in performance (in %) of intact target funds

	ΔOAR (-2,2)	ΔCAPM (-2,2)	Δ4-Factor (-2,2)	ΔCAPM (-2,2)	Δ4-Factor (-2,2)
	(i)	(ii)	(iii)	(iv)	(v)
ΔACF	0.362***	0.385***	0.396***	0.250**	0.242*
	(3.118)	(3.047)	(2.995)	(2.221)	(1.939)
$\Delta LFNDTNA$	-3.342***	-3.435***	-3.524***	-2.215***	-2.207***
	(-5.522)	(-5.237)	(-4.935)	(-6.581)	(-6.482)
$\Delta LFNDAGE$	3.338**	4.420***	4.211***	2.888**	2.819**
	(2.205)	(3.103)	(3.229)	(2.355)	(2.241)
$\Delta TURNR$	-0.275	-0.226	-0.224	-0.698	-0.674
	(-0.878)	(-0.846)	(-0.598)	(-0.974)	(-1.005)
$\Delta OPEX$	-35.397	-15.562	-17.935	10.347	-6.388
	(-0.357)	(-0.587)	(-0.854)	(0.333)	(-0.755)
$\Delta NFLOW$	0.634***	0.946**	0.822**	0.704**	0.777**
	(3.134)	(2.308)	(2.505)	(2.200)	(2.398)
$\Delta LFAMTNA$	-4.285***	-4.157***	-4.235***	-1.997***	-1.953***
	(-5.148)	(-4.656)	(-4.548)	(-3.894)	(-3.446)
$\Delta LNINVOBJ$	0.611	0.795	0.766	3.114*	3.149**
	(0.975)	(0.708)	(0.379)	(1.834)	(2.152)
$\Delta LNPFOLIO$	1.378*	1.297	1.535	0.866	0.840
	(1.861)	(1.303)	(1.221)	(0.860)	(0.869)
$\Delta EXITFEE$	293.396	980.238	864.393	104.488	100.045
	(0.355)	(0.037)	(0.273)	(0.034)	(0.075)
Performance	Net	Net	Net	Gross	Gross
Investment styles	Yes	Yes	Yes	Yes	Yes
R^2	8.5%	26.9%	26.7%	9.5%	9.4%
N	590	590	590	590	590

Table 4.9
Resources for Private Information Production and Fund Family's *ACF*.

In Table 4.9, we examine the effect of the information environment of a fund family and its percentage of asset concentration in the active management segment (*ACF*). To this end, we use several different proxies of the amount of resources allocated by a fund family to information production: an indicator variable which is equal to 1 if the firm has a brokerage division under its control in the same physical location of the fund advisor managing the firm's mutual funds (*BKR_DIVISION*), and the number of active-only fund managers employed by the fund family across other mutual funds (*NUM_ACTMGRS*). We also use three additional resource-based proxies: the number of buy-side analysts (*NUM_BUYANALYSTS*); the number of registered broker-dealers (*NUM_BKR-DEALERS*) and the number of security traders (*NUM_TRADERS*) employed by the brokerage division of the fund family. The table documents the estimated coefficients of Fama & MacBeth (1973) cross sectional regressions with heteroskedasticity and autocorrelation consistent (HAC) standard errors with a lag of order 3 (we report t-statistics in parentheses). One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	BKR_DIVISION	NUM_ACTMGRS	NUM_BUYANALYSTS	NUM_BKR-DEALERS	NUM_TRADERS
	(i)	(ii)	(iii)	(iv)	(v)
ACF	0.583**	15.426***	21.554***	7.115***	8.486*
	(2.436)	(3.968)	(5.577)	(6.583)	(1.861)
Controls	Yes	Yes	Yes	Yes	Yes
N	8,315	8,315	538	8,315	540

Table 4.10
Relationship between Family Active Concentration and Fee-Setting Policies.

Table 4.10 presents the Fama & MacBeth (1973) estimates for the monthly regression of fund fees on selected fund and fund family characteristics over the period from 1993 to 2015. We use various proxies of fund fee-setting policies including: (i) funds' annual operating expense (*OPEX*); (ii) funds' marketing and distribution costs (*12B-1*); (iii) funds' annual management fees (*MGMTFEE*); (iv) funds' exit fees (*EXITFEE*), and (v) funds' front-end load (*FRONTLOAD*). The main independent variable of interest is the percentage asset-based concentration of the fund family in active mutual funds (*ACF*). Lagged control variables include: the logarithm of funds' total assets under management (*LFNDTNA*); the logarithm of funds' age (*LFNDAGE*); funds' portfolio turnover (*TURNR*); investors' net investment flow (*NFLOW*); the cumulative returns of the fund over the past 12 months (*PRET*); the logarithm of fund family's TNA (*LFAMTNA*); the logarithm of fund family's total number of investment objectives (*LNINVOBJ*); the logarithm of fund family's total number of portfolios (*LNPFOLIO*); funds' exit fee (*EXITFEE*); a dummy variable which equals 1 if more than 75% of fund family assets are issued to institutional share (*DUMMY_INST*). The table reports the estimated coefficients of Fama & MacBeth (1973) cross sectional regressions with heteroskedasticity and autocorrelation consistent (HAC) standard errors with a lag of order 3 (t-statistics are reported in parentheses). All regressions include dummy variables to control for differences in mutual fund investment styles. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	OPEX	12B-1	MGMTFEE	EXITFEE	FRONTLOAD
	(i)	(ii)	(iii)	(iv)	(v)
ACF	-0.014	-0.011*	-0.003	0.000	0.020
	(-1.377)	(-1.830)	(-0.404)	(0.164)	(0.903)
LFNDTNA	-0.070***	-0.048***	-0.022***	-0.000***	-0.000
	(-20.334)	(-20.510)	(-14.558)	(-3.294)	(-0.894)
LFNDAGE	0.063***	-0.005	0.068***	-0.000*	-0.000***
	(5.668)	(-0.989)	(9.142)	(-1.969)	(-3.565)
TURNR	0.066***	-0.027***	0.094***	-0.000	0.000
	(8.252)	(-5.868)	(18.754)	(-1.192)	(1.005)
NFLOW	-0.380***	-0.217***	-0.163***	0.004***	0.007***
	(-5.711)	(-3.176)	(-6.778)	(5.578)	(3.966)
PRET	0.186**	-0.223***	0.409***	0.003***	0.002***
	(2.366)	(-6.485)	(5.027)	(3.337)	(3.401)
LFAMTNA	-0.006	0.046***	-0.052***	-0.000***	-0.018**
	(-1.334)	(10.130)	(-23.061)	(-3.320)	(-2.293)
LNINVOBJ	0.158***	0.107***	0.052***	0.001***	-0.001***
	(14.863)	(12.858)	(6.594)	(4.003)	(-3.885)
LNPFOLIO	-0.095***	-0.086***	-0.009	-0.001***	-0.001
	(-12.689)	(-14.693)	(-1.395)	(-8.049)	(-0.755)
EXITFEE	-0.136	-4.474***	4.338***		
	(-0.116)	(-5.561)	(7.530)		
Investment styles	Yes	Yes	Yes	Yes	Yes
Std Error	HAC3	HAC3	HAC3	HAC3	HAC3
R^2	35.0%	33.6%	31.7%	5.7%	8.1%
N	162,133	162,133	162,133	162,133	162,133

Table 4.11
Fund Family Active Concentration, Outsourcing Decisions and Performance.

Table 4.11 presents the estimated coefficients of monthly regressions with time-fixed effect of mutual fund performance on selected fund and fund family characteristics over the period 1993 to 2015. The dependent variable is the fund gross performance estimated using any of the following factor models: (i) the CAPM model (*CAPM*); (ii) the Carhart (1997) four-factor model (*4-FACTOR*); and (iii) the four-factor model augmented with the excess returns of the MSCI (inclusive of Europe, Australia, and the Far East) and the Lehman US Aggregate Bond Index (*6-FACTOR*). To mitigate any look-ahead bias, we estimate fund portfolio risk-adjusted returns as a one-month abnormal return from the factor model, where the loadings on the various factors are estimated over the previous 36 months (with a minimum of 30 observations). In column (iv) we use the characteristic selectivity measure of stock-picking skills *CS*, defined in Daniel *et al.* (1997). In column (v) we consider Kacperczyk *et al.*'s (2008) return gap measure, *RETGAP*, computed as the difference between fund i's gross returns and the gross returns predicted based on its lagged holdings. To examine whether outsourcing affects the concentration-performance relationship, we interact *ACF* with a dummy variable which equals 1 when a fund is outsourced (*OUTSOURCING*). Other lagged control variables include: the logarithm of funds' total assets under management (*LFNDTNA*); the logarithm of funds' age (*LFNDAGE*); funds' portfolio turnover (*TURNR*); funds' annual operating expense (*OPEX*); investors' net investment flow (*NFLOW*); the cumulative returns of the fund over the past 12 months (*PRET*); the logarithm of fund family's TNA (*LFAMTNA*); the logarithm of fund family's total number of investment objectives (*LNINVOBJ*); the logarithm of fund family's total number of portfolios (*LNPFOLIO*); funds' exit fee (*EXITFEE*); a dummy variable which equals 1 if more than 75% of fund family assets are issued to institutional share (*DUMMY_INST*), and the residual from the first stage logit regression (*RESIDUAL_FIRST_STAGE*) of the 2SRI estimation (see Chen *et al.*, 2013). To be consistent with Chen *et al.* (2013), we estimate all models using time-series-cross-section regressions with time fixed effects, and standard errors clustered by family (t-statistics are documented in parentheses). All regressions include dummy variables for investment styles. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	CAPM	4-FACTOR	6-FACTOR	CS	RETGAP
	(i)	(ii)	(iii)	(iv)	(v)
ACF	0.233***	0.222***	0.221***	0.259***	0.336***
	(4.929)	(4.658)	(4.654)	(3.771)	(4.533])
*ACF*OUTSOURCING*	0.020	0.017	0.017	-0.015	-0.012
	(0.572)	(0.482)	(0.491)	(-0.136)	(-0.089)
OUTSOURCING	-0.075***	-0.076***	-0.074***	-0.082***	-0.075**
	(-2.670)	(-2.705)	(-2.646)	(-2.769)	(-2.501)
LFNDTNA	-0.068***	-0.069***	-0.068***	-0.067***	-0.126***
	(-5.892)	(-5.951)	(-5.892)	(-4.157)	(-3.409)
LFNDAGE	-0.089	-0.100*	-0.098*	-0.044	0.019
	(-1.642)	(-1.855)	(-1.803)	(-2.351)	(0.482)
TURNR	0.057***	0.054***	0.055***	0.033**	0.039**
	(3.231)	(3.049)	(3.096)	(2.248)	(2.261)
OPEX	-2.655	-2.739	-2.336	-1.685	1.083
	(-0.622)	(-0.630)	(-0.533)	(-0.523)	(0.475)
NFLOW	-0.273	-0.273	-0.274	-0.153	-0.106
	(-1.129)	(-1.122)	(-1.127)	(-1.330)	(-0.772)
PRET	0.459**	0.456**	0.460**	0.400**	0.645**
	(2.549)	(2.512)	(2.539)	(2.266)	(2.198)
LFAMTNA	0.002	0.002	-0.000	-0.002	-0.091***
	(0.074)	(0.077)	(-0.002)	(-0.010)	(-3.688)
LNINVOBJ	-0.187**	-0.187**	-0.189**	-0.188**	0.012
	(-2.381)	(-2.374)	(-2.389)	(-2.306)	(0.181)
LNPFOLIO	0.111**	0.112**	0.114**	0.118**	0.091**
	(2.224)	(2.240)	(2.278)	(2.283)	(2.304)
EXITFEE	2.480	2.575	2.505	2.367	1.907
	(1.062)	(1.090)	(1.057)	(1.658)	(1.476)
RESIDUAL_FIRST_STAGE	0.161***	0.092***	0.132***	0.191***	0.269***
	(3.728)	(3.187)	(3.708)	(3.658)	(3.965)
Investment styles	Yes	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes	Yes
Std Error	Family	Family	Family	Family	Family
R^2	34.1%	33.4%	34.5%	35.9%	35.7%
N	160,682	160,682	160,682	122,769	126,214

Table 4.12
Flow-related Liquidity Risk of Concentrated versus Diversified Fund Families Around September 2008.

Table 4.12 quantifies the extent of flow-related liquidity risk experienced by fund families with different asset concentration in active fund products in the periods surrounding the default of Lehman Brothers on September 2008. Panel A reports the yearly change in average style-adjusted net cash flows in the years before and after the flow-related liquidity shock of September 2008 for quintile portfolios of sorted family-level active concentration index, *ACF*. The changes in the average style-adjusted net cash flows, $\Delta NFLOW$, are computed as the difference between the post-September 2008 averages and the pre-September 2008 averages over the 12-, 24-, and 36-month windows before and after the September 2008 event. In Panel B, we illustrate the estimated loadings of the change in the flow-related liquidity risk proxy in the 12 months before and after September 2008 on fund family' degree of active concentration, *ACF*. The dependent variable is the flow-related liquidity risk of a fund family as measured by the change in the annual style-adjusted net cash flow averages computed in the 12 months after September 2008 (inclusive) and the 12 months before September 2008, $\Delta NFLOW$. The main independent variable of interest is the percentage active concentration, *ACF*. We also interact this variable with: (i) the variable *PCT_INST* which is computed as the percentage of fund family assets in institutional share classes as Schmidt *et al.* (2016) show that flow-related liquidity risk tend to concentrate mostly among these classes; and (ii) the degree of fund family's index deviations (*FAMDEV*) as discussed in Table 4.5 to better capture the degree of active concentration of the family. Other lagged fund family control variables, *Controls*, are those described in Table 4.3, and are untabulated for brevity. All independent variables are the averages of the variables in the year prior to September 2008 to account for any endogenous movement in observables due to unobserved shocks. Standard errors are adjusted for heteroskedasticity and clustered at the fund family level (H/Family), and are reported below the coefficients in parentheses. One, two and three asterisks indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A—Fund family's net cash flow changes across quintile portfolios of sorted *ACF*

		$\Delta NFLOW$	
	Mean ACF	[T-1 year; T+1 year]	[T-3 year; T+3 year]
Low ACF	39.60%	1.74%	-4.31%
Q2	75.91%	-0.71%	-3.31%
Mid ACF	86.21%	-0.58%	-6.34%
Q4	93.51%	-1.32%	-1.90%
High ACF	99.39%	-8.60%	-9.95%
Mid - Low		-2.32**	-2.03*
High - Mid		-8.02***	-3.618*
High - Low		-10.33***	-5.63*

Panel B—Fund family's net cash flow changes: a multivariate regression analysis

	$\Delta NFLOW$		
	(i)	(ii)	(iii)
ACF	-0.158***	-0.084**	-0.381*
	(-2.933)	(-2.316)	(-1.664)
*ACF * PCT_INST*		-0.285***	
		(-3.756)	
*ACF * FAMDEV*			-2.410***
			(-3.051)
*ACF * FAMDEV* PCT_INST*			-1.003***
			(-4.112)
Investment styles	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Std.Errors	H/Family	H/Family	H/Family
N	542	542	542

Chapter 5

Conclusion

5.1 Summary of Main Results

This thesis focuses on the mutual fund industry and investigates the interaction between mutual fund managers and fund investors in both the short-term money market mutual fund segment and the long-term equity fund segment. The three research papers in Chapters 2–4 explore the causes and consequences of mutual fund manager' risk-taking incentives across these two mutual fund groups.

Chapter 2, which is based on the research paper '*Out of Sight, Out of Mind: Information Insensitivity and Risk-taking of Prime Institutional Money Market Funds*' investigates the economic implications of the mark-to-market net asset value (NAV) pricing framework for prime institutional money market funds' (PIFs') risk choices. The new reform requires daily disclosure of PIFs' market-based NAVs, and forces PIFs' adoption of the floating NAV (FNAV) pricing framework. We show that the increasing information sensitivity of NAV pricing in the PIF segment improves the overall resiliency of the money market fund (MMF) industry by reducing the effect of information opacity on managerial risk-taking incentives, thus increasing investors' informational advantage.

Our findings show that in response to a more informationally sensitive NAV, PIFs have significantly improved their risk profile by shortening aggregate portfolio maturity, lowering gross yields, boosting daily and weekly portfolio liquidity, and increasing their holdings of safe assets in an attempt to relax investors' incentives to acquire information to reduce investors' adverse selection under the CNAV pricing regime. Additionally, this study investigates, for the first time, the role of mark-to-market pricing on PIFs' risk choices under a more informationally sensitive market and finds that the FNAV trading rule reduces market fragility by reducing the "first-mover advantage" among investors. This, in turn, enables fund managers to proportionally increase their risk exposure after the implementation date of the FNAV trading rule.

Chapter 3, which is based on the research paper '*Floating NAV Pricing under Single- versus Multi-strike Prime Institutional Money Market Funds*' explores, for the first time, the implications of the intraday FNAV strike system of PIFs for their risk-taking incentives. Since 14 October 2016, PIFs have adopted the FNAV trading rule, which reduces significantly the money-likeness feature of PIF products because investors are no longer able to redeem shares at a constant $1.00 on an hourly basis. To cater to investors with different liquidity needs, PIFs started to offer multi-strike fund products, which offer investors multiple redemption windows throughout the day. Undoubtedly, a multi-strike FNAV system provides institutional investors with more frequent access to cash during the day. However, it also brings new challenges to PIF managers as multiple NAV strike times could heighten their exposure to unanticipated asset–liability mismatches throughout the day.

Using a unique dataset on the indraday strike system of PIFs, we show that PIF investors expressed a clear preference for multiple redemption windows by allocating significantly more money to multi-strike funds than to single-strike funds. We find that multi-strike funds are more likely to have an investor clientele with higher liquidity demand thus suggesting a greater difficulty for funds to formulate accurate cash flow projections. The results show that, to limit their exposure to heightened flow-related liquidity risk, multi-strike funds have reduced their maturity risk, increased portfolio liquidity, reduced portfolio holdings of risky assets relative to safe assets and intensified their reach for yield. We also show that institutional investors are prepared to pay a premium for their more frequent access to intraday liquidity. Importantly, we confirm that the heterogeneity in prime funds' risk-taking behavior across multi- and single-strike funds is not explained by cross-sectional differences in investors' risk preferences.

Chapter 4, which is based on the research paper '*Jack of All Trades versus Specialists: Fund Family Specialization and Mutual Fund Performance*' explores the impact of specialization decisions by a fund family, as reflected by its asset-based concentration in the active management segment (ACF), on the performance of its equity mutual funds. Generally, a fund family's decision to specialize its product offering in the active management segment depends on many factors including its belief about the overall managerial ability to outperform the market, which is revealed by its fund product mix offered to investors. This study addresses, for the first time, whether the choice of operational scope of a fund family has implications for investors' wealth. This issue is important as investors often first identify a fund family and then choose from among the mutual funds offered by that family. Therefore, a fund family's choice of asset-based specialization in the active or passive management segments could affect investors' wealth across family funds, and their exposure to family-level liquidity risk.

The results of this study show that active funds of fund families with higher ACF enjoy superior performance and greater investor capital allocation. Importantly, funds of fund families with higher ACF exhibit greater reliance on private information production, a clear signal of managerial skill. These findings are not explained by heterogeneity in total ownership costs and outsourcing arrangements of the fund family. By exploiting a quasi-experiment involving fund families' sponsorship acquisition events, it is confirmed that fund performance deteriorates markedly when the acquiring fund family has lower ACF than the selling fund family. Last, it is shown that funds affiliated to fund families with higher ACF enjoy significant institutional advantages from better family-level allocation of resources to information production.

5.2 Contributions and Future Research

The results of the three research papers contribute to the asset management discipline by exploring the relation between fund managers' risk-taking behavior and investors' capital allocation decisions. This section summarizes the major contributions of each research paper, and discusses some directions for future research.

Chapter 2 assesses the economic implications for the 2014 SEC reform on PIFs' risk choices and thus the resulting fund performance. This research paper extends the literature on information sensitivity of debt-on-debt securities by investigating empirically the effect of a more informationally sensitive debt on PIFs' risk-taking incentives under normal market conditions. It contributes to this strand of the literature by showing for the first time the impact of greater investors informational advantage as a result of enhanced disclosure on deterring excessive risk-taking of MMFs. Our findings support the beneficial effect of the mark-to-market pricing by showing prime funds' weaker risk-taking incentives after the reform implementation.

Chapter 3 considers the post-reform period during which PIFs have adopted the FNAV pricing framework. This study contributes to the literature on risk-taking incentives of MMFs by exploring, for the first time, the role of intraday strike systems of PIFs in explaining the heterogeneity in PIFs' risk-taking behavior for those offering multiple redemption windows or a single redemption deadline to their investors. It is shown that multi-strike funds' weaker incentives to pursue risk are driven by their greater exposure to the unanticipated asset–liability mismatches during the multiple redemption windows throughout the day. Moreover, the results of this research paper contribute to the previous literature on mutual fund liquidity risk. Specifically, we investigate closely the relation between the flow-related liquidity risk of money funds and fund managers' risk choices without the confounding effect of fund performance. Our findings suggest that multi-strike funds react to the greater cash flow volatility of investors' demand by targeting lower aggregate portfolio maturity, greater percentages of liquid assets, and lower percentage holdings of risky assets.

We argue that the new reform has contributed to reducing investors' information production costs, and thus adverse selection among investors, by enhancing PIFs' disclosure requirements. Future research could further explore the changes in prime institutional investor clientele by investigating the level of investor sophistication pre- and post-reform. To examine the changes in prime funds' investor composition, investor-level data is required to distinguish retail investors from institutional investors, and to identify financial and nonfinancial institutions. One potential data source could be the Investment Company Institute. Unfortunately, we did not have access to this source of data to test directly the effect of changing investor sophistication on the relationship between information sensitivity and risk-taking incentives of PIF managers.

Future research could also investigate the implication of regulatory changes in the money market industry for funds' risk-taking incentives by focusing on the 2017 European MMF reform. European MMFs offer both variable NAV and constant NAV products. The European Securities and Markets Authority (ESMA) accepted the amended regulatory framework on 21 July 2017 to be implemented on 21 Jan 2019. The new regulation aims to improve the overall resilience of the European MMF industry by introducing stricter liquidity requirements, tightening portfolio-holdings requirement, and requiring fund managers to disclose various portfolio information on a weekly basis. It would thus be interesting to extend our study to non-US MMFs and explore the change in the risk-taking behavior of funds with variable versus constant NAV following the ESMA reform. Additionally, one could also quantify the impact of regulatory changes on the short-term financing of US and non-US banks and financial institutions, who rely heavily on MMFs as their short-term financing providers.

The results of Chapter 4 reveal the performance benefits enjoyed by mutual funds offered by fund families whose product offerings reflect greater specialization in the active management segment. The contribution of this research paper is threefold. This study contributes to the growing literature on the effect of a fund family's product diversity on investor wealth and capital allocation by highlighting the performance implications of fund families' product diversity across the unrelated segments of active and passive investing. In this light, the study contributes to the extant literature on the effect of side-by-side management of different fund products of a fund family on fund performance. Finally, by emphasizing the performance benefits of a fund family's decision to purse segment specialization, this study also contributes to the debate on the value of active management in the mutual fund industry. Our findings suggest that mutual fund investors would be better off purchasing active mutual funds across specialized fund families than concentrating their fund share purchases within a single specialized fund family.

Future research could further explore the implications of fund family specialization by investigating other mutual fund products, such as hybrid funds and fixed income funds. Our study restricts the analysis to the large sample of equity funds that fall into one of the traditional investment objective classifications. It would be interesting to explore further the impact of fund family specialization on fund performance and ascertain whether these results can be extended to other investment styles.

Appendix A

Abbreviation Definitions

Abbreviation	**Definition**
ABCP	asset-backed commercial papers
BNKOB	bank obligations
CAPM	Capital Asset Pricing Model
CNAV	constant net asset value
CP	commercial papers
DBNKOB	domestic bank obligations
FBNKOB	foreign bank obligations
FED	Federal Reserve
FNAV	floating net asset value
FOMC	Federal Open Market Committee
FRNS	floating-rate notes
HAC	heteroskedasticity and autocorrelation consistent
IAPD	Investment Adviser Public Disclosure
ICI	Investment Company Institute
IV	instrument variable
MFDB	Mutual Fund Database
MMF	money market fund
MSCI	Morgan Stanley Capital International
MSFND	multi-strike (money market) fund
NAV	net asset value
PIF	prime institutional (money market) fund
REPO	tri-party repurchase agreement
SEC	Securities and Exchange Commission
SSFND	single-strike (money market) fund
TD	non-negotiable time deposits
TNA	total net asset
US	United States
ZIRP	Zero Interest Rate Policy

Appendix B

Variable Definitions

Variable Name	Definition
$\alpha_{4-FACTOR}$	A fund's net performance estimated using the Carhart four-factor model.
12B-1	A fund's marketing and distribution costs.
4-FACTOR	A fund's net performance estimated using the Carhart four-factor model.
6-FACTOR	A fund's net performance estimated using the six-factor model.
ACF	One minus the percentage of a fund family's total assets invested in index mutual funds and ETF products.
ACTSHR	The active share measure (see Cremers & Petajisto, 2009).
ADVFEE	A fund's annual advisory fee computed as the difference between a fund's total operating expenses and 12b-1 fees.
BKR_DIVISION	A dummy variable, which equals 1 if the firm has a brokerage division under its control in the same physical location of the fund advisor, and 0 otherwise.
CAPM	A fund's net performance estimated using the CAPM model.
ChgLabel	A dummy variable for label changes.
Closure	A dummy variable for fund closure.

CS	The measure of stock picking skills (see Daniel *et al.*, 1997).
CUMUFLOW	The 30-day cumulative net cash flows.
D_Strike	A dummy variable, which equals 1 for multi-strike funds, and 0 otherwise.
DLA	The percentage of a fund's weekly liquid assets.
DTM	A security's remaining days to maturity.
DUMMY_INST	A dummy variable, which equals 1 if more than 75% of a fund family's assets are issued to institutional share, and 0 otherwise.
EXCWAL	A fund's *WAL* over that of the average fund in the government institutional MMF segment.
EXCWAM	A fund's *WAM* over that of the average fund in the government institutional MMF segment.
EXITFEE	A fund's redemption fees.
FAMDEV	The degree of volatility of excess returns of the average fund offered by the fund family.
FAMMKTS	The average percentage of fund families' market share.
FAMRPI	The reliance on public information (see Kacperczyk & Seru, 2007) of the average fund offered by the fund family.
FAMTNA	A fund family's total net assets.
FAMTURNR	The intensity of portfolio turnover of the average fund offered by the fund family.
FEERATIO	A fund's annual charged expense ratio.
FLOWVOL	The 30-day standard deviation of a fund's net cash flows.
FLOWVOL90	The 90-day standard deviation of a fund's net cash flows.
FNDAGE	The number of years since a fund's inception.
FNDTNA	A fund's total net assets.
FRONTLOAD	A fund's front-end load.
GRADSCHOOL	A dummy variable, which equals 1 if the the fund manager has a graduate diploma (MA, MBA, or PhD), and 0 otherwise.

GYIELD	Daily gross annualized yield as a percentage of fund's TNA.
HML	The difference between high and low book-to -market stocks.
HR	The difference between a fund's percentage holdings of risky assets (i.e., bank obligations) and safe assets (i.e., US treasury and agency securities and repurchase agreements).
INDUSTRYSIZE	The total industry size.
IVYLEAGUE	A dummy variable, which equals 1 if the fund manager has any degree from one of the Ivy League academic institutions, and 0 otherwise.
LFAMTNA	The logarithm of a fund family's TNA.
LFNDAGE	The logarithm of a fund's age since inception.
LFNDTNA	The logarithm of a fund's TNA.
LNINVOBJ	The logarithm of a fund family's total number of distinct investment objectives.
LNPFOLIO	The logarithm of a fund family's total number of portfolios.
MGMTEAM	A dummy variable, which equals 1 if a fund is managed by a team of fund managers, and 0 otherwise.
MGMTFEE	A fund's annual management fees.
MOM	The difference between stocks with high and low past returns.
N_Strike	The number of strike times offered by a fund.
NFLOW	Investors' net investment flows as a percentage of a fund's TNA.
NINVOBJ	The number of distinct investment objectives of a fund family.
NPFOLIO	The number of mutual fund portfolios of a fund family.
NUM_ACTMGRS	The number of active-only fund managers employed by the fund family across other mutual funds.
NUM_BKR-DEALERS	The number of registered broker-dealers.

NUM_BUYANALYSTS	The number of buy-side analysts.
NUM_TRADERS	The number of security traders.
NUMFAM	The total number of fund families.
NYIELD	Daily net annualized yield as a percentage of a fund's TNA.
OAR	A fund's objective-adjusted returns.
OPEX	A fund's annual operating expense.
OUTSOURCING	A dummy variable, which equals 1 if a fund is outsourced, and 0 otherwise.
PCT_INST	The percentage of a fund family's assets in institutional share classes.
POST2014	A dummy variable, which equals 1 for the period from 23 July 2014 to 31 March 2018, and 0 otherwise.
POST2016	A dummy variable, which equals 1 for the period from 14 October 2016 to 31 March 2018, and 0 otherwise.
PRET	The cumulative returns of a fund over the past 12 months.
RESIDUAL_FIRST_STAGE	The residual from the first stage logit regression.
RETGAP	The difference between a fund's gross returns and the gross returns predicted based on its lagged holdings (see Kacperczyk *et al.*, 2008).
RISKY	The percentage holdings of risky assets including bank obligations, asset-backed commercial papers, and financial and nonfinancial commercial papers.
RPI	A fund advisor's degree of reliance on public information (see Kacperczyk & Seru, 2007).
RSI	A fund advisor's degree of reliance on private information (see Kacperczyk & Seru, 2007).
R-SQUARED	A fund's R^2 in (see Amihud & Goyenko, 2013).
SINGLEFND	A dummy variable for single-fund families.
SMB	The difference between small and large capitalization stocks.

Spread	The difference between a fund's yield and the FED policy rate.
SpreadGov	The difference between a fund's yield and the average yield of government institutional funds.
SpreadHR	The difference between a fund's yield and the average yield of a portfolio of funds with matched portfolio *HR*.
SpreadWAM	The difference between a fund's yield and the average yield of a portfolio of funds with matched portfolio *WAM*.
TOP5FAMMKTS	The total market share of the top 5 fund families.
TRKERR	A fund's tracking error, computed as the standard deviation of the residual of the four-factor model.
TURNR	The average portfolio turnover ratio.
WAL	Weighted average maturity of a fund's portfolio.
WAM	Weighted average life of a fund's portfolio.
WLA	The percentage of a fund's daily liquid assets.

Appendix C

Additional Regression Results

In this section, we include additional multivariate regression results for Chapters 2 and 4. Table C.1 repeats the analysis of Table 2.3 of Chapter 2 by replacing *POST2016* with *POST2016Apr*, which is an indicator variable identifying the period from 14 April 2016, the compliance disclosure date. All prime institutional funds (PIFs) have to disclose their mark-to-market net asset value (NAV) no later than 14 April 2016. Unsurprisingly, we observe that the estimated coefficients of both *POST2014* and *POST2016APR* are significantly negative, indicating that PIFs respond to the enhanced disclosure by lowering their aggregate portfolio maturity risk.

Table C.2 repeats the analysis of Table 4.3 of Chapter 4 by replacing gross-of-fee performance with net-of-fee performance as the dependent variable of cross-sectional regressions. The results are qualitatively similar to those illustrated in Table 4.3. The estimated coefficient (0.036) in column (i) of Table C.2 when the dependent variable is the after-fee CAPM alpha, suggests that a one standard deviation (19%) increase in *ACF* would translate into an 8-basis-point (0.19*0.036*12) increase in the annual performance of the average equity mutual fund. Although the economic magnitude is slightly lower than that obtained using before-fee returns, the evidence confirms that investors can benefit from investing in active funds of more specialized fund families even when advisory fees are taken into account.

Table C.1
Risk-taking Incentives of Prime Money Market Funds around the Disclosure Compliance Date.

Table C.1 presents the estimated coefficients of multivariate regressions of PIFs' risk-taking around the time of the announcement of the new reform as well as the time of the compliance disclosure date. The dependent variables include funds' weighted average maturity (*WAM*), funds' weighted average life (*WAL*), and excess *WAM* (*EXCWAM*) and excess *WAL* (*EXCWAL*) over the average fund in the government institutional segment. *POST2014* is a dummy variable, which equals 1 for the period from 23 July 2014 to 31 March 2018, and 0 otherwise. *POST2016APR* is an indicator variable, which identifies the period from 14 April 2016. Lagged control variables include the logarithm of funds' total assets under management (*LFNDTNA*); the level of annual expense ratio charged by funds (*FEERATIO*); the logarithm of funds' number of years since inception (*LFNDAGE*); the logarithm of fund sponsors' total assets under management (*LFAMTNA*); the percentage change in fund assets accounted for capital appreciation (*NFLOW*); and funds' 30-day standard deviation of fund net cash flows (*FLOWVOL*). We account for any time-invariant fund sponsor characteristics by introducing a sponsor-fixed effect. We also apply a time-fixed effect to control for any unobservable economic trends. We cluster standard errors at the day dimension to account for any cross-sectional dependence of residuals. t-statistics are reported in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(i) WAM	(ii) WAL	(iii) WAM	(iv) WAL	(v) EXCWAM	(vi) EXCWAL
POST2014	-15.318***	-1.924***	-13.960***	-21.450***	-9.171***	-12.970***
	(-438.946)	(-19.438)	(-389.061)	(-433.275)	(-262.819)	(-131.037)
POST2016APR	-20.610***	-4.176***	-6.808***	10.723***	-18.083***	-12.686***
	(-381.116)	(-84.362)	(-222.617)	(213.786)	(-334.374)	(-256.304)
LFNDTNA	0.440***	0.726***	0.469***	0.712***	0.440***	0.726***
	(45.888)	(38.170)	(41.854)	(35.296)	(45.888)	(38.170)
FEERATIO	11.981***	22.262***	11.636***	21.590***	11.981***	22.262***
	(31.022)	(29.737)	(30.574)	(29.267)	(31.022)	(29.737)
LFNDAGE	0.528***	1.152***	0.577***	1.271***	0.528***	1.152***
	(22.320)	(20.200)	(26.449)	(21.621)	(22.320)	(20.200)
LFAMTNA	-0.275***	-0.196***	-0.253***	-0.161**	-0.275***	-0.196***
	(-6.277)	(-2.585)	(-5.820)	(-2.130)	(-6.277)	(-2.585)
NFLOW	0.003***	0.000	0.003***	0.000	0.003***	0.000
	(8.382)	(1.404)	(8.368)	(1.180)	(8.382)	(1.404)
FLOWVOL			-0.001***	-0.000		
			(-13.827)	(-0.405)		
Sponsor FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.645	0.613	0.644	0.612	0.565	0.799
N	272,617	257,450	271,414	256,351	272,617	257,450

Table C.2
Relationship between Family Active Concentration and Net Performance.

Table C.2 presents the Fama & MacBeth (1973) estimates of monthly regressions of fund after-fee performance on selected fund and fund family characteristics over the period 1993 to 2015. The dependent variable is the funds' net performance estimated using any of the following factor models: (a) the CAPM model (*CAPM*), in column (i); (b) the Carhart (1997) four-factor model (*4-FACTOR*), in column (ii); and (c) the four-factor model augmented with the excess returns of the MSCI (inclusive of Europe, Australia, and the Far East) and the Lehman US Aggregate Bond Index (*6-FACTOR*), in column (iii). The main independent variable of interest is the degree of asset concentration (in percentage) of the fund family business in active fund products (*ACF*). Lagged control variables include: the logarithm of funds' total assets under management (*LFNDTNA*); the logarithm of funds' age (*LFNDAGE*); funds' portfolio turnover (*TURNR*); funds' annual operating expense (*OPEX*); investors' net investment flow (*NFLOW*); the cumulative returns of the fund over the past 12 months (*PRET*); the logarithm of fund family's TNA (*LFAMTNA*); the logarithm of fund family's total number of investment objectives (*LNINVOBJ*); the logarithm of fund family's total number of portfolios (*LNPFOLIO*); funds' exit fee (*EXITFEE*); and a dummy variable which equals 1 if more than 75% of fund family assets are issued to institutional share (*DUMMY_INST*). The table reports estimated coefficients of Fama & MacBeth (1973) cross sectional regressions with heteroskedasticity and autocorrelation consistent (HAC) standard errors with a lag of order 3 (t-statistics are reported in parentheses). All regressions include dummy variables for fund investment objectives. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	CAPM	4-FACTOR	6-FACTOR
	(i)	(ii)	(iii)
ACF	0.036***	0.031**	0.039***
	(2.287)	(2.258)	(2.266)
LFNDTNA	-0.017***	-0.019***	-0.019***
	(-2.693)	(-3.362)	(-3.399)
LFNDAGE	0.017	0.017	0.017
	(1.069)	(1.073)	(1.080)
TURNR	0.033	0.030	0.032
	(1.046)	(0.981)	(1.019)
OPEX	-0.495	-0.725	-0.521
	(-0.251)	(-0.372)	(-0.268)
NFLOW	0.015	0.017	0.025
	(0.061)	(0.076)	(0.110)
PRET	2.272	2.336	2.321
	(0.726)	(0.779)	(0.773)
LFAMTNA	0.059***	0.059***	0.058***
	(6.408)	(6.304)	(6.202)
LNINVOBJ	-0.119***	-0.120***	-0.119***
	(-2.417)	(-2.403)	(-2.392)
LNPFOLIO	0.002	0.003	0.004
	(0.057)	(0.076)	(0.101)
EXITFEE	-1.424	-1.143	-1.968
	(-0.233)	(-0.554)	(-0.563)
DUMMY_INST	0.003	0.002	0.004
	(0.175)	(0.097)	(0.239)
R^2	13.6%	14.7%	16.6%
N	175,411	175,411	175,411

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