Federal Reserve Bank of New York
Staff Reports

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Staff Report No. 753
December 2015

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JEL classification: G00, G20, G23

Abstract

Do asset managers reach for yield because of competitive pressures in a low-rate environment? I propose a tournament model of money market funds (MMFs) to study this issue. When funds care about relative performance, an increase in the risk premium leads funds with lower default costs to increase risk-taking, while funds with higher default costs decrease risk-taking. Without changes in the premium, lower risk-free rates reduce the risk-taking of all funds. I show that these predictions are consistent with MMF risk-taking during the 2002-08 period and that rank-based performance is indeed a key determinant of money flows to MMFs.

Key words: reach for yield, money market funds

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Do money market funds "reach for yield" because of competitive pressure when risk-free rates decrease? Are there differences in the cross-section? What is the proper notion of competitive pressure for money market funds? To answer these questions, I propose a tournament model of money market funds and test its predictions on the period 2002–2008.

"Reach for yield" refers to the tendency to buy riskier assets in order to achieve higher returns. Recently, there has been much debate about asset managers reaching for yield in a low risk-free rate environment, especially in competitive industries. Asset managers are typically compensated with asset-based fees, and it has been widely observed that investors positively respond to fund performance. This induces asset managers to compete among each other over relative performance to attract money flows. The concern is that lower returns on safe assets might exacerbate this risk-taking incentive and lead asset managers to delve into riskier assets.[1] US prime money market funds (MMFs), in particular, are seen as a leading example of asset managers reaching for yield because of competitive forces.[2] Both regulators and academics have lately paid close attention to prime MMFs because of their crucial role in the recent financial crisis. However, although the possible reach for yield of MMFs is central to the agenda of regulators and academics, there is a relative lack of theoretical and empirical literature on the topic.

The two economic forces at work in the MMF industry are: *fund competition over performance* and *risk of "breaking the buck."* To capture these features, I model the industry as a static fund tournament with a continuum of risk-neutral funds that have heterogeneous default costs. The cost of default in the model represents the cost of "breaking the buck" in the real world. The heterogeneity of default costs captures the real-world heterogeneity of reputational damages to fund sponsors in case their funds default. These damages include outflows from other funds in the same family and losses in the sponsor's franchise value.[3] In terms of methodological contribution, to the best of my knowledge, this is the first paper that solves a tournament model with a continuum of players in a fully analytic way without first-order approximations.

First, I show that the tournament has a unique Nash equilibrium, fund risk-taking strictly decreases with the cost of default, and the equilibrium default probability is strictly positive for (almost) all funds. Funds trade off expected costs of default for the expected gains of outperforming competitors by taking on more risk. The fund with the highest default cost anticipates that in equilibrium, it will have the lowest expected rank of performance and optimally chooses to keep its default probability at zero regardless of other funds' actions. Funds with slightly lower default costs anticipate this and keep their default probability slightly above zero to outperform the highest-default-cost fund in expectation. The same reasoning applies to all other funds in descending order of default costs. That is, in equilibrium, funds with lower default costs face higher competitive pressure because they have to outperform a larger fraction of competitors and

[1] See FSOC (2013), OFR (2013), Bernanke (2013), Haldane (2014), and Yellen (2014).

[2] Stein (2013): *"[...] A leading example here comes from the money market fund sector, where even small increases in a money fund's yield relative to its competitors can attract large inflows of new assets under management. [...]"*

[3] This notion of sponsor's reputation concern was introduced by Kacperczyk and Schnabl (2013).

hence take on more risk. I show that the fund-specific equilibrium competitive pressure is uniquely determined by the distribution of default costs in the industry and independent of asset returns. Importantly, competition causes the equilibrium default probability to be positive for (almost) all funds regardless of the scale of default costs in the industry. This result comes from the strategic nature of the tournament and would not hold if funds' payoff depended on absolute performance.

The equilibrium default probability depends on asset returns only via a tournament version of the standard risk premium, which is exogenously given. This tournament risk premium is the risk-taking incentive of competition: it measures the marginal gain in expected performance rank from investing in the risky asset. An increase of the risk premium leads all funds to increase their equilibrium default probability, but in terms of the amount of risky investment, it generates a bifurcation in the fund population. Consider an increase in the riskiness of the risky assets that causes the premium to rise. Funds with higher default costs face lower competitive pressure, are less attracted by the increase in the premium, and will increase their default probability less. If the increase in risk is sufficiently large, they will be forced to cut their risky investment to keep the default probability sufficiently close to zero. On the other hand, funds with lower default costs face a higher competitive pressure, are more attracted by the increase in the premium, and will increase their default probability more. If they face sufficiently high competition, they will increase their risky investment despite the increase in risk. This bifurcation comes from the heterogeneity of competitive pressure in equilibrium.

Importantly, the equilibrium default probability does not depend explicitly on the level of the risk-free rate. This is because, absent default, funds only care about relative performance, and if they default, they pay a fixed idiosyncratic default cost. The equilibrium risky investment, however, does depend on the level of the risk-free rate because the share of safe assets in a fund's portfolio works as a buffer against default risk. If the return on the safe asset decreases, funds are forced to cut their risky investment to keep the same default probability. That is, holding the premium constant, a decrease in the risk-free rate decreases the risky investment of all funds. This anti-reach-for-yield behavior is stronger for funds with higher default costs, which implies that the cross-sectional differential in risky investment increases when the risk-free rate decreases.

These results show that to understand the risk-taking of MMFs, it is critical to distinguish the role of the level of risk-free rates from the role of risk premia. Risk premia trigger risk-taking but affect funds with low and high default costs in opposite ways. Low risk-free rates increase the buffer of safe assets necessary to maintain the equilibrium default probability and therefore reduce risky investment for all funds. Both effects are peculiar to MMFs and come from their distinctive feature of a stable net asset value and consequent risk of "breaking the buck."

In my empirical analysis, I show that these predictions are consistent with the risk-taking of MMFs from January 2002 to August 2008. I choose this time window because it includes *both* a significant surge in the risk premia available to MMFs (August 2007–August 2008) *and* a prolonged period of low Treasury rates (January 2003–July 2004); at the same time, it does not include the

run on MMFs of September 2008, the consequent government intervention, and the ensuing long lasting debate on new regulation that might have altered the standard risk-taking incentives of MMFs. Importantly, the concern of a possible "reach for yield" of financial intermediaries in a low interest rate environment, and particularly MMFs, emerged for the first time precisely in the 2003–2004 period (FDIC, 2004; Rajan, 2006). To map the model to the data, I identify the fund's cost of default with the sponsor's reputation concern introduced by Kacperczyk and Schnabl (2013) and measured as the share of non-MMF business in the sponsor's total mutual fund business.

First, I show that the rank of fund performance, and not the raw performance, determines money flows to MMFs, confirming the importance of relative performance competition in the industry and justifying the choice of a tournament model. Second, I provide evidence supporting the model's predictions on the level of risky investment in the time series. Figure 1 shows that from August 2007 to August 2008, when the premia available to MMFs increased significantly, funds with higher default costs (i.e., higher reputation concerns) decreased their net risky investment, while funds with lower default costs increased it, as predicted by the model. This observation is confirmed by

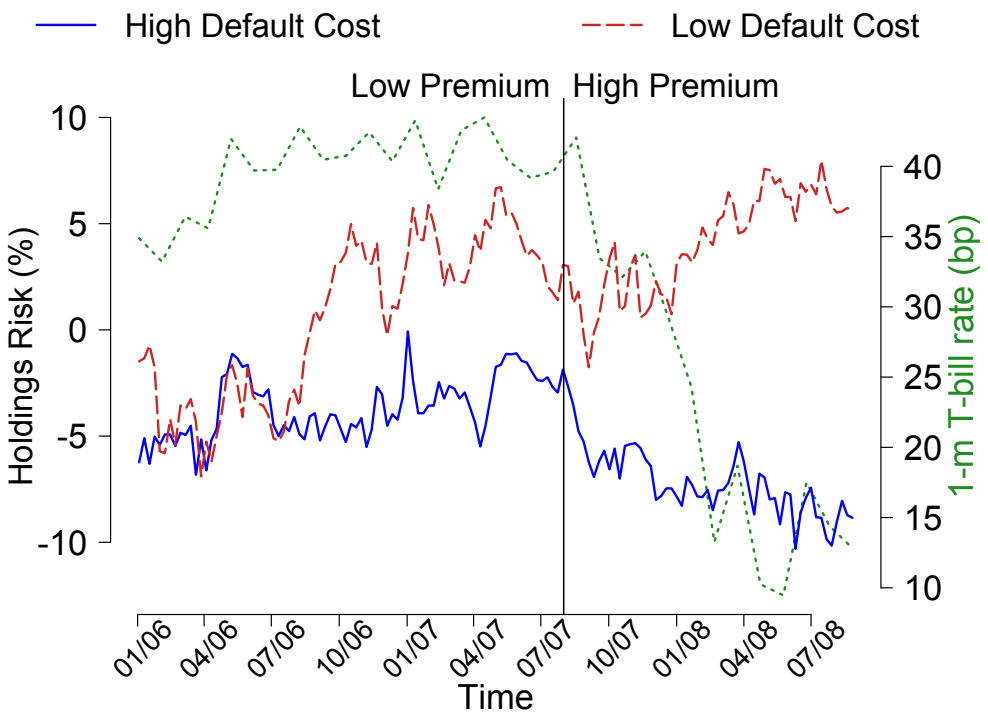


Figure 1: MMF risk-taking in the time series: high- vs. low-default-cost funds. The solid blue (dashed red) line is the average percentage of risky assets net of the safe assets in the portfolio of funds whose sponsor's reputation concern is continuously above (below) the industry median throughout January 2006–August 2008. The vertical black line separates the sample in two sub-periods: one in which the risk premia available to MMFs are relatively low (before August 2007) and one in which the risk premia available to MMFs are relatively high (after August 2007). The dotted green line is the monthly return on 1-month T-bills. The scale for the average net holdings is on the left y-axis. The scale for the T-bill rate is on the right y-axis. See Section 6 for details.

the results in Table 4, in which I disentangle the effect of risk-free rates from that of risk premia over the 2002–2008 period.[4] After an increase of 1% in the premium, there is a clear bifurcation in MMF risk-taking: funds with default costs continuously above the industry median decrease the share of risky assets net of safe assets in their portfolios by 3.8 percentage points, while funds with default costs continuously below the median increase it by 3.1 percentage points. On the other hand, after a decrease of 1% in the 1-month T-bill rate, all funds decrease their net risky investment by an amount between 21 and 26 percentage points. Interestingly, I find that when risk-free rates decrease, the shift to safer asset classes predicted by the model is compensated by a lengthening of portfolio maturity, which is stronger for funds with lower default costs.

Finally, I test the model's predictions on the cross-sectional risk-taking differential, for which identification of the effects of risk-free rates and risk premia is easier than for the level of risky investment in the time series. I fully exploit all cross-sectional variation in sponsor's reputation concerns and find that as predicted by the model, the cross-sectional differential increases when either risk premia go up or risk-free rates go down. An increase of 1% in the premium increases the difference in net risky investment between funds in the lowest and highest percentile of default costs by 6.5 percentage points. A decrease of 1% in the 1-month T-bill rate increases the same difference by 49.0 percentage points. These results are statistically significant at the 5% level and economically important, considering that over the 2002–2008 period the standard deviation of the risk premium is 0.45%, that of the risk-free rate is 0.12%, and the overall standard deviation of MMF net risky investment is 25%. Similar results are obtained when the risk-taking differential is measured in terms of portfolio maturity or spread.

The reminder of the paper is organized as follows. The next section reviews the literature. Section 1 describes prime MMFs and their institutional setting. Section 2 introduces the model. Section 3 characterizes and discusses the equilibrium. Sections 4 and 5 present comparative statics with respect to the distribution of asset returns and the distribution of default costs in the industry. Section 6 presents the empirical analysis and tests the model's predictions. Section 7 concludes. Appendix A analyzes in detail the risk-taking opportunities of MMFs in terms of available asset classes. The Internet Appendix (IA) contains proofs, data description, summary statistics, and robustness checks.

Related literature

This paper belongs to the recent growing literature on the risk-taking and systemic importance of MMFs.[5] The most closely related paper is Kacperczyk and Schnabl (2013), hereafter simply KS. KS empirically observe that in the period August 2007–August 2008, funds whose sponsors have lower reputation concerns took on more risk than funds whose sponsors have higher reputation

[4] My main proxy for the risk premium is an index of spreads of risky securities available to MMFs, while the risk-free rate is proxied with the 1-month T-bill rate. See Section 6 for details.

[5] E.g., Baba *et al.* (2009), McCabe (2010), Squam Lake Group (2011), Hanson *et al.* (2014), Chernenko and Sunderam (2014), Strahan and Tanyeri (2015), Schmidt *et al.* (2015).

concerns. This paper extends their work in that: (1) I propose a new model of MMFs that not only formalizes the observations of KS but also provides novel predictions on MMF risk-taking in both the cross-section and the time series; (2) I disentangle the effect of risk-free rates from that of risk premia; (3) I run my empirical analysis on a larger sample that goes back to 2002; (4) I show that the rank of performance is the true determinant of money flows to MMFs.

The only other papers studying the reach for yield of MMFs are Chodorow-Reich (2014), and Di Maggio and Kacperczyk (2015). Chodorow-Reich (2014) looks at the cross-section of MMFs in terms of administrative costs. Di Maggio and Kacperczyk (2015) look at the cross-section of MMFs in terms of affiliation to financial conglomerates.[6] Both papers are empirical and specifically focus on the effects of the unconventional monetary policy (i.e., the zero lower bound) introduced in December 2008. Chodorow-Reich (2014) finds that MMFs with higher administrative costs did reach for higher returns in 2009–11 but not thereafter. Di Maggio and Kacperczyk (2015) find that in periods of extremely low Fed funds rates, independent MMFs reached for higher returns than MMFs associated with conglomerates. My paper, which considers a different form of cross-sectional heterogeneity, adds to these works by: providing a model that explains how competition and risk-free rates affect MMFs' reach for yield, disentangling the direct effect of monetary policy from that of risk premia, and analyzing a sample with a prolonged period of low risk-free rates but without runs and government interventions.

Parlatore (2015) is the only other paper that I am aware of that presents a model of MMFs. Her model studies the effects of the new regulation put forward by the Securities and Exchange Commission (SEC), i.e., the transition from a stable NAV (net asset value) to a floating NAV. This paper contributes to that debate by showing that the stable NAV, creating a risk of default and the consequent need for a buffer of safe assets, generates a channel of monetary policy that reduces risky investment when risk-free rates decrease. On a broader theoretical level, this paper belongs to the literature on fund tournaments. Most of that literature focused on the relative risk-taking of interim winners and losers in a dynamic context (Goriaev *et al.*, 2003; Basak and Makarov, 2012, 2014). In this paper, in contrast, heterogeneity comes from the cost of default, which is an intrinsic property of the funds. Under a technical point of view, most theoretical papers on fund tournaments consider tournaments with only two players (winner and loser). Basak and Makarov (2012) solve a tournament with a continuum of funds assuming that a fund's payoff only depends on its performance relative to the population average. The methodological contribution of this paper is to develop a technique to solve tournaments with a continuum of players without resorting to such approximations.

On a broader level, this paper belongs to the literature on the transmission of monetary policy to financial intermediaries (Borio and Zhu, 2012). Most of that literature focuses on banks (Adrian and Shin, 2009; Landier *et al.*, 2015). This paper contributes by studying how the level of risk-free

[6] This is also a form of sponsor's reputation concerns but is significantly different from the one I use in my empirical analysis. See Section 6 for details.

rates affects the risk-taking of important non-bank financial institutions such as prime MMFs.

1 Prime Money Market Funds: Institutional Features

US prime MMFs are open-ended mutual funds that invest in money market instruments. Prime MMFs are pivotal players in the financial markets. As of the end of 2013, they had roughly $1.5 trillion in assets under management and held approximately 40% of the global outstanding volume of commercial papers (ICI, 2013). In particular, they are a critical source of short-term financing for financial institutions. As of May 2012, they provided roughly 35% of such funding and 73% of their assets consisted of debt instruments issued by large global banks (Hanson *et al.*, 2014).

Similarly to other mutual funds, MMFs are paid fees as a fixed percentage of their assets under management and are therefore subject to the tournament-like incentives generated by a positive flow-performance relation. On the other hand, contrary to regular mutual funds, MMFs aim to keep the net asset value (NAV) of their assets at $1 per share. They do so by valuing assets at amortized cost and providing daily dividends as securities progress toward their maturity date. Since their deposits are not insured by the government and are daily redeemable, MMFs are subject to the risk of runs. If a fund "breaks the buck," i.e. its NAV drops below $1, it will likely suffer a run, as happened on September 16, 2008, when Reserve Primary Fund, the oldest MMF, broke the buck because its shares fell to 97 cents after writing off debt issued by Lehman Brothers.

MMFs are regulated under Rule 2a-7 of the Investment Company Act of 1940. This regulation restricts fund holdings to short-term, high-quality debt securities. For example, it limits commercial paper holdings to those that carry either the highest or second-highest rating from at least two of the nationally recognized credit rating agencies. During the period January 2002–August 2008, MMFs were not permitted to hold more than 5% of investments in second tier (A2-P2) paper or to hold more than a 5% exposure to any single issuer (other than the government and agencies). Also, weighted average maturity of the portfolio was capped to 90 days. In 2010, after the turmoil generated by the collapse of Reserve Primary Fund, the SEC adopted amendments to Rule 2a-7, requiring funds to invest in even higher-quality assets of shorter maturities. E.g., the weighted average maturity is now capped to 60 days (SEC Release No. IC-29132).

On July 23, 2014, the SEC approved a new set of rules for MMFs (SEC Release No. IC-31166). The main pillar of these rules is that institutional prime MMFs will have to sell and redeem shares based on the current market-based value of the securities in their underlying portfolios. That is, they will have to move from a stable NAV to a floating NAV. The goal is to eliminate the risk of runs when the NAV falls below $1. This new regulation, which will take effect on October 2016, has encountered the strong opposition of the industry.[7]

[7] ICI, "A Bad Idea: Forcing Money Market Funds to Float Their NAVs" (January 2013).

2 A Model of Money Market Funds

The model is a static fund tournament with a continuum of risk neutral funds of measure 1. Funds are indexed by $c \in [\underline{c}, \overline{c}] \subseteq \mathbb{R}_+$, where c represents the idiosyncratic cost of default defined below. c is distributed in the population according to a continuously differentiable distribution function F_c, with positive density f_C.

Each fund is endowed with the same amount of initial deposits, $D > 0$. At the end of the tournament, deposits pay a gross interest rate equal to 1 to some outside investor. Funds can invest in two assets: a risk-free asset with deterministic gross return $R_f > 1$, and a risky asset with random gross return R distributed on $[\underline{R}, \overline{R}] \subset \mathbb{R}_+$ according to a continuously differentiable distribution function F_R, with positive density f_R.

ASSUMPTION 1. $\underline{R} < 1$ *and* $median(R) > R_f$.

As discussed below, Assumption 1 provides the proper notion of risk premium in a tournament context. Funds can neither short-sell nor borrow.

Let $x_c \in [0, D]$ be the risky investment of fund c. The ex post profit of fund c's portfolio is

$$\pi(x_c) = (R - R_f)x_c + (R_f - 1)D$$

Hereafter, when it causes no confusion, $\pi(x_c)$ will be simply denoted as π_c and will be referred to as fund c's *performance*. Fund c is said to default, or "*break the buck*," if $\pi_c < 0$. In that case, fund c pays a fixed cost equal to its type.

If a fund does not default, its payoff is proportional to its assets under management (AUM) at the end of the tournament. Conditional on no default, fund c's final AUM are

$$AUM(c) = (Rk(\pi_c) + a)\, D,$$

where $Rk(\pi_c)$ is the rank of fund c's performance at the end of the tournament, and a is the fraction of money flows that does not depend on relative performance. $Rk(\pi_c)$ represents a positive flow-performance relation. a can be regarded as the effect of advertising or the overall attractiveness of the industry. For simplicity, a is assumed to be the same for all funds and positive.

Given a profile of ex post performance $\pi : [\underline{c}, \overline{c}] \to \mathbb{R}$, the rank of a performance equal to y is

$$Rk(y) := \int_{\{c\,:\,\pi_c < y\}} \mathrm{d}F_c(c) \tag{1}$$

That is, the rank of a fund's performance is equal to the measure of funds with worse performance. $Rk(\pi_c) \in [0, 1]$ for all c, $Rk(\pi_c) = 1$ if c has the (strictly) highest performance, and $Rk(\pi_c) = 0$ if c

has the lowest performance.[8] Then, the ex post payoff of fund c is

$$\begin{cases} \gamma\,(Rk(\pi_c)+a)\,D & \text{if } \ c \ \text{ does not default} \\ -c & \text{if } \ c \,\text{defaults} \end{cases}$$

where $\gamma \in (0,1)$ represents the management fee paid by the outside investors. The combination of asset-based fee and positive flow-performance relation generates the fund tournament.

Under a strategy profile $x : [\underline{c}, \overline{c}] \to [0, D]$, the expected payoff of fund c is

$$v_c(x_c, x_{-c}) = \underbrace{\gamma\, D\, \mathbb{E}_R[Rk(\pi_c)+a|\pi_c \geq 0]\mathbb{P}_R(\pi_c \geq 0)}_{\text{expected tournament reward}} - \underbrace{c\,\mathbb{P}_R(\pi_c < 0)}_{\text{expected cost of default}} \tag{2}$$

where x_{-c} is the risky investment of all funds except c, and $\mathbb{E}_R[\cdot]$ and $\mathbb{P}_R(\cdot)$ are the expected value and probability measure over the risky return R, respectively.

Finally, all information above is common knowledge.

Discussion of model's assumptions

The interest rate on deposits equal to 1 represents the stable NAV of \$1 in the MMF industry. The cost of default c represents sponsor's costs when the NAV of its MMF falls below \$1. These costs include reputational costs, as well as negative spillovers to other parts of sponsor's business.

The safe asset can be regarded as a Treasury bill, while the risky asset can be regarded as a bank obligation, or some other risky fixed-income security. Under Assumption 1, negative realizations of the risky return can trigger a default if the fund is too exposed to the risky asset. The premium on the risky asset is in terms of its median because in a tournament context, fund payoffs depend only on relative performance. The ex post rank of performance is equal to the ex ante rank of risky investment when the realized risky return is above the risk free-rate, while it is equal to the reverse ex ante rank of risky investment when the realized risky return is below the risk free-rate. Hence, there is a tournament risk-taking incentive if and only if the risky return is more likely to be above the risk-free rate than below it, i.e., $median(R) > R_f$.

The assumption that a fund's payoff is proportional to its AUM is consistent with the fee structure typically used in the MMF industry (ICI, 2013). The assumption that a fund's AUM at the end of the tournament depend on the fund's net return only via the flow-performance relation is consistent with the common practice in the MMF industry of redistributing dividends to keep the NAV fixed at \$1. The assumption that short-selling and borrowing are not allowed is also consistent with the regulation of MMFs.

The assumption that fund performance is a major determinant of fund flows is supported by

[8] Under this definition of rank, the aggregate end-of-the-game AUM coming from the tournament are equal to half of the initial aggregate deposits. Since the model is static, this plays no role, and for notational simplicity, I omit the normalization factor 2 in my definition.

a vast empirical literature (Chevalier and Ellison, 1997). In Section 6.2, I show empirically that the rank of performance, and not the raw performance, is the main determinant of money flows to MMFs, which supports the choice of a tournament model.

Contrary to the majority of the positive theoretical literature on fund tournaments (Basak and Makarov, 2012), the above model does not assume a convex flow-performance relation. Although there is some evidence that the flow-performance relation for MMFs is convex (Christoffersen and Musto, 2002), that risk-taking channel is shut off to focus on the incentives generated by the tournament nature of fund competition alone.[9] However, the qualitative predictions of the model hold under any payoff function (convex or concave) that increases with the performance rank.

In the above model, the flow-performance relation is exogenously given. In mapping the model to the data, this amounts to assume that investors do not take into account funds' costs of default when making their investment decisions. That is, investors do not risk-adjust fund performance based on the sponsor's reputation concerns. In Section 6.2, I show that this assumption is satisfied in the data. In Appendix IA.5, I also present a random utility model that rationalizes this assumption and discuss possible ways to formally endogeneize a rank-based flow-performance relation.

Under specification (1), the rank of a fund's performance is equal to the measure of funds with strictly lower performance. In Appendix IA.1, I consider the more general specification in which the rank of a fund's performance is equal to the measure of funds with strictly lower performance plus a fraction ($\delta \in [0, 1]$) of the funds with the same performance. All theoretical results in the paper are proved under this general specification, deriving conditions on δ for their validity.

The assumption that fund flows also depend on factors that are not related to relative performance (e.g., advertising) has been vastly documented in the empirical literature on mutual funds (Jain and Wu, 2000). The assumption is made mainly for technical reasons as it ensures the existence of an equilibrium without imposing further conditions on the primitives of the model. However, the model can be solved and gives the same results even if that assumption is relaxed ($a = 0$) and substituted with a regularity condition on the distribution of default costs.

Finally, the above model abstracts away from any agency problem that may arise within the fund management company; that is, funds are identified with their sponsors.

3 The Nash Equilibrium

This section analytically characterizes the unique Nash equilibrium of the tournament. Before characterizing the equilibrium, I introduce the following variable:

$$x_0 := \frac{R_f - 1}{R_f - \underline{R}} D \in (0, D).$$

[9] Moreover, Spiegel and Zhang (2013) argue that the empirically observed convexity of the flow-performance relation in the mutual fund industry is due solely to misspecification of the empirical model.

x_0 is the maximum risky investment such that the probability of default is zero. Given a risky investment $x \in [0, D]$, the probability of default is zero for $x \leq x_0$ and strictly positive for $x > x_0$. Hereafter, I refer to x_0 as the *critical risky investment.* $D - x_0$ is the minimum buffer of safe assets required to fully insure the fund against the risk of default. Importantly, x_0 strictly increases with the risk-free rate: the minimum buffer of safe assets necessary to avoid breaking the buck is larger when the risk-free rate is lower.

As solution concept, I use the standard definition of Nash equilibrium for games with a continuum of players introduced by Aumann (1964).

Definition 1. *A risky investment strategy $x : [\underline{c}, \overline{c}] \to [0, D]$ is a Nash equilibrium of the game defined by (2) if and only if*

$$\upsilon_c(x_c, x_{-c}) \geq \upsilon_c(z, x_{-c}) \qquad \textit{for all } z \in [0, D]\,,$$

almost everywhere (a.e.) on $[\underline{c}, \overline{c}]$.

Hereafter, for simplicity, I drop the "*a.e.*" notation. All following results are true *a.e.* on $[\underline{c}, \overline{c}]$.[10]

Proposition 1. *Any equilibrium risky investment $x(c)$ must be strictly decreasing, continuously differentiable with strictly negative derivative, and $\lim_{c \to \overline{c}} x(c) = x_0$.*

The first part of Proposition 1 is the differentiability and strict monotonicity of any equilibrium. This result comes from the fact that the payoff of funds depends on the rank order of their actions.[11] The second part of Proposition 1 reveals that any equilibrium must be in the region of positive default probability, as summarized by the following corollary.

Corollary 1. *In equilibrium, the probability of "breaking the buck" is strictly positive for all funds and decreasing in the cost of default.*

If there is a positive mass of funds investing in the region of zero default probability (bounded above by x_0), each fund's expected payoff in that region will strictly increase with risky investment. Hence, each fund has an incentive to invest at least x_0 in the risky asset. Since any equilibrium risky investment decreases with default costs, the expected performance rank also decreases with default costs from Assumption 1. Hence, the fund with highest default costs invests exactly x_0 because it anticipates that it will have the lowest expected rank and optimally chooses to keep its default probability at zero, regardless of other funds' actions. The pressure of competition drives all other funds to invest more than x_0 in the attempt to outperform their competitors. That is, the strategic interactions of the tournament make all MMFs (except the one with highest default costs) not perfectly safe ex ante. Since investors have historically perceived MMFs as safe as insured deposits, Corollary 1 can be regarded as the most basic form of excessive risk-taking by MMFs.

[10] Since F_c is absolutely continuous with respect to the Lebesgue measure, "*a.e.*" and "$F_c - a.e.$" coincide.

[11] Similar results are obtained in auction theory (Krishna, 2010).

Importantly, it holds true regardless of the scale of default costs in the industry, i.e. even if all funds have extremely large default costs. This result will not hold if fund payoffs depend on absolute performance. In fact, in that case, it is easy to see that all funds whose default cost is sufficiently large in absolute terms will invest x_0 in the risky asset and have zero default probability.

To explicitly determine the equilibrium, I proceed as follows. Under Assumption 1, the expected rank of a fund's performance increases with the ex ante rank of its risky investment. Since any equilibrium is decreasing, the rank of a fund's risky investment is equal to the mass of funds with higher default costs. That is, given an equilibrium investment profile $x(c)$, the rank of a risky investment y is $1-F_C(x^{-1}(y))$. Since any equilibrium is differentiable with negative first derivative, I can take the first-order condition of the objective function (2) with respect to $x(c)$ and obtain an ordinary differential equation (ODE) in $\mathrm{d}x(c)/\mathrm{d}c$. The ODE, together with the boundary condition given by Proposition 1, provides a well-defined Dirichlet problem. Under regularity conditions on the primitives of the model, the Dirichlet problem can be solved exactly, and the solution is unique. Finally, I prove that the unique solution of the Dirichlet problem is indeed the unique equilibrium of the tournament by checking a second-order condition.

Proposition 2. *A Nash equilibrium exists if and only if* $\mathbb{E}_C\left[\frac{\gamma D}{\gamma D(F_C(c)+a)+c}\right] \leq \log\left(1+\frac{F_R(1)}{1-2F_R(R_f)}\right)$. *If a Nash equilibrium exists, it is unique, the equilibrium default probability is*

$$p(c) = 2 \underbrace{q}_{\substack{\textit{tournament}\\ \textit{incentive}}} \cdot \underbrace{Q(c)}_{\substack{\textit{incentive}\\ \textit{multiplier}}},$$

and the equilibrium risky investment is

$$x(c) = \frac{R_f - \underline{R}}{R_f - F_R^{-1}(p(c))}\, x_0\,, \tag{3}$$

where

$$q := 0.5 - F_R(R_f) > 0\,,$$
$$Q(\widetilde{c}) := \exp\left\{\gamma D\, \mathbb{E}_C\left[(\gamma D\,(F_C(c)+a)+c)^{-1}\,|c>\widetilde{c}\right](1-F_C(\widetilde{c}))\right\} - 1,$$

$F_R^{-1}(\cdot)$ *is the quantile function of* R*, and* $\mathbb{E}_C[\cdot]$ *is the expected value over the cost of default.*

The equilibrium default probability is uniquely determined by q and $Q(c)$. q is common to all funds, strictly positive under Assumption 1, and is referred to as the *tournament incentive*. To understand its role as risk-taking incentive, note that the ex post rank of fund c's performance,

$Rk(\pi_c)$, depends on the ex ante rank of fund c's risky investment, $Rk(x_c)$, in the following way

$$Rk(\pi_c) = \begin{cases} Rk(x_c) & \text{if } R > R_f, \text{ i.e. with probability } 1 - F_R(R_f) \\ \\ 1 - Rk(x_c) & \text{if } R < R_f, \text{ i.e. with probability } F_R(R_f) \end{cases}$$

The incentive to increase the default probability by investing in the risky asset increases with the difference between the above probabilities, i.e. $2q$. Within the debate on a competition-driven reach for yield of MMFs, q represents the *incentive to reach for yield*. Larger q means larger default probability and more risky investment for all funds. q is the only risk-taking incentive in the model and, as discussed below, a proxy for the standard risk premium.

$Q(c)$ is fund-specific, positive, strictly decreasing in the cost of default, and goes to zero as c goes to $\overline{c}$. $Q(c)$ is referred to as the *incentive multiplier* because it determines a fund's sensitivity to the tournament incentive by measuring the competitive pressure faced by the fund in equilibrium. To see this, consider the fund with the highest cost of default, $\overline{c}$. As discussed above, $\overline{c}$ anticipates that, in equilibrium, its expected performance will have the lowest rank. Hence, it decides to keep the probability of default equal to zero by investing x_0 in the risky asset, regardless of other players' actions. That is, $\overline{c}$ is not affected by fund competition, and $Q(\overline{c}) = 0$. Funds with slightly lower default costs anticipate that $\overline{c}$ will invest x_0. Hence, in order to outperform $\overline{c}$, they choose a default probability slightly greater than zero by investing a little bit more than x_0 in the risky asset. This reasoning extends to the other funds in descending order of default costs. In other words, each fund faces competitive pressure only from the funds with higher default costs. Figure 2 shows the equilibrium risky investment and the incentive multiplier as functions of the cost of default.

A closer look at $Q(c)$ provides a deeper understanding of how competition works in the MMF tournament. The competitive pressure faced by an agent in a competitive context depends on: (1) *how many* competitors she has, and (2) *how competitive* her competitors are. For a fund $\widetilde{c}$ in the MMF tournament, the multiplier $Q(\widetilde{c})$ captures both effects through the interaction term:

$$\mathbb{E}_C \left[\left(\underbrace{\gamma D \left(F_C(c) + a \right) + c}_{\substack{\text{marginal cost} \\ \text{of risky investment}}} \right)^{-1} \middle| \, c > \widetilde{c} \right] \cdot \underbrace{\left(1 - F_C(\widetilde{c})\right)}_{\substack{\text{mass of funds with} \\ \text{higher default costs}}}$$

$1 - F_C(\widetilde{c})$ represents the mass of fund $\widetilde{c}$'s competitors, i.e. the mass of funds with higher default costs. $\mathbb{E}_C \left[\left(\gamma D \left(F_C(c) + a \right) + c \right)^{-1} | c > \widetilde{c} \right]$ captures the competitiveness of fund $\widetilde{c}$'s competitors: it is the average of their inverse marginal cost of increasing the default probability by investing in the risky asset. Investing more in the risky asset increases the ex post performance rank if the realized risky return is above the risk-free rate, but it decreases the ex post performance rank if the realized

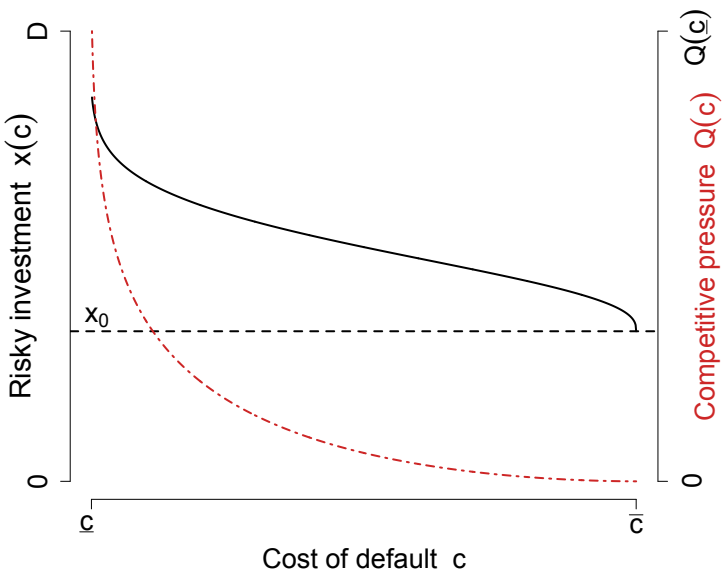


Figure 2: Equilibrium risky investment and competitive pressure. The solid black line (left y-axis) is the equilibrium risky investment, $x(c)$, as function of the default cost. The horizontal dashed black line is the maximum risky investment such that the probability of default is zero, x_0. The dot-dashed red line (right y-axis) is the incentive multiplier, $Q(c)$, as function of the default cost. $Q(c)$ measures the competitive pressure faced by each fund in equilibrium.

risky return falls below the risk-free rate. Hence, for a competitor c, increasing the probability of default by investing more in the risky asset has both a *direct cost*, its explicit cost of default c, and an *opportunity cost*, the AUM it will receive at the end of the tournament if it does not default and the risky return falls below the risk-free rate. Since the equilibrium risky investment decreases as the cost of default increases, this opportunity cost is $\gamma D\left(F_C(c)+a\right)$. The economic intuition is: the lower the competitors' marginal cost of risky investment is, the more competitive they are. Figure 3 shows the two components of competitive pressure at work.

$Q(c)$ shows that in the MMF tournament, competitive pressure is fund-specific and depends only on the distribution of default costs in the industry; it does not depend on the risk-free rate or the return distribution.

Standard risk premium, approximate equilibrium, and sufficient conditions

The tournament incentive is a spread between risky and safe returns in terms of probabilities. Under mild regularity conditions on the distribution of risky returns, it can be directly related to the standard risk premium.[12]

Lemma 1. *Suppose F_R is twice differentiable at $\mu := \mathbb{E}[R]$ and $|F_R(\mu) - 0.5|$ is small. Then,*

$$q \approx f_R(\mu)\left(\mu - R_f\right) \qquad for \;\; small \;\; \mu - R_f > 0.$$

[12]Hereafter, $f \approx g(x)$ for small x means $f = g(x) + o(x)$ in the standard small $o(\cdot)$ notation.

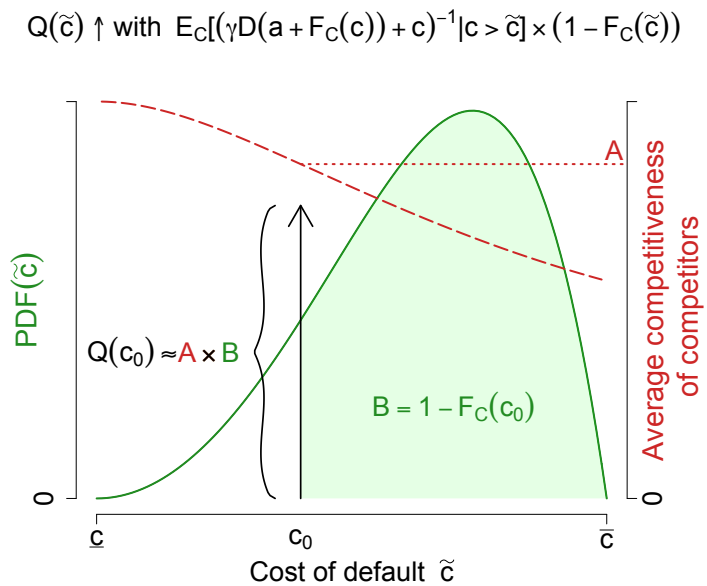


Figure 3: Components of the equilibrium competitive pressure. The solid green line (left y-axis) is the density of the distribution of default costs in fund population, f_C. The green shaded area is the mass of funds with default costs higher than c_0 and represents the mass of fund c_0's competitors. The dashed red line (right y-axis) is the average inverse marginal cost of risky investment for funds with default costs higher than $\widetilde{c}$ as a function of $\widetilde{c}$ and represents their competitiveness. The upward arrow is the product of the mass of fund c_0's competitors and their competitiveness (B and A, respectively) and represents the competitive pressure faced by c_0 in equilibrium.

If the distribution of risky returns is sufficiently smooth, with its mean and median being close, q is linearly proportional to the standard risk premium $(\mu - R_f)$ when the standard risk premium is small. Since the spread on the risky securities available to MMFs is typically very small, the approximation provided by Lemma 1 is likely to hold in the data. This relation suggests using a measure of risk premium as proxy for the tournament incentive in the empirical analysis.

For some comparative statics below, the equilibrium risky investment (3) is not easily tractable. However, under mild regularity conditions, it can be written in a more tractable form.

Corollary 2. *Suppose F_R is twice differentiable on $[\underline{R}, 1]$ and $f_R(\underline{R}) > 0$. Then, for small equilibrium default probability, i.e. small $qQ(c)$, the equilibrium risky investment is*

$$x(c) \approx \left(1 + \frac{2qQ(c)}{f_R(\underline{R})(R_f - \underline{R})}\right) x_0 \,. \tag{4}$$

If the distribution of risky returns is sufficiently smooth in its left tail, the equilibrium risky investment is proportional to the tournament incentive, normalized by a measure of tail risk and scaled by the fund-specific multiplier. Approximation (4) always holds for funds with higher default costs because they keep the default probability close to zero. It also holds for all funds if the maximum competitive pressure in the industry, $Q(\underline{c})$, is sufficiently small. In Section 4, I use (4) to study

how the cross-sectional risk-taking differential reacts to changes in the risk premium and riskiness of the risky asset.

Finally, the following corollary provides two sufficient conditions, with a straightforward economic interpretation, for the existence of the equilibrium.

Corollary 3. *The equilibrium exists if*

$$\textit{either} \quad \left(e^{1/a}-1\right)^{-1} \geq \frac{2q}{F_R(1)}\,; \qquad \textit{or} \quad \left(e^{\gamma D/\underline{c}}-1\right)^{-1} \geq \frac{2q}{F_R(1)}$$

The first condition says that the fraction of AUM that does not depend on fund performance must be sufficiently greater than the tournament incentive, normalized by the probability that the risky return falls below the rate on deposits ($1). The second condition says that the minimum default cost in the industry must be sufficiently greater than the normalized tournament incentive. Both conditions are likely to hold in the MMF industry, where the spread on eligible risky securities is small, and therefore q is also small (Lemma 1). Moreover, the second condition is likely to hold more generally because the cost of "breaking the buck," as happened to Reserve Primary Fund, is arguably very high in absolute terms even for those funds with relatively low default costs.

4 Shocks to Asset Returns

This section studies how the equilibrium responds to changes in the risk-free rate and distribution of risky returns. The goal of this section is to characterize the reach for yield of MMFs in response to changes in the available investment opportunities.

The equilibrium default probability, $p(c)$, depends on asset returns only via the tournament incentive, $q = 0.5 - F_R(R_f)$. It does not explicitly depend on the level of the risk-free rate or other parts of the risky return distribution. This is because, absent default, the payoff only depends on relative performance, and in the case of default, the payoff is a fund-specific fixed cost that is independent of how much the fund defaulted.

Proposition 3. *The equilibrium default probability $p(c)$ increases with the tournament incentive q for all funds, with the effect being stronger for funds with lower default costs.*

Proposition 3 follows immediately from the formula for the equilibrium default probability, $p(c) = 2qQ(c)$. An increase in q increases the equilibrium default probability of all funds (except the highest-default-cost fund, for which $Q(\overline{c}) = 0$). Since the effect of q is weighted by the idiosyncratic multiplier $Q(c)$, it is stronger for funds with lower default costs.

The equilibrium risky investment, on the other hand, does depend on the level of the risk-free rate and the risky return distribution. The distribution of risky returns affects risky investment via $F_R^{-1}(p(c))$. Importantly, only the left tail of the distribution matters. This is because, from the no-short-selling constraint, $x(c) \leq D$ and hence the equilibrium default probability must be smaller

than or equal to the probability that the risky return falls below 1, i.e. $p(c) \leq F_R(1)$. The risk-free rate, on the other hand, affects the equilibrium risky investment both explicitly via its level, R_f, and implicitly via the tournament incentive, $q = 0.5 - F_R(R_f)$. In the following section, I study the effects of these variables on funds' risky investment both separately and jointly. This allows me to make predictions on the risky investment of MMFs when changes in the risk-free rate, risk premium, and riskiness of the risky assets occur simultaneously and to disentangle the different channels.

4.1 Changes in risk premium, holding risk-free rate constant

First, I consider the effect of changes in the risk premium holding the risk-free rate constant. In the real world, the premium on risky assets usually increases with their riskiness. To mimic this scenario in my model, I consider an increase in the tournament incentive accompanied by an increase in the left tail of the return distribution (which is the only part of the distribution affecting equilibrium risky investment). In real-world terms, this increase in the left tail of the return distribution corresponds to an increase in the default risk of the risky debt securities held by MMFs.

I show that under realistic conditions, the risky investment of funds with high default costs and that of funds with low default costs respond in opposite ways to such changes. The increase in the tournament incentive increases the equilibrium default probability of all funds. On the other hand, for any equilibrium default probability, a shift to the left of the return distribution mechanically reduces the corresponding amount of risky investment. In equilibrium, the heterogeneous competitive pressure determines which effect dominates, generating a bifurcation in the fund population.

Let $H := \dfrac{F_R(r)}{F_R(1)}$ for all $r \in [\underline{R}, 1]$ be the left tail of F_R, renormalized to 1 to have a proper distribution function. Suppose there is a stochastic shift from $H^{(1)}$ to $H^{(2)}$, both with support $[\underline{R}, 1]$, such that $H^{(1)}$ dominates $H^{(2)}$ in terms of likelihood ratio order ($H^{(1)} \succ_{LRD} H^{(2)}$). Finally, suppose the tournament incentive goes from $q^{(1)}$ to $q^{(2)} > q^{(1)}$.

Proposition 4. *Let $H^{(1)} \succ_{LRD} H^{(2)}$ and $q^{(1)} < q^{(2)}$.*

(i) If $\dfrac{q^{(2)}}{q^{(1)}} > (\geq) \sup \dfrac{H^{(2)}}{H^{(1)}}$, all funds (weakly) increase their risky investment.

(ii) If $\dfrac{q^{(2)}}{q^{(1)}} < \sup \dfrac{H^{(2)}}{H^{(1)}}$,

- *(a) funds with relatively high costs of default decrease their risky investment;*
- *(b) funds with relatively low costs of default increase their risky investment if and only if they face sufficiently high competitive pressure.*

Moreover, if $\dfrac{H^{(2)}}{H^{(1)}}$ is decreasing, the cutting point between (a) and (b) is unique.

Part (i) provides a predictable result: if the increase in the tournament incentive is sufficiently larger than the increase in the riskiness of the risky asset, all funds increase their risky investment.

Part (ii) considers the more realistic and interesting scenario when the increase in the probability of low returns and the increase in the tournament incentive are of comparable sizes; namely, when the growth in the tournament incentive is smaller than the maximum growth in the left tail of the return distribution. The intuition for this case is as follows. Funds with higher default costs face lower competitive pressure and increase their default probability less, keeping it sufficiently close to zero. Therefore, their risky investment is more sensitive to shocks in the probability of very low returns. Under likelihood ratio dominance, $\frac{q^{(2)}}{q^{(1)}} < \sup \frac{H^{(2)}}{H^{(1)}}$ implies that the growth in the likelihood of very low returns is greater than the growth in the tournament incentive. Hence, even though their default probability increases, funds with higher default costs are forced to decrease their risky investment.[13] On the other hand, funds with lower default costs have a larger incentive multiplier, due to larger competitive pressure, and are more sensitive to shocks in the tournament incentive. If competitive pressure on those funds is sufficiently high, the increase in q dominates, and they increase their risky investment despite the increase in risk.

Importantly, the same bifurcation will also occur if, instead of assuming likelihood ratio dominance in the left tail, we model the increase in default risk by assuming a decrease in the lowest possible return (i.e., $\underline{R}^{(2)} < \underline{R}^{(1)}$). This confirms the robustness of the above economic intuition.

These results suggest that the cross-sectional risky investment differential increases with the premium and riskiness of the risky asset. When competitive pressure on funds with lower default costs is high, this intuition is formalized by Proposition 4 (ii). To have a formal result for when competitive pressure on those funds is low, I use the approximate equilibrium (4):

$$x_{app}(c) := (1 + 2\widetilde{q}Q(c))\, x_0, \qquad \textit{where} \quad \widetilde{q} := \frac{q}{f_R(\underline{R})(R_f - \underline{R})}$$

As discussed above, this approximation is valid for all funds when the competitive pressure on funds with lower default costs is low. Since $\widetilde{q}$ incorporates both the tournament incentive and the risk of low returns, I differentiate the approximate equilibrium w.r.t. (with respect to) $\widetilde{q}$ to capture the effect of a simultaneous change in both variables.

Corollary 4. $\frac{\mathrm{d}}{\mathrm{d}\widetilde{q}} \left| \frac{\mathrm{d}x_{app}(c)}{\mathrm{d}c} \right| > 0$ *for all c.*

Corollary 4 confirms that the cross-sectional risky investment differential increases with the risk premium also when competitive pressure on funds with lower default costs is low.

4.2 Changes in risk-free rate, holding risk premium constant

Here I consider changes in the risk-free rate holding the tournament incentive, $q = 0.5 - F_R(R_f)$, constant. Since q is proportional to the standard risk premium, this amounts to assume that the

[13] Except the highest-default-cost fund, which always invests x_0. Since by assumption $H^{(1)}$ and $H^{(2)}$ have the same support, x_0 does not change after the shock.

risk premium remains constant when the risk-free rate changes. This exercise can be seen as a rigid shift of the risky return distribution together with the risk-free rate.

Holding the tournament incentive constant, a decrease in the risk-free rate does not change the equilibrium default probability of any fund. On the other hand, it forces all funds to invest more in the safe asset to keep the same probability of default in equilibrium.

Proposition 5. *Holding the tournament incentive q constant, the equilibrium risky investment strictly increases with the risk-free rate for all funds.*

This effect on equilibrium risky investment is stronger for funds with relatively higher default costs. To see this, consider the following scenario. Suppose that the competitive pressure on the fund with the lowest default cost, $\underline{c}$, is sufficiently high so that its equilibrium default probability is exactly equal to $F_R(1)$. That is, $\underline{c}$ fully invests its portfolio in the risky asset: $x(\underline{c}) = D$. Holding q constant, this equilibrium investment is unaffected by changes in the level of the risk-free rate. On the other hand, in equilibrium, the fund with the highest default cost invests exactly x_0, which increases with the risk-free rate. Hence, when the risk-free rate decreases, holding q constant, the risky investment differential between funds with the highest and lowest default costs increases. This intuition is summarized by the following corollary.

Corollary 5. *Holding q constant, if $\underline{R} > 2 - R_f$, the cross-sectional risky investment differential increases when the risk-free rate decreases. That is, if $\underline{R} > 2 - R_f$,*

$$\frac{\partial}{\partial R_f}\left|\frac{\mathrm{d}x(c)}{\mathrm{d}c}\right| < 0 \quad \textit{for all } c.$$

The partial derivative w.r.t. R_f indicates that $q = 0.5 - F_R(R_f)$ is being held constant. The assumption that the lowest possible return on the risky asset is not too low is likely to hold in the data,[14] since MMFs can only invest in securities of the highest credit quality and short maturity. Moreover, for the approximate equilibrium (4), the result of Corollary 5 holds true without any assumption on $\underline{R}$, further confirming the above economic intuition.

4.3 Simultaneous changes in risk premium and risk-free rate

Finally, in the real world, periods of low risk-free rates are often associated with periods of high risk premia. Here I do comparative statics for this scenario. For simplicity, I hold the distribution of risky returns constant so that a decrease in the risk-free rate, R_f, mechanically increases the tournament incentive, $q = 0.5 - F_R(R_f)$. This corresponds to a mechanical, contemporaneous increase in the risk premium (Lemma 1).[15] In the following proposition, the symbol of total derivative with respect to R_f indicates that q is allowed to vary with R_f, while the distribution

[14] Unless the gross risk-free rate is exactly 1, which is ruled out by model assumption.

[15] For simplicity, I do not consider a simultaneous increase in the left tail of the return distribution because from the previous section, I already know that its effect has the same sign as that of a decrease in R_f.

of returns is held constant. That is, $\mathrm{d}x/\mathrm{d}R_f > 0$ means that risky investment decreases when the risk-free rate decreases and the tournament incentive (i.e., the premium) increases. In this section, I denote the tournament incentive by $q(R_f)$ to make its dependence on the risk-free rate explicit.

ASSUMPTION 2. *The reverse hazard rate of the risky return, $\frac{f_R}{F_R}$, is non-increasing on $[\underline{R}, 1)$.*

Proposition 6. *Under Assumption 2, there exists $c^* \in (\underline{c}, \overline{c})$ s.t.*

i) $\dfrac{\mathrm{d}x(c)}{\mathrm{d}R_f} > 0$ *for all $c > c^*$;*

ii) $\dfrac{\mathrm{d}x(c)}{\mathrm{d}R_f} < 0$ *for all $c < c^*$ if and only if the competitive pressure on the funds with the lowest cost of default, $Q(\underline{c})$, is sufficiently high.*

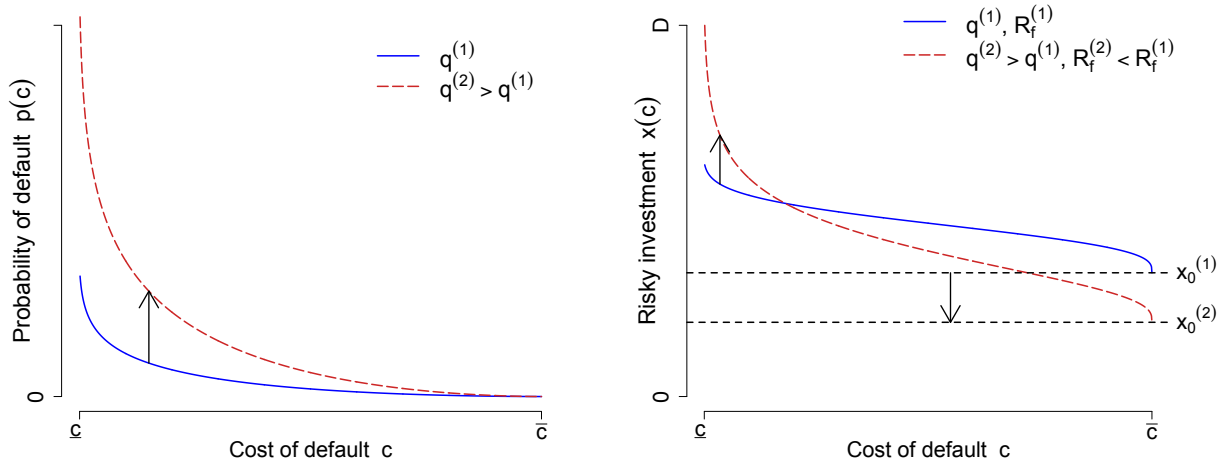
A decrease in the risk-free rate that mechanically increases the tournament incentive also increases the equilibrium default probability of (almost) all funds, with the effect being stronger for funds with lower default costs. On the other hand, holding the default probability constant, a decrease in the risk-free rate decreases the equilibrium risky investment of all funds, with the effect being stronger for funds with higher default costs. The idiosyncratic incentive multiplier $Q(c)$ determines which effect dominates by measuring the relative importance of fund competition. To see this, take the fund with the highest cost of default, $\overline{c}$. $\overline{c}$ is unaffected by competition ($Q(\overline{c}) = 0$) and always keeps the equilibrium default probability equal to zero by investing exactly x_0. Since x_0 increases with R_f, after a decrease in the risk-free rate, $\overline{c}$ is forced to cut its risky investment to keep its default probability equal to zero, even though $q(R_f)$ increases. On the other hand, funds with relatively low costs of default face a higher competitive pressure, captured by higher $Q(c)$. If competition is sufficiently strong, $Q(c)$ is sufficiently large and the effect on the default probability via $q(R_f)$ dominates. Figure 4 qualitatively shows this result.

Finally, note that Assumption 2 is very weak. Many common distributions with support in $\mathbb{R}_+$ satisfy a decreasing reverse hazard rate condition in the left tail, including uniform, log-normal, Beta, chi-squared, and exponential (Shaked and Shanthikumar, 1994). Even more importantly, Assumption 2 is not necessary for part (i) of Proposition 6.

5 Shocks to the competitive environment

Until now, I have considered how fund risk-taking responds to changes in investment opportunities. This section studies how it responds to changes in the competitive environment. As discussed in Section 3, the equilibrium fund-specific competitive pressure is uniquely determined by the distribution of default costs. Suppose the distribution of default costs shifts from $F_C^{(1)}$ to $F_C^{(2)}$, both with support $[\underline{c}, \overline{c}]$.

Proposition 7. *If $F_C^{(2)} \succ_{LRD} F_C^{(1)}$, there exist $c_* \leq c^* \in (\underline{c}, \overline{c})$ s.t. equilibrium default probability and risky investment decrease for all $c \in (\underline{c}, c_*)$ and increase for all $c \in (c^*, \overline{c})$.*



(a) Equilibrium default probability

(b) Equilibrium risky investment

Figure 4: Equilibrium risk-taking when the premium q increases and the risk-free rate R_f decreases. Left panel: default probability (unaffected by R_f). Right panel: risky investment.

The intuition is as follows. The equilibrium risk-taking of a fund $\widetilde{c}$ depends on the distribution of default costs only through the incentive multiplier $Q(\widetilde{c})$, which strictly increases with

$$\mathbb{E}_C\left[(\gamma D(F_C(c)+a)+c)^{-1}\,|c>\widetilde{c}\right](1-F_C(\widetilde{c}))=\int_{\widetilde{c}}^{\overline{c}}\frac{f_C(u)\mathrm{d}u}{\gamma D(F_C(u)+a)+u}\,. \tag{5}$$

The fund with the highest default cost, $\overline{c}$, is unaffected by shocks to the distribution of default costs because it is unaffected by competition. That is, $Q(\overline{c})=0$ under any F_C. For the other funds with relatively high default costs, the LRD shift increases both the mass of competitors ($f_C^{(2)}(u)>f_C^{(1)}(u)$ in the upper tail) and their competitiveness by lowering the opportunity cost of risky investment ($F_C^{(2)}(u)<F_C^{(1)}(u)$ everywhere). As a result, for large $\widetilde{c}$, the right-hand side of (5) increases, increasing the multiplier and hence the risk-taking of funds with relatively high default costs. On the other hand, for the fund with the lowest default cost $\underline{c}$, the mass of competitors remains equal to 1, and their average opportunity cost of risky investment does not change.[16] However, the LRD shift decreases the average competitiveness of $\underline{c}$'s competitors by increasing their average cost of default. Hence, for $\underline{c}$ (and by continuity for other funds with relatively low default costs), a shift of F_C to the right decreases the incentive multiplier and hence the risk-taking.[17]

Intuitively, if the distribution of default costs shifts to the right (i.e., the fraction of funds with relatively high default costs increases), competition becomes relatively stronger for funds with higher default costs and relatively weaker for funds with lower default costs. Again, this result

[16] Specifically, $\int_{\underline{c}}^{\overline{c}}\frac{f(u)\mathrm{d}u}{\gamma D(F(u)+a)}=\frac{1}{\gamma D}\log\left(1+a^{-1}\right)$ for any CDF F on $[\underline{c},\overline{c}]$.

[17] The assumption of LRD is made for simplicity. For Proposition 7 to hold, it is sufficient to assume a first-order stochastic dominance shift such that the two density functions cross only a finite number of times.

shows that in the MMF tournament, competitive pressure is not a global property of the industry but a local property of each fund.

Proposition 7 suggests that shocks to the competitive landscape might have surprising effects in the aggregate. For example, if the right tail of the distribution of default costs is sufficiently fat, an increase in the fraction of funds with relatively high default costs could increase aggregate risk-taking rather than decrease it. This is because the increase in risk-taking by funds with higher default costs could more than offset the decrease in risk-taking by funds with lower default costs.

Model Predictions: Summary

The model makes the following testable predictions.

P.1 Funds with lower costs of default always hold more risky assets.

P.2 Holding the risk-free rate constant, an increase in the risk premium:

(a) decreases the risky investment of funds with higher default costs;

(b) increases the risky investment of funds with lower default costs (if and only if they face sufficiently high competitive pressure);

(c) always increases the cross-sectional differential.

P.3 Holding the risk premium constant, a decrease in the risk-free rate:

(a) decreases the risky investment of all funds;

(b) increases the cross-sectional differential.

The following empirical analysis provides evidence that supports predictions P.1 to P.3.

The model also makes predictions on the equilibrium default probability: (1) all funds have a strictly positive probability of "breaking the buck," which decreases with fund's cost of default; (2) for each fund, the probability of "breaking the buck" increases with the risk premium, with the effect being stronger for funds with lower default costs, and is independent of the level of the risk-free rate. These predictions come from the strategic, competitive nature of the tournament and will not hold if funds' payoff depend on their absolute performance. In that case, in fact, all funds whose default cost is sufficiently large in absolute terms would keep their default probability at zero, which in turn would also have implications on fund risky investment that are different from those of my model.

Since in the data I do not observe MMF portfolio holdings at the security level, I cannot test the predictions on default probability. However, Brady *et al.* (2012) find that between 2007 and 2011 (i.e., when the risk premia available to MMFs increased significantly), at least 21 MMFs would have broken the buck if they had not received sponsor support, and that sponsor support was frequent and significant: 78 MMFs (out of a total of 341) received sponsor support in 123 instances for a

total amount of at least $4.4 billion. This evidence supports the tournament model's prediction of widespread excessive risk-taking by MMFs.

Finally, my model makes predictions on the effect of changes in the competitive landscape of the industry: when the fraction of funds with relatively high default costs increases, funds with lower default costs decrease their risk-taking, while funds with higher default costs increase it. Testing this prediction is left for future work.

6 Empirical Analysis

As other recent studies on prime MMFs, I focus on institutional funds because they exhibit a stronger flow-performance relation than retail funds (KS; Chernenko and Sunderam, 2014). I consider the period from January 2002 to August 2008 because in this period there were significant variations in both the risk premia and the risk-free rates available to MMFs.[18] I use those variations to identify the differential effects of risk premia and risk-free rates on MMF risk-taking and test the model's predictions.

Mapping the model to the data

To map the model to the data, I use the notion of sponsor's reputation concern introduced by KS. The fund's cost of default in the model is the sponsor's cost of possible negative spillovers in the data. The rationale is that sponsors with a larger share of non-MMF business expect to incur larger costs if the NAV of their MMFs falls below $1. This is because of possible outflows from other mutual funds managed by the same sponsor or a loss of sponsor's other business and franchise value due to reputational damages.

I follow KS and proxy sponsor's reputation concern with

$$Fund\,Business = \frac{\text{sponsor's mutual fund assets not in institutional prime MMFs}}{\text{sponsor's total mutual fund assets}}$$

Fund Business is the share of sponsor's mutual fund assets that are not in institutional prime MMFs. Another plausible measure of sponsor's reputation concern is affiliation to financial conglomerates (e.g., banks or insurance companies). However, this proxy (*Conglomerate*) is a binary variable, while in my model the cost of default is a continuous variable. *Fund Business* is continuous by construction and therefore is the most natural choice.

The tournament incentive q in the model is mapped into the risk premium in the data. My main proxy for the risk premium is an index of realized spreads of the risky securities available to MMFs relative to US treasuries. This index is defined and discussed below. For robustness, I also use

[18] I do not consider the period after August 2008 because the industry-wide run occurred after Reserve Primary broke the buck (September 16, 2008), the ensuing government intervention (from September 19, 2008 to September 18, 2009), and debate on the new regulation of the industry (with the first reforms adopted in March 2010, and the last amendments adopted in July 2014) might have significantly altered the standard risk-taking incentives of MMFs.

the excess bond premium for financial firms introduced by Gilchrist and Zakrajsek (2012). Since MMFs mainly invest in debt securities issued by financial firms, this is an appropriate measure of the premium available to MMFs.

My main proxy for the risk-free rate is the return on 1-month T-bills. Since MMFs are restricted to invest only in high-quality, short-term securities, and US treasuries have historically been the safest asset class available to MMFs, this is the appropriate proxy for the model's risk-free rate. In my robustness checks, I also proxy the model's risk-free rate with the 3-month T-bills rate.

The data set

Following KS, I construct a data set that maps MMFs to their sponsors. Data on individual MMFs are provided by iMoneyNet. Data on fund sponsors are from the CRSP Mutual Fund Database. For the time period considered in this paper, iMoneyNet data are the most comprehensive source of information on MMF holdings. They have also been used by KS, Chodorow-Reich (2014), and Di Maggio and Kacperczyk (2015). iMoneyNet data are at the weekly share-class level and contain information on yields, assets under management, expense ratio, age, portfolio composition by instrument type, and weighted average maturity. Since my model is at the fund level, I aggregate share classes by fund and compute fund characteristics as the weighted average of the share class values, with assets per share class as weights. Details are in Appendix IA.2.

Data on the returns of the asset classes available to MMFs are from FRED. Data on the Gilchrist and Zakrajsek (2012) excess bond premium are from Simon Gilchrist's website: `http://people.bu.edu/sgilchri/Data/data.htm`. Data on T-bill rates are from Kenneth French's website (`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`) and CRSP.

Summary statistics

Table IA.2.1 in Appendix IA.2 shows summary statistics for all U.S. institutional prime MMFs as of January 3, 2006. I chose this date to make my results comparable to those of KS, also reported in Table IA.2.1. The results are very similar, confirming that my data set is consistent with theirs. In January 2006, the sample includes 143 funds and 82 sponsors. The average fund size is \$6.3 billion, and the average fund age is 11.2 years. The average spread (i.e., the annualized gross yield before expenses minus the yield of the 1-month T-bill) is 7.5 basis points; the average expense ratio is 35.9 basis points. In terms of assets holdings, funds hold 31.4% in commercial paper, 19.9% in floating-rate notes, 13.4% in repurchase agreements, 13.6% in asset-backed commercial paper, 12.4% in bank obligations, 5.9% in U.S. Treasuries and agency-backed debt, and 3.4% in time deposits. The average family size is \$73.3 billion, and the average *Fund Business* is 74.5%.

Table IA.2.1 also checks that as of January 2006, funds with different levels of sponsor's reputation concern do not significantly differ along other dimensions. Columns (2) and (3) show summary statistics for funds whose sponsors have *Fund Business* above and below the industry median, respectively. Both groups are quite similar in terms of other observable characteristics. The main

difference is that on average, funds with higher *Fund Business* are smaller and less likely to be part of financial conglomerates. These results suggest that the extent of a sponsor's non-MMF business is not systematically correlated with other observable fund characteristics. In particular, Figure IA.2.2 shows that for most of the 2002–2008 period, *Fund Business* is not statistically significantly correlated with either fund's incurred expenses or affiliation to a financial conglomerate, which are the dimensions of cross-sectional heterogeneity considered by Chodorow-Reich (2014) and Di Maggio and Kacperczyk (2015), respectively. This means that my results are not driven by the same cross-sectional variation analyzed in those papers.

Appendix IA.2 also analyzes the distributional properties of *Fund Business*. Figure IA.2.1 and Table IA.2.2 show that there is significant cross-sectional variation over the whole period, which supports the validity of a "continuum-of-funds" approach and helps the identification of the effect of *Fund Business* on the cross-sectional risk-taking differential. They also show that while the cross-sectional distribution of *Fund Business* is relatively stable over time, there is also significant time-series variation at the fund level.

6.1 Investment opportunities: risk premium vs. risk-free rate

Prime MMFs can invest only in U.S. treasuries, GSE debt, repurchase agreements, certificate of deposits (i.e., time deposits and bank obligations), floating-rate notes, commercial papers, and asset-backed commercial papers. Among these securities, U.S. treasuries, GSE debt, and repos are the safest ones. Certificates of deposits (CDs), floating-rate notes (FRNs), commercial papers (CPs), and asset-backed commercial papers (ABCPs) have historically been the riskiest ones.

To investigate the time variation in the investment opportunities available to MMFs, I construct an index of spreads of the risky securities available to MMFs. The index contains the 3-month CD rate, 3-month LIBOR (often used as reference rate for FRNs), 3-month AA financial CP rate, and 3-month AA ABCP rate. Data are at the monthly level from FRED. The index is

$$Spread\ Index_t = \left(a_{2002}^{CD}\, r_t^{CD} + a_{2002}^{FRNS}\, r_t^{LIBOR} + a_{2002}^{CP}\, r_t^{CP} + a_{2002}^{ABCP}\, r_t^{ABCP}\right) - GS3M_t \qquad (6)$$

where r_t^K is the interest rate of asset category K in month t, and $GS3M_t$ is the 3-month constant maturity rate on T-bills. The coefficient a_{2002}^K is the industry average relative weight of category K in the portfolios of institutional prime MMFs as of January 1, 2002. Weights are held constant as of January 2002 to alleviate possible endogeneity issues. a's are normalized to sum up to 1. Figure 5 shows *Spread Index* (red line) from January 2002 to August 2008. Before July 2007, *Spread Index* was relatively flat and consistently below 0.6%, with an average value of 0.2%. From July 2007, *Spread Index* started to rise, reaching 1.3% in August 2007 and a maximum of 1.9% in August 2008, with an average value of 1.3% from August 2007 to August 2008.

Spread Index is an ex post measure of the premia available to MMFs and reflects default risk. Figure 5 also shows the excess bond premium for financial firms from Gilchrist and Zakrajsek

(2012), hereafter referred to as *GZ Premium* (blue line), which by construction does not reflect default risk. The pattern is partly similar to that of *Spread Index*. It was positive until February 2003, and then negative and relatively flat until July 2007, with an average value of −0.2% from January 2002 to July 2007. In August 2007, it was positive again and started to rise steadily, reaching a maximum of 1.9% in August 2008, with an average value of more than 1% from August 2007 to August 2008.

Figure 5 also shows the 1-month T-bill monthly return (green line). The 1-month T-bill rate experienced significant fluctuations from January 2002 to August 2008. It was around 15 basis points (bp) until August 2002. Then it fell and remained relatively low until June 2004, reaching a minimum of 6 bp in May 2004, with an average value of 8 bp from January 2003 to June 2004.[19] It increased steadily from July 2004 until May 2006 and remained at around 40 bp from then until August 2007. Finally, it started to decrease sharply in September 2007 and remained low until the end of the sample, with an average value of 22 bp from September 2007 to August 2008.

Importantly, the fact that my proxies for the risk premium and risk-free rate do not comove and have significant variation over the period considered helps identify and disentangle their differential effects on MMF risk-taking.

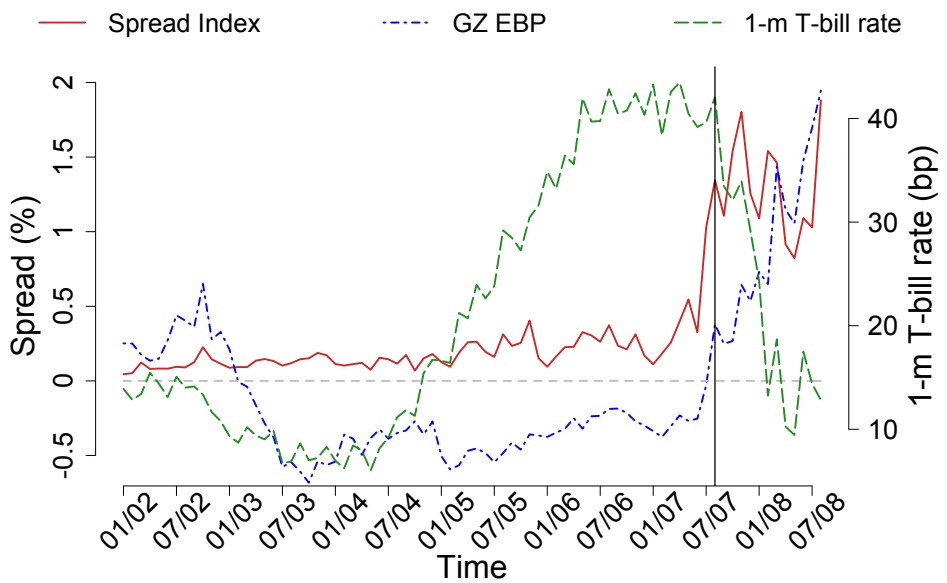


Figure 5: Risk premia & risk-free rate. *Spread Index* (solid red line) is an index of spreads on the risky securities available to prime MMFs, weighted according to the industry average holdings as of January 2, 2002 (see equation (6)). *GZ EBP* (dot-dashed blue line) is the the excess bond premium for financial firms from Gilchrsit and Zakrajsek (2012). The dashed green line, whose scale is on the right y-axis, is the monthly return on the 1-month T-bill. Data are monthly.

[19] Interestingly, the debate on a possible "reach for yield" of MMFs in a low interest rate environment emerged for the first time exactly during this period of historically low Treasury rates (FDIC, 2004).

Proxies of risk-taking

Since *Spread Index* and *GZ Premium* aggregate risk premia across different instrument types, they do not identify the single, riskiest asset class available to MMFs in the period of analysis. To do that, since I do not observe fund portfolios at the individual security level, I run a panel regression with current fund spread on the left-hand side (LHS) and past fund holdings by instrument category, together with a set of controls, on the right-hand side (RHS). The coefficient on each instrument category measures its contribution to fund yields, and I identify the instrument category with the largest coefficient as the riskiest one.[20] Details on the regression specification are in Appendix A, and results are in Table A.1. According to this definition of risky asset, I find that bank obligations were the riskiest asset class over the whole period. For robustness, I also run the same regression specification on non-overlapping time windows, and for each sub-period I rank asset classes by their estimated coefficient. I find that bank obligations are the instrument category with the highest average rank. In view of these results, I use the percentage holdings of bank obligations net of U.S. treasuries, GSE debt, and repos as a measure of portfolio risk in terms of asset class composition. I refer to this measure as *Holdings Risk* and use it as the main proxy for fund risk-taking.

To have a finer measure of risk-taking that captures possible changes in MMF investment opportunities over time, I also introduce $Holdings\ Risk^{dyn}$. For each month, $Holdings\ Risk^{dyn}$ is the percentage holdings of the riskiest asset class in that month (according to the above definition) net of U.S. treasuries, GSE debt, and repos in a fund's portfolio.

I also use three other proxies for fund risk-taking: *Spread*, *Maturity Risk*, and *Safe Holdings*. *Spread* is fund's gross yield minus the 1-month T-bill rate. Since in the MMF industry there is little scope for managerial skill, fund spreads tend to reflect portfolio risk.[21] *Maturity Risk* is the weighted average maturity of assets in a fund's portfolio. *Safe Holdings* is the share of U.S. treasuries, GSE debt, and repos in a fund's portfolio and can be considered as the most robust measure of MMF risk-taking. As mentioned above, Treasuries, GSE debt, and repos have consistently been the safest instruments available to prime MMFs.

6.2 Flow-performance relation and tournament assumption

This section analyzes the flow-performance relation in the MMF industry during the period of analysis. In particular, it tests the modeling assumptions that investor money flows are determined by the rank of fund performance (like in a tournament), and not by their raw performance. To estimate the sensitivity of fund flows to past performance, I run the following regression:

$$Fund\ Flow_{i,t+1} = \alpha_i + \mu_t + \beta Performance_{i,t} + \gamma \cdot X_{it} + \varepsilon_{i,t+1} \tag{7}$$

[20] KS and Chodorow-Reich (2014) use the same method and obtain similar results.

[21] As noted by KS, a potential problem with *Spread* is that it may vary over time just because the yields of individual assets in the portfolio change and not because fund managers make any portfolio adjustment.

where $Fund\ Flow_{i,t+1}$ is the percentage increase in fund i's size from week t to week $t+1$, adjusted for earned interests and trimmed at the 0.5% level to mitigate the effect of outliers. $Performance_{i,t}$ is a measure of fund i's performance in week t (see below). $X_{i,t}$ is a vector of fund-specific controls that includes the natural logarithm of fund size in millions of dollars ($Log(Fund\ Size)$), fund expenses in basis points ($Expense\ Ratio$), fund age in years (Age), the natural logarithm of the fund family size in billions of dollars ($Log(Family\ Size)$), and the volatility of fund flows ($Flow\ Volatility_{i,t}$), measured as the standard deviation of weekly fund flows over the previous quarter. μ_t denotes week fixed effects, which account for variations in the macroeconomic environment, and α_i denotes fund fixed effects, which account for unobserved time-invariant fund characteristics. The coefficient of interest is β.

In my first specification, $Performance_{i,t}$ is the raw spread ($Spread_{i,t}$), i.e. the annualized gross yield of fund i in week t minus the yield of the 1-month T-bill in week t. The raw spread is expressed in percentages. Results are in Column (1) of Table 1. Standard errors are heteroskedasticity-and-autocorrelation (HAC) robust. As common in the empirical mutual fund literature, I find that the flow-performance relation is positive and statistically significant when performance is measured in terms of raw spreads. In the MMF industry, however, the cross-sectional distribution of spreads is typically very compressed, and a difference of even a few basis points can crucially alter fund flows. Hence, raw measures of past performance might not be appropriate to explain investor money flows. In my second specification, $Performance_{i,t}$ is the spread rank ($Spread\ Rank_{i,t}$), i.e. the rank of fund i's spread in week t. The rank is expressed in percentiles normalized over the interval $[0, 1]$, with $Spread\ Rank = 0$ for the worst performance and $Spread\ Rank = 1$ for the best one. Column (2) of Table 1 shows the results. Again, when the spread rank is the main explanatory variable, the flow-performance relation is positive and statistically significant. Moreover, the adjusted R^2 slightly increases (by 0.2%).

These results suggest that ranks might be more important than raw performance in explaining money flows to MMFs. To test this hypothesis, I estimate model (7) including both measures of performance. Results are in Column (3) of Table 1. When both raw spreads and spread ranks are included, the spread rank remains positive and statistically significant, while the raw spread becomes statistically insignificant. These results indicate that performance rank, not raw performance, determines fund flows in the MMF industry.[22] In terms of economic importance, moving from the lowest to the highest rank of past performance increases subsequent fund flows by roughly 1% per week, which implies that a fund could increase its annual revenue by roughly 68% by moving from the lowest to the highest rank.[23]

In the mutual fund literature, there is empirical evidence that the flow-performance relation

[22] Massa (1998) and Patel, Zeckhauser, and Hendricks (1994) obtained similar results for equity mutual funds. Moreover, since regression (7) includes time fixed effects, this result indicates that it is not even the performance relative to the time-varying industry average that determines money flows, but it is really the performance rank.

[23] An increase equal to the cross-sectional average of the within-fund standard deviation of *Spread Rank*, which is roughly 0.22, increases future fund flows by 0.23% per week, i.e. by 13% per year. A standard-deviation shock to *Spread*, which is roughly 40 bp, would increase fund flows only by 10% per week, i.e. by 5% per year.

is convex in raw performance. To check that convexity is not driving my results, I run regression (7) including also $Spread^2$ on the RHS to capture possible convexity effects. When only *Spread* and $Spread^2$ are included, they are both positive and statistically significant, indicating some convexity in the relation between money flows to MMFs and their raw performance. However, when *Spread Rank* is also included, both *Spread* and $Spread^2$ lose their statistical and economic significance, while *Spread Rank* remains positive and statistically and economically significant, indicating that it is really relative performance that matters in the MMF industry.

For robustness, I also run regression (7) using the rank of *Fund Flow* as the dependent variable to mitigate the effect of outliers without resorting to trimming (Table IA.3.1), and using only time fixed effects (Table IA.3.2). Results are similar. As further robustness checks, I also run regression (7) trimming the distribution of fund flows at different thresholds (e.g., 1% and multiples of the interquartile range), and on separate time windows. Results are similar and omitted for brevity.

For the period from January 2006 to August 2008, KS show that the flow-performance relation is not explicitly affected by the reputation concerns of fund sponsors. That is, investors do not risk-adjust fund yields based on sponsors' reputation concerns. In Appendix IA.3, I use their same regression specification to show that this is true starting from January 2002. This evidence indicates that the flow-performance relation can be taken as exogenous in the context of my model.

6.3 Risk-taking Pre and Post July 2007

In this section, I show that funds with lower default costs always take on more risk (prediction P.1) and that the cross-sectional risk-taking differential increases when either the risk premium goes up or the risk-free rate goes down (predictions P.2c and P.3b). Here I follow KS and do not disentangle the effect of risk premia from that of risk-free rates. That is, I am not testing predictions P.2c and P.3b separately. To make my results comparable to those of KS, I consider the sample from January 2006 to August 2008 and divide it into two sub-periods: January 2006–July 2007, characterized by relatively high risk-free rates and low risk premia, is referred to as the *Pre* period, and August 2007–August 2008, characterized by relatively low risk-free rates and high risk premia, is referred to as the *Post* period.

Preliminary empirical support for the above predictions is provided by Figure 1. Fig. 1 shows the net risky investment (*Holdings Risk*) of funds whose sponsors have reputation concerns (*Fund Business*) consistently below the industry median (dashed red line) and funds whose sponsors have reputation concerns consistently above the industry median (solid blue line). In my model, the first group corresponds to funds with relatively low default costs, while the second one corresponds to funds with relatively high default costs. Starting from July 2007 (Fig. 5), there was both a decrease in risk-free rates and an increase in the premia available to MMFs. As predicted by the model, Fig. 1 shows that funds with higher default costs tend to take on less risk over the whole period and that this differential increases in the period of high risk premia and low risk-free rates: funds with lower default costs do "reach for yield," while funds with higher default costs do

the opposite.

To give a quantitative estimate of this evidence, I run the following weekly regression on the balanced panel of MMFs continuously active from January 2006 to August 2008 (there are 122 such funds):

$$Risk_{i,t} = \alpha_i + \mu_t + \beta_1 FB\,Rank_{i,t-k} + \beta_2 Post_t * FB\,Rank_{i,t-k} + \gamma \cdot (X_{i,t-k}, Post_t * X_{i,t-k}) + \varepsilon_{i,t} \tag{8}$$

where $FB\ Rank_{i,t}$ is the rank of fund i's $Fund\ Business$ in week t and is expressed in percentiles normalized to $[0, 1]$. $FB\ Rank = 0$ for those funds whose sponsor has the lowest reputation concern, and $FB\ Rank = 1$ for those funds whose sponsor has the highest reputation concern. $Post$ is an indicator variable equal to 1 for the $Post$ period and 0 for the pre period. X is the set of fund-specific controls defined in (7), without $FlowVolatility$. Both $FB\ Rank$ and X are lagged by k weeks to mitigate endogeneity issues. For robustness, I run various regression specifications with different values of k, namely, $k = 1, 4, 8$, and 12 (i.e., 1 week, 1, 2, and 3 months). μ_t and α_i denote week and fund fixed effects, respectively. I use four measures of fund risk-taking ($Risk$): $Holdings\ Risk$, $Holdings\ Risk^{dyn}$, $Maturity\ Risk$, and $Spread$, as defined in Section 6.1.

The coefficients of interest are β_1 and β_2. β_1 measures the effect of reputation concerns on fund risk-taking in the Pre period. β_2 measures how this effect changes from the Pre to the $Post$ period. In the model, these coefficients correspond to the derivative of the equilibrium risky investment w.r.t. the cost of default in different interest rate environments. Since in the $Post$ period risk premia increased and risk-free rates decreased significantly, the model predicts: $\beta_1 < 0$ and $\beta_2 < 0$.

Table 3 shows the results for $k = 4$ and 8. Reported standard errors are heteroskedasticity autocorrelation spatial correlation (HACSC) robust to account for correlations within and across funds. Both β_1 and β_2 are negative for all measures of risk-taking, with β_2 being always statistically significant, and β_1 being statistically significant for all measures except $Holdings\ Risk^{dyn}$. The effects are also economically important. Going from the highest to the lowest rank of $Fund\ Business$ increases $Holdings\ Risk$ by roughly 7 percentage points (pp) in the Pre period and 14 pp in the $Post$ period, $Holdings\ Risk^{dyn}$ by roughly 4 pp in the Pre period and 12 pp in the $Post$ period, portfolio maturity by roughly 5 days in the Pre period and 12 days in the $Post$ period, and spread by roughly 4 bp in the Pre period and 13 bp in the $Post$ period.[24]

For robustness, I also run regression (8) using the share of safe holdings ($Safe\ Holdings$) as the dependent variable. In that case, the model predicts $\beta_1 > 0$ and $\beta_2 > 0$. Columns (7) and (8) of Table 3 show the results, which confirm the predictions of the model. Going from the highest to the lowest rank of $Fund\ Business$ decreases the holdings of safe assets by 1.2 percentage points in the Pre period and 7.5 percentage points in the $Post$ period, with the differential β_2 being statistically significant at the 1% level.

[24] At the weekly level, the overall standard deviation of $Holdings\ Risk$ is 23 pp, of $Holdings\ Risk^{dyn}$ is 24 pp, of $Maturity\ Risk$ is 12 days, and of $Spread$ is 68 bp.

Since in the model a fund's risky investment is determined by its rank in the distribution of default costs, the rank of *Fund Business* is a natural explanatory variable in regression (8). However, I also run regression (8) using raw *Fund Business* as the main explanatory variable. Results are similar and can be found in Table IA.4.1 in Appendix IA.4.

Contrary to KS, I find that funds with lower reputation concerns take on more risk also in the *Pre* period. To check the robustness of my results, in Appendix IA.4, I run the exact same regression specification as KS. Results are in Table IA.4.2 and are quantitatively and qualitatively similar to those of KS. The main difference is that for *Holdings Risk*, *Holdings Risk*^{dyn}, and *Safe Holdings*, the effect of *Fund Business* is statistically significant also in the *Pre* period, consistent with the results in Tables 3 and IA.4.1. On the other hand, as KS, for both *MaturityRisk* and *Spread*, I find that the effect of *Fund Business* is statistically insignificant in the *Pre* period. See Appendix IA.4 for a detailed discussion.

6.4 Risky investment in the time series: risk premium vs. risk-free rate

My model predicts that, holding the risk-free rate constant, an increase in the premium caused by an increase in the riskiness of the risky asset increases the risky investment of funds with lower default costs and decreases that of funds with higher default costs (predictions P.2a, b). On the other hand, holding the premium constant, a decrease in the risk-free rate decreases the risky investment of all funds (prediction P.3a). This section disentangles these two effects and shows evidence in support of model's predictions.

Hereafter, I consider the period from January 2002 to August 2008 and only MMFs that remain in the data set throughout the whole period. There are 85 such funds. On this balanced panel, I run the following regression:

$$\begin{aligned} Risk_{i,t} =& \alpha_i + \beta_{rp}\widehat{rp}_t + \beta^H_{rp}\widehat{rp}_t * High\ FB_i + \beta^L_{rp}\widehat{rp}_t * Low\ FB_i + \\ &+ \beta_{rf} rf_t + \beta^H_{rf} rf_t * High\ FB_i + \beta^L_{rf} rf_t * Low\ FB_i + \gamma \cdot X_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{9}$$

Risk is either *Holdings Risk*, *Holdings Risk*^{dyn}, or *Maturity Risk* defined as in Section 6.1.[25] $\widehat{rp}$ is a proxy for the risk premium: *Spread Index* in the main specification. rf is the return on 1-month T-bills. Since data on $\widehat{rp}$ are at the monthly level, weekly fund-specific data are averaged over months, and regression (9) is at the monthly level. $High\ FB_i$ ($Low\ FB_i$) is a dummy variable that is equal to 1 if fund i's *Fund Business* is above (below) the industry median over the whole period and 0 otherwise. X is the set of fund-specific controls defined in (8) plus *Fund Business*. All fund-specific time-varying controls are lagged to mitigate endogeneity issues. α_i denote fund fixed effects.

In terms of the model, $High\ FB_i = 1$ represents funds with high default costs, and $Low\ FB_i = 1$ represents funds with low default costs. $\beta_{rp} + \beta^H_{rp}$ and $\beta_{rf} + \beta^H_{rf}$ represent how the risky investment

[25] Since *Spread* mechanically covaries with the risk-free rate, I do not use it as proxy for risk-taking in (9).

of MMFs with higher default costs responds to changes in the risk premium and risk-free rate, respectively. $\beta_{rp} + \beta_{rp}^L$ and $\beta_{rf} + \beta_{rf}^L$ represent the corresponding sensitivities for funds with lower default costs. The model predicts: $\beta_{rp} + \beta_{rp}^H < 0 < \beta_{rp} + \beta_{rp}^L$, and $\beta_{rf} + \beta_{rf}^H > \beta_{rf} > \beta_{rf} + \beta_{rf}^L > 0$. For robustness, I also run regression (9) with $Safe\ Holdings$ as dependent variable. In that case, the inequalities are reversed.

Table 4 shows the results. Reported standard errors are HACSC robust to account for correlations within and across funds. The results confirm the predictions of the model. As for the effect of the risk premium, an increase of 1% in $Spread\ Index$ generates a clear bifurcation in the cross-section of funds: funds whose sponsors have $Fund\ Business$ consistently below the median increase their $Holdings\ Risk$ by 3.1 pp and their $Holdings\ Risk^{dyn}$ by 6.9 pp, while funds whose sponsors have $Fund\ Business$ consistently above the median decrease their $Holdings\ Risk$ by 3.8 pp and their $Holdings\ Risk^{dyn}$ by 2.2 pp. These results are statistically significant and economically important.[26] We observe a qualitatively similar bifurcation also when risk-taking is measured as $Maturity\ Risk$ or $Safe\ Holdings$: funds with low default costs increase their portfolio maturity by 3.8 days (statistically significantly) and decrease the share of safe assets in their portfolios by 0.5 pp, while funds with high default costs increase the share of safe assets in their portfolios by 1.1 pp (statistically significantly) and decrease their portfolio maturity by 3.2 days.

Changes in the risk-free rate have different effects depending on whether risk-taking is measured in terms of portfolio holdings or maturity. After a decrease of 1% in the 1-month T-bill rate, funds with high default costs decrease their $Holdings\ Risk$ by 25.6 pp, their $Holdings\ Risk^{dyn}$ by 41.4 pp, and increase their $Safe\ Holdings$ by 25.8 pp, as predicted by the model. These effects are statistically significant at the 1% level and economically important.[27] The effects on funds with low default costs have the same sign but are smaller in magnitude for $Holdings\ Risk$ (−20.8 pp) and $Safe\ Holdings$ (+19.9 pp), as predicted by the model. On the other hand, I find that a decrease in the risk-free rate increases the portfolio maturity of all funds. A decrease of 1% in the 1-month T-bill rate increases $Maturity\ Risk$ by 23.3 days for funds with high default costs and by 33.3 days for funds with low default costs. Both effects are statistically and economically significant.

These results indicate that holding the risk premium constant, lower risk-free rates cause MMFs to tilt their portfolios toward safer asset classes, as predicted by the model and contrary to the conventional "reach for yield" argument. However, this shift to safer assets is partly compensated by a lengthening of portfolio maturity. Since my model is static and considers only credit risk, it cannot predict this counterbalancing portfolio adjustment.

In the model, funds with higher default costs decrease their risk-taking after an increase in the premium because the increase in the premium is assumed to be accompanied by an increase in the default risk of the risky asset. Absent the increase in default risk, all funds should increase their risk-

[26] Over the period of analysis, the standard deviation of $Spread\ Index$ is 0.45%. At the monthly level, the overall standard deviation of $Holdings\ Risk$ is 25%, of $Holdings\ Risk^{dyn}$ is 26%, of $Maturity\ Risk$ is 14 days, and of $Safe\ Holdings$ is 18%. See Table 2 for more summary statistics.

[27] Over the period of analysis, the standard deviation of the 1-month T-bill rate is 0.12%.

taking after an increase in the premium, with the effect being stronger for funds with lower default costs (see Section 4.1). Table 5 shows the results of regression (9) when the risk premium is proxied with *GZ Premium*, which by construction does not reflect default risk. In agreement with model predictions, an increase of *GZ Premium* increases the risk-taking of all MMFs, with the effect being more statistically and economically significant for the funds with lower *Fund Business*. As for the effect of the risk-free rate, the results in Table 5 are qualitatively and quantitatively similar to those obtained when the premium is proxied with *Spread Index*, confirming the predictions of the model on the effect of risk-free rates on the asset class composition of MMF portfolios.

As robustness checks, I run regression (9) using the 3-month T-bill rate as a proxy for the risk-free rate (Table IA.4.3), and lagging all fund-specific time-varying RHS variables by 2 months (Table IA.4.4). I also estimate regression (9) using the distribution of *Fund Business* in month $t-1$ to identify funds with high and low default costs in month t (i.e., both *High FB* and *Low FB* are time-varying and lagged by one month w.r.t. the LHS variable). The details of this latter specification are in Appendix IA.4, and results are in Table IA.4.5. For all these robustness checks, results are similar to those in Table 4.

Finally, as predicted by the model and observed in Section 6.3, regression (9) also shows that over the whole period January 2002–August 2008, funds with lower *Fund Business* tend to take on more risk on average, with the effect being statistically significant for *Holdings Risk*, *Holdings Risk*^{dyn}, and *Safe Holdings*. On the other hand, the effect of *Fund Business* on *Maturity Risk* is not statistically significant.

6.5 Cross-sectional risk-taking differential: risk premium vs. risk-free rate

This section focuses on the cross-sectional risk-taking differential, for which identification of the effects of risk premia and risk-free rates is easier than for the level of risky investment in the time series. My model predicts that the cross-sectional risk-taking differential increases not only when the risk premium goes up (P.2c) but also when the risk-free rate goes down (P.3b). To test both predictions at the same time and disentangle the two effects, I run the following regression on the sample of MMFs continuously active from January 2002 to August 2008:

$$Risk_{i,t} = \alpha_i + \mu_t + \beta_1 FB\ Rank_{i,t-1} * \widehat{rp}_t + \beta_2 FB\ Rank_{i,t-1} * rf_t + \gamma \cdot X_{i,t-1} + \varepsilon_{i,t} \tag{10}$$

where *Risk*, *FB Rank*, and X are defined as in (8), with the only difference that now X also includes the interaction terms of all controls with $\widehat{rp}$ and rf. $\widehat{rp}$ is a proxy for the risk premium: *Spread Index* in the main specification. rf is the 1-month T-bill return. Since *Spread Index* is estimated at the monthly level, regression (10) is also at the monthly level. Fund-specific weekly-observed quantities are averaged over months. All RHS fund-specific variables are lagged by 1 month to mitigate endogeneity issues. μ_t and α_i denote time and fund fixed effects, respectively. The inclusion of time fixed effects prevents me from identifying the effect of risk premia and risk-free

rates on the level of MMF risk-taking but allows me to control for all time-varying macroeconomic conditions affecting it.

The coefficients of interest are β_1 and β_2. In the context of the model, β_1 represents the cross-derivative of fund risky investment w.r.t. the cost of default and the risk premium. β_2 represents the cross-derivative of fund risky investment w.r.t. the cost of default and the risk-free rate. The model predicts: $\beta_1 < 0$ (prediction P.2c) and $\beta_2 > 0$ (prediction P.3b). For robustness, I also run regression (10) using *Safe Holdings* as dependent variable. In that case, the inequalities are reversed.

Results are in Table 6 and confirm the predictions of the model. Reported standard errors are HACSC robust to account for correlations within and across funds. First, funds with lower *Fund Business* rank (i.e., with lower default costs) always take on more risk in terms of *Holdings Risk*, *Holdings Risk*^{dyn}, and *Safe Holdings*, as predicted by the model and observed in Sections 6.3 and 6.4. As for the effect of the risk premium, after an increase of 1% in *Spread Index*, the cross-sectional risk-taking differential between funds in the lowest and highest percentile of *Fund Business* increases by 6.5 pp when measured in terms of *Holdings Risk*, by 8.1 pp when measured in terms of *Holdings Risk*^{dyn}, by 3.5 days when measured in terms of *Maturity Risk*, by 6.7 bp when measured in terms of *Spread*, and by 4.5 pp when measured in terms of *Safe Holdings*. The results for *Safe Holdings*, *Maturity Risk*, and *Spread* are statistically significant at the 1% level, while those for *Holdings Risk* and *Holdings Risk*^{dyn} are significant at the 5% level. Since the standard deviation of *Spread Index* over the period of analysis is 0.45%, all these results are also economically important. In fact, the time-series standard deviation of the within-month average risk-taking differential between funds in the lowest and highest percentile of *Fund Business* is 23.8 pp for *Holdings Risk*, 23.6 pp for *Holdings Risk*^{dyn}, 9.4 days for *Maturity Risk*, 8.7 bp for *Spread*, and 13.9 pp for *Safe Holdings*.

As for the effect of the risk-free rate, after a decrease of 1% in the 1-month T-bill rate, the cross-sectional risk-taking differential between funds in the lowest and highest percentile of *Fund Business* increases by 49.0 pp when measured in terms of *Holdings Risk*, by 45.3 pp when measured in terms of *Holdings Risk*^{dyn}, by 10.6 days when measured in terms of *MaturityRisk*, by 6.5 bp when measured in terms of *Spread*, and by 31.1 pp when measured in terms of *Safe Holdings*. The results for *Holdings Risk*, *Holdings Risk*^{dyn}, and *Safe Holdings* are statistically significant at the 1%, while that for *Maturity Risk* is statistically significant at the 10% level.[28] Since the standard deviation of the 1-month T-bill rate over the period of analysis is 0.13%, all these results are also economically important.

I run several robustness checks that can be found in Appendix IA.4. I run regression (10) using *Fund Business* instead of its rank as the main explanatory variable (Table IA.4.6), using *GZ Premium* as a proxy for $\widehat{rp}$ (Table IA.4.7), using the 3-month T-bill rate as a proxy for rf (Table IA.4.8), and lagging all fund-specific RHS variable by two months instead of one (Table IA.4.9).

[28]The results for *Spread* may be insignificant because *Spread* does not necessarily reflect active risk-taking.

Results are always similar and confirm the predictions of the model.

7 Conclusions

In this paper, I propose a novel tournament model of money market funds (MMFs) to study whether competition over relative performance generates "reach for yield" in a low risk-free rate environment. First, the model shows that in equilibrium competitive pressure is heterogeneous across funds: funds with lower default costs face a higher competitive pressure and therefore take on more risk. Second, the model shows that to understand the "reach for yield" of MMFs, it is critical to distinguish the role of risk-free rates from that of risk premia. When the risk premium increases because of an increase in the riskiness of the underlying asset, this generates a bifurcation in the fund population: funds with lower default costs increase their risky investment because, facing higher competitive pressure, they are more sensitive to the increase in the chance of outperforming their competitors; funds with higher default costs decrease their risky investment because, aiming to keep the default probability closer to zero, they are more sensitive to the increase in the probability of low returns. On the other hand, contrary to the standard view, low risk-free rates reduce the risky investment of all funds, with the effect being stronger for funds with higher default costs. This is because a decrease in the risk-free rate increases the buffer of safe assets necessary to keep the probability of default at the equilibrium level.

The empirical analysis is over the period January 2002–August 2008 and confirms the predictions of the model. When risk premia increased, funds whose sponsors had low reputation concerns (i.e., funds with low default costs) increased risk-taking, while funds whose sponsors had high reputation concerns decreased risk-taking. On the other hand, holding the premium constant, when risk-free rates decreased, all funds shifted their portfolios toward safer asset classes. Finally, I also show that the performance rank, not the raw performance, determines money flows to MMFs, justifying the modeling assumption of a tournament and showing that relative performance competition is indeed a key incentive for MMFs.

These results shed light on the transmission of monetary policy to MMFs and contribute to the recent debate on the new regulation recently approved by the SEC. The risk-free rate (i.e., the return on Treasuries) affects fund risk-taking through the risk of "breaking the buck" typical of MMFs, which comes from the fact that they aim to keep a stable NAV. This channel of monetary policy, peculiar to MMFs, goes in the opposite direction of the conventional "reach for yield" argument and reduces fund risk-taking in a low risk-free rate environment. Under the new regulation, taking effect in October 2016, institutional prime funds will move from a stable NAV to a floating NAV. This institutional change, while possibly eliminating the risk of runs, might actually lead all institutional prime MMFs to take on more risk.

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	$Fund\ Flow_{i,t+1}$				
	(1)	(2)	(3)	(4)	(5)
$Spread\ Rank_{i,t}$		1.107***	1.040***		1.011***
		(0.149)	(0.158)		(0.152)
$Spread_{i,t}$ (%)	1.558**		0.255	1.494***	0.269
	(0.695)		(0.301)	(0.501)	(0.238)
$Spread^2_{i,t}$				0.283*	0.100
				(0.160)	(0.100)
$Log(Fund\ Size)_{i,t}$	−1.196***	−1.239***	−1.239***	−1.204***	−1.241***
	(0.181)	(0.180)	(0.180)	(0.182)	(0.181)
$Expense\ Ratio_{i,t}$	−0.002	−0.002	−0.002	−0.002	−0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$Age_{i,t}$	−0.122***	−0.121**	−0.121**	−0.121**	−0.120**
	(0.047)	(0.049)	(0.049)	(0.048)	(0.049)
$Flow\ Volatility_{i,t}$	−0.021*	−0.011	−0.013	−0.034*	−0.018
	(0.012)	(0.008)	(0.008)	(0.018)	(0.011)
$Log(Family\ Size)_{i,t}$	−0.050	−0.046	−0.046	−0.053	−0.048
	(0.061)	(0.061)	(0.060)	(0.060)	(0.060)
Week fixed effect	Y	Y	Y	Y	Y
Fund fixed effect	Y	Y	Y	Y	Y
Observations	48,543	48,543	48,543	48,543	48,543
Adj. R^2 (within)	0.007	0.009	0.009	0.008	0.009
R^2 (overall)	0.042	0.043	0.043	0.042	0.043

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1: Flow-performance relation: performance rank matters more than raw performance. The sample is all U.S. institutional prime MMFs from 1/1/2002-8/31/2008. The dependent variable is $Fund\ Flow$, computed as the percentage change in total net assets from week t to week $t+1$, adjusted for earned interests and trimmed at the 0.5%. Independent variables are the weekly annualized spread from $t-1$ to t, its rank in percentiles normalized to $[0,1]$, logarithm of fund size, fund expense ratio, fund age, volatility of fund flows based on past 12-week fund flows, and logarithm of fund family size. All regressions are at the weekly level and include week and fund fixed effects. Standard errors are HAC robust. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively.

	Min	1st Qu.	Median	Mean	3rd Qu.	Max.	Std. Dev.
Fund default cost							
Fund Business	0.00	0.59	0.74	0.71	0.90	1.00	0.23
Fund risk-taking							
Holdings Risk (%)	−100.0	−20.3	−5.4	−7.8	6.5	73.0	25.0
Holdings Risk^{dyn} (%)	−100.0	−21.0	−5.8	−7.4	6.5	97.0	26.1
Safe Holdings (%)	0.0	8.3	17.8	21.5	29.6	100.0	18.2
Maturity Risk (days)	1.0	34.5	43.8	43.5	52.3	90.0	13.7
Spread (bp)	−260.3	16.4	29.3	40.9	45.0	322.1	47.8
Macroeconomic variables							
1-month T-bill rate (%)	0.06	0.10	0.16	0.21	0.34	0.43	0.12
Spread Index (%)	0.04	0.12	0.17	0.37	0.32	1.88	0.45
GZ Premium (%)	−0.68	−0.38	−0.27	−0.04	0.25	1.95	0.56

Table 2: Overall summary statistics of the proxies for fund default costs, fund risk-taking, and macroeconomic conditions (i.e., risk-free rate and risk premium). For fund-level variables, the sample is all US institutional prime MMFs from January 2002 to August 2008. Data are monthly. *Fund Business* is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. *Holdings Risk* is the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of US treasuries, GSE debt, and repos (i.e., the safe assets) in a fund's portfolio. For each month, *Holdings Risk*^{dyn} is the percentage of that month's riskiest asset class (as identified through regression (A.1) in Appendix A) net of safe assets in a fund's portfolio. *Safe Holdings* is the percentage of safe assets in a fund's portfolio. *Maturity Risk* is the average portfolio maturity in days. *Spread* is a fund's annualized gross yield minus the yield of the 1-month T-bill in basis points. As for the macroeconomic variables, *Spread Index* is the index of spreads of the risky securities available to prime MMFs defined by (6). *GZ Premium* is the excess bond premium for financial firms from Gilchrist and Zakrajsek (2012).

	$Holdings\ Risk_{i,t}$		$Holdings\ Risk^{dyn}_{i,t}$		$Maturity\ Risk_{i,t}$		$Spread_{i,t}$		$Safe\ Holdings_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	k=4	k=8	k=4	k=8	k=4	k=8	k=4	k=8	k=4	k=8
$FB\ Rank_{i,t-k}$	-6.628^{***}	-6.449^{***}	-1.178	-0.954	-5.183^{**}	-4.325^{*}	-4.123	-5.044^{*}	1.207	0.941
	(2.157)	(2.141)	(3.288)	(3.553)	(1.841)	(2.032)	(2.820)	(2.656)	(1.914)	(1.927)
$FB\ Rank_{i,t-k} * Post_t$	-7.541^{**}	-7.159^{**}	-8.427^{*}	-7.998^{*}	-6.962^{***}	-6.895^{***}	-8.790^{***}	-8.796^{***}	5.214^{***}	4.966^{***}
	(2.573)	(2.481)	(4.197)	(3.932)	(1.553)	(1.596)	(2.268)	(2.266)	(1.680)	(1.601)
$Controls_{i,t-k}$	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
$Controls_{i,t-k} * Post_t$	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	16,470	15,982	16,470	15,982	16,470	15,982	16,470	15,982	16,470	15,982
Adj. R^2 (within)	0.027	0.026	0.012	0.012	0.044	0.041	0.014	0.014	0.022	0.021
R^2 (overall)	0.759	0.762	0.463	0.459	0.588	0.591	0.960	0.960	0.756	0.759

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3: Cross-sectional risk-taking differential in the *Pre* and *Post* period. The sample is all U.S. institutional prime MMFs continuously active from 1/1/2006 to 8/31/2008 ($n = 122$). Data are weekly ($T = 139$). The dependent variables are: the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., US treasuries, GSE debt, and repos) in a fund's portfolio (*Holdings Risk*) in columns (1)–(2); the percentage of each week's riskiest asset class net of safe assets in a fund's portfolio ($Holdings\ Risk^{dyn}$) in columns (3)–(4); average portfolio maturity (*Maturity Risk*) in days in columns (5)–(6); the weekly annualized fund spread (*Spread*) in basis points in columns (7)–(8); and the percentage of safe assets in a fund's portfolio (*Safe Holdings*) in columns (9)–(10). For a detailed discussion of $Holdings\ Risk^{dyn}$, see Section 6.1 and Appendix A. *FB Rank* is the rank of *Fund Business*, which is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. *FB Rank* is expressed in percentiles normalized to $[0, 1]$. *Post* is an indicator variable equal to 1 from 8/1/2007 to 8/31/2008, and 0 otherwise. The other independent variables (*Controls*) are fund assets, expense ratio, fund age, and fund family size. All regressions include week and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 12-week lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics are roughly 2.97, 2.20 1.82, respectively.

	(1)	(2)	(3)	(4)
	$Holdings\ Risk_{i,t}$	$Holdings\ Risk^{dyn}_{i,t}$	$Maturity\ Risk_{i,t}$	$Safe\ Holdings_{i,t}$
$\widehat{rp}_t$	−0.387	0.498	−1.091	−0.862
	(0.613)	(0.719)	(1.286)	(1.001)
$\widehat{rp}_t * Low\ FB_i$	3.533***	6.375***	4.920***	0.377
	(1.106)	(1.990)	(0.863)	(0.468)
$\widehat{rp}_t * High\ FB_i$	−3.450**	−2.717**	−2.145**	1.949***
	(1.329)	(1.052)	(0.957)	(0.631)
rf_t	24.207***	32.992***	−22.035***	−20.901***
	(6.320)	(5.261)	(5.475)	(3.154)
$rf_t * Low\ FB_i$	−3.372	13.622	−11.278*	0.943
	(3.597)	(7.455)	(5.408)	(3.169)
$rf_t * High\ FB_i$	1.359	8.448*	−1.228	−4.889
	(4.728)	(4.444)	(6.235)	(4.227)
$Fund\ Business_{i,t-1}$	−9.555*	−17.064**	1.629	3.457**
	(4.981)	(6.928)	(4.588)	(1.324)
$Controls_{i,t-1}$	Y	Y	Y	Y
Fund Fixed Effects	Y	Y	Y	Y
Observations	6,715	6,715	6,715	6,715
Adj. R^2 (within)	0.089	0.077	0.182	0.098
R^2 (overall)	0.654	0.429	0.448	0.656
$\beta_{rp} + \beta^L_{rp}$	3.146**	6.873**	3.829*	−0.485
$\beta_{rp} + \beta^H_{rp}$	−3.837***	−2.219*	−3.236	1.087*
$\beta_{rf} + \beta^L_{rf}$	20.835**	46.614***	−33.313***	−19.958***
$\beta_{rf} + \beta^H_{rf}$	25.566***	41.440***	−23.263**	−25.790***

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4: Reach for yield: risk premium vs. risk-free rate. The sample is all U.S. institutional prime MMFs continuously active from 1/1/2002 to 8/31/2008 ($n = 85$). Data are monthly ($T = 80$). The dependent variables are: the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., US treasuries, GSE debt, and repos) in a fund's portfolio ($Holdings\ Risk$) in column (1); the percentage of each month's riskiest asset class net of safe assets in a fund's portfolio ($Holdings\ Risk^{dyn}$) in column (2); average portfolio maturity ($Maturity\ Risk$) in days in column (3); and the percentage of safe assets in a fund's portfolio ($Safe\ Holdings$) in column (4). For a detailed discussion of $Holdings\ Risk^{dyn}$, see Section 6.1 and Appendix A. The risk premium $\widehat{rp}$ is the index of spreads available to MMFs defined by equation (6). The risk-free rate rf_t is the return on 1-month T-bills. $High$ (Low) FB_i is a binary variable equal to 1 if fund i's $Fund\,Business$ is continuously above (below) the cross-sectional median throughout the whole period, and 0 otherwise. $Fund\ Business$ is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. $Controls$ are: fund assets, expense ratio, fund age, fund family size, and $Fund\ Business$. All regressions include fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 8-month lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85. For the Wald statistics they are roughly 9.31, 4.94, and 3.35.

	(1)	(2)	(3)	(4)
	$Holdings\ Risk_{i,t}$	$Holdings\ Risk^{dyn}_{i,t}$	$Maturity\ Risk_{i,t}$	$Safe\ Holdings_{i,t}$
$\widehat{rp}_t$	4.358***	2.586**	0.286	−1.786***
	(0.700)	(0.963)	(1.411)	(0.543)
$\widehat{rp}_t * Low\ FB_i$	0.878*	6.011***	3.875***	−0.486
	(0.419)	(0.865)	(0.916)	(0.449)
$\widehat{rp}_t * High\ FB_i$	−1.950	−1.641*	2.021*	1.147
	(1.406)	(0.832)	(1.047)	(0.678)
rf_t	30.963***	36.923***	−22.176**	−24.162***
	(3.930)	(3.598)	(7.431)	(2.728)
$rf_t * Low\ FB_i$	−3.764	14.666**	−6.046	1.309
	(3.734)	(5.593)	(5.705)	(3.130)
$rf_t * High\ FB_i$	−0.889	7.689	2.340	−3.699
	(4.888)	(4.180)	(6.518)	(4.054)
$Fund\ Business_{i,t-1}$	−5.513	−11.855*	3.855	3.454***
	(6.454)	(5.863)	(3.208)	(0.955)
$Controls_{i,t-1}$	Y	Y	Y	Y
Fund Fixed Effects	Y	Y	Y	Y
Observations	6,715	6,715	6,715	6,715
Adj. R^2 (within)	0.102	0.087	0.186	0.103
R^2 (overall)	0.659	0.435	0.451	0.658
$\beta_{rp} + \beta^L_{rp}$	5.236***	8.597***	4.161*	−2.272*
$\beta_{rp} + \beta^H_{rp}$	2.408	0.945	2.307	−0.639
$\beta_{rf} + \beta^L_{rf}$	27.199***	51.589***	−28.222**	−22.853***
$\beta_{rf} + \beta^H_{rf}$	30.074***	44.612***	−19.836	−27.861***

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5: Reach for yield: risk premium vs. risk-free rate. The sample is all U.S. institutional prime MMFs continuously active from 1/1/2002 to 8/31/2008 ($n = 85$). Data are monthly ($T = 80$). The dependent variables are: the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., US treasuries, GSE debt, and repos) in a fund's portfolio ($Holdings\ Risk$) in column (1); the percentage of each month's riskiest asset class net of safe assets in a fund's portfolio ($Holdings\ Risk^{dyn}$) in column (2); average portfolio maturity ($Maturity\ Risk$) in days in column (3); and the percentage of safe assets in a fund's portfolio ($Safe\ Holdings$) in column (4). For a detailed discussion of $Holdings\ Risk^{dyn}$, see Section 6.1 and Appendix A. The risk premium $\widehat{rp}$ is the excess bond premium for financial firms from Gilchrist and Zakrajsek (2012). The risk-free rate rf_t is the return on 1-month T-bills. $High$ (Low) FB_i is a binary variable equal to 1 if fund i's $Fund\ Business$ is continuously above (below) the cross-sectional median throughout the whole period, and 0 otherwise. $Fund\ Business$ is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. $Controls$ are: fund assets, expense ratio, fund age, fund family size, and $Fund\ Business$. All regressions include fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 8-month lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85. For the Wald statistics they are roughly 9.31, 4.94, and 3.35.

	(1)	(2)	(3)	(4)	(5)
	$Holdings\ Risk_{i,t}$	$Holdings\ Risk^{dyn}_{i,t}$	$Maturity\ Risk_{i,t}$	$Spread_{i,t}$	$Safe\ Holdings_{i,t}$
$FB\ Rank_{i,t-1}$	-11.075^{**}	-3.512	4.120	-0.534	3.953^{*}
	(3.765)	(5.383)	(3.020)	(1.961)	(2.011)
$FB\ Rank_{i,t-1} * \widehat{rp}_t$	-6.459^{**}	-8.144^{**}	-3.516^{***}	-6.663^{***}	4.489^{***}
	(2.795)	(3.189)	(1.094)	(1.038)	(1.238)
$FB\ Rank_{i,t-1} * rf_t$	49.024^{***}	45.321^{***}	10.570^{*}	6.490	-31.093^{***}
	(10.856)	(12.640)	(5.642)	(4.934)	(8.867)
$Controls_{i,t-1}$	Y	Y	Y	Y	Y
$Controls_{i,t-1} * \widehat{rp}_t$	Y	Y	Y	Y	Y
$Controls_{i,t-1} * rf_t$	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y
Fund Fixed Effects	Y	Y	Y	Y	Y
Observations	6,715	6,715	6,715	6,715	6,715
Adj. R^2 (within)	0.042	0.018	0.025	0.107	0.021
R^2 (overall)	0.660	0.510	0.558	0.953	0.658

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 6: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime MMFs continuously active from 1/1/2002 to 8/31/2008 ($n = 85$). Data are monthly ($T = 80$). The dependent variables are: the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., US treasuries, GSE debt, and repos) in a fund's portfolio (*Holdings Risk*) in column (1); the percentage of each month's riskiest asset class net of safe assets in a fund's portfolio ($Holdings\ Risk^{dyn}$) in column (2); average portfolio maturity (*Maturity Risk*) in days in column (3); the annualized fund spread (*Spread*) in basis points in column (4); and the percentage of safe assets in a fund's portfolio (*Safe Holdings*) in column (5). For a detailed discussion of $Holdings\ Risk^{dyn}$, see Section 6.1 and Appendix A. *FB Rank* is the rank of *Fund Business*, which is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. *FB Rank* is expressed in percentiles normalized to $[0, 1]$. The risk premium $\widehat{rp}$ is the index of spreads available to MMFs defined by equation (6). The risk-free rate rf_t is the return on 1-month T-bills. *Controls* are: fund assets, expense ratio, fund age, fund family size, and their interaction terms with $\widehat{rp}$ and rf. All regressions include month and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 8-month lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85.

Appendix A Risk-taking opportunities of MMFs

This section analyzes the risk-taking opportunities of prime MMFs from January 2002 to August 2008 and identifies the riskiest (in the sense of having the largest spread w.r.t. treasuries) asset class available to MMFs in that period. To have a complete historical perspective and determine what asset classes have historically been perceived by MMFs as the riskiest ones, I also consider an extended time window, starting from January 1999. The analysis is at the level of the asset classes in MMF portfolios as reported by iMoneyNet. Since I do not directly observe the yield of the individual instruments, following KS I infer the spread of each instrument via the regression

$$Spread_{i,t+1} = \alpha_i + \mu_t + \sum_j \beta_j Holdings_{i,j,t} + \gamma \cdot X_{i,t} + \varepsilon_{i,t+1} \tag{A.1}$$

where $Spread_{i,t+1}$ is the gross yield of fund i in week t+1 minus the 1-month T-bill weekly return, $Holdings_{i,j,t}$ denotes fund i's fractional holdings of instrument type j in week t, α_i and μ_t denote fund and week fixed effects, respectively. The instrument types include repurchase agreements, time deposits, bank obligations (i.e., negotiable deposits), floating-rate notes, commercial papers, and asset-backed commercial papers. The omitted category is Treasuries and GSE debt. X is the set of fund-specific controls defined in (7) without $Flow\ Volatility$, which is not relevant for this analysis.[29] The coefficients of interest are β_j, which measure the return on money market instrument j in week $t+1$ relative to that of Treasuries and GSE debt.

Table A.1 shows the results. All standard errors are HAC robust. Columns (1) and (2) use weekly data. Columns (3) and (4) use monthly data (i.e., weekly variables are averaged over months, and regression (A.1) is run on this monthly sample). Columns (1) and (3) are for the period 01/1999–08/2008. Columns (2) and (4) are for the period 01/2002–08/2008. Similarly to the results of KS for the period 01/2006–08/2008, *Bank Obligations* show the largest contribution to fund yields relative to treasuries and GSE debt. This result holds true both for the period 01/2002–08/2008 and for the period 01/1999-08/2008. The yield of a fund fully invested in bank obligations would have been roughly 25 basis points higher than the yield of a fund fully invested in Treasury and agency debt. Right after bank obligations, $ABCP$ is the asset class with the largest contribution to fund spread.

To have a more granular identification of the riskiest asset class over time, I also split the sample in monthly and quarterly sub-periods and estimate regression (A.1) separately over these non-overlapping time windows using weekly data. For each sub-period, I calculate the rank of each asset class based on its contribution to fund spreads: asset class j has rank 1 if it has the largest contribution (i.e., largest β_j) and rank 1/6 if it has the smallest contribution (i.e., smallest β_j). Then, I take the average rank over the whole period. Column (5) shows the results when regression (A.1) is run on monthly sub-panels, and column (6) shows the results when regression (A.1) is run

[29] However, my results are robust to the inclusion of $Flow\ Volatility$ on the RHS of (A.1).

on quarterly sub-panels. *Bank Obligations* have the largest average rank, followed by *ABCPs*.

	$Spread_{i,t+1}$				*Average Rank*	
	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio Holdings						
$Repurchase\ Agreements_{i,t}$	9.08***	14.09***	7.38**	12.25***	0.496	0.402
	(3.20)	(3.83)	(3.32)	(3.83)		
$Time\ Deposits_{i,t}$	8.74**	5.87	5.33	1.19	0.556	0.513
	(4.43)	(5.42)	(6.28)	(6.72)		
$Bank\ Obligations_{i,t}$	23.26***	25.30***	21.87***	24.22***	0.625	0.679
	(3.27)	(4.08)	(3.24)	(3.87)		
$Floating\text{-}Rate\ Notes_{i,t}$	20.46***	22.80***	19.58***	21.93***	0.601	0.620
	(3.38)	(4.32)	(3.27)	(4.15)		
$Commercial\ Papers_{i,t}$	17.95***	21.11***	16.51***	19.79***	0.608	0.624
	(3.18)	(4.02)	(2.94)	(3.63)		
$Asset\text{-}Backed\ CP_{i,t}$	21.85***	24.28***	20.61***	22.75***	0.615	0.662
	(3.30)	(4.09)	(3.20)	(3.90)		
Fund Characteristics						
$Log(Fund\ Size)_{i,t}$	0.71*	1.30**	0.61	0.99*		
	(0.43)	(0.58)	(0.39)	(0.53)		
$Expense\ Ratio_{i,t}$	0.05	0.03	0.02	0.01		
	(0.03)	(0.03)	(0.03)	(0.03)		
$Age_{i,t}$	−0.12	−0.37	−0.14	−0.36*		
	(0.14)	(0.23)	(0.13)	(0.19)		
$Log(Family\ Size)_{i,t}$	−0.01	0.24	−0.02	0.26		
	(0.14)	(0.33)	(0.14)	(0.37)		
Time fixed effect	Y	Y	Y	Y		
Fund fixed effect	Y	Y	Y	Y		
Observations	68,846	49,133	15,978	11,377		
Adj. R^2 (within)	0.056	0.074	0.054	0.071		
R^2 (overall)	0.967	0.970	0.969	0.974		

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A.1: Contribution to fund yields by asset class. The sample is all U.S. institutional prime MMFs. The dependent variable, *Spread*, is the annualized fund yield minus the 1-month T-bill rate. Holdings variables are the fraction of assets invested in repurchase agreements, bank deposits, bank obligations, floating-rate notes, commercial papers (CP), and asset-backed CP. The omitted category is U.S. Treasury and GSE debt. Fund characteristics are logarithm of fund size, expense ratio, fund age, and logarithm of fund family size. All regressions are at the fund level. Columns (1) and (2) are at the weekly frequency. Columns (3) and (4) are at the monthly frequency (i.e., monthly averages of weekly observations). Columns (1) and (3) are for the period 1/1999-08/2008. Column (2) and (4) are for the period 1/2002-08/2008. All regressions include time and fund fixed effects. Standard errors are HAC robust. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. Columns (5) and (6) report the average monthly and quarterly rank of each asset class in terms of contribution to fund yields. The ranks are obtained from separate regressions on non-overlapping monthly and quarterly sub-periods, respectively (see Appendix A).

In view of the results of this section, bank obligations can be regarded as the riskiest security available to MMFs over the January 2002–August 2008 period, consistently with the result of KS for the January 2006–August 2008 period. This justifies the definition of the risk measure

Holdings Risk as the percentage of assets held in bank obligations net of U.S. treasuries, GSE debt, and repos.

Internet Appendix to
"Competition, Reach for Yield, and Money Market Funds"

Gabriele La Spada

This appendix contains supplemental material to the paper "Competition, Reach for Yield, and Money Market Funds." Appendix IA.1 contains the proofs of the theoretical results. Appendix IA.2 describes the data set and analyzes the distributional properties of the proxy for sponsor's reputation concerns (i.e., *Fund Business*). Appendix IA.3 presents robustness checks for the empirical results on the flow-performance relation. Appendix IA.4 presents robustness checks for the empirical results on fund risk-taking, in both the time series and the cross-section. Appendix IA.5 presents a random utility model that rationalizes a purely rank-based flow-performance relation from investors' perspective. Sections, equations, tables, and figures of the original paper are referred to with the same numbering as in the paper.

Appendix IA.1 Proofs

Here I introduce the following notation: $\Omega = (\underline{c}, \overline{c}) \subseteq \mathbb{R}_+$, and $\lambda(\cdot)$ is the measure induced by $F_C(\cdot)$. That is, for any $C = (c_1, c_2) \subseteq \Omega$, the measure of funds with default cost between c_1 and c_2 is $\lambda(C) = F_C(c_2) - F_C(c_1)$. Hereafter, "NE" stands for Nash equilibrium.

Preliminary general results

Before proving the results in the main text, I prove some general properties of any NE of the tournament under the following, more general definition of ex post rank of fund performance:

$$Rk_\pi(c) := \int_{\{c':\pi_{c'}<\pi_c\}} \mathrm{d}F_C(c') + \delta \int_{\{c':\pi_{c'}=\pi_c\}} \mathrm{d}F_C(c'), \qquad \text{with } \delta \in [0,1].$$

Under this more general definition of performance rank, the flow of outside investors' money into a fund at the end of the tournament is equal to the mass of funds with strictly worse performance plus a term proportional to the mass of funds with equal performance. The results presented in the body of the paper are for the special case $\delta = 0$. From the funds' perspective, we can interpret δ as a "premium" for pooling. In a general equilibrium setting, we would expect that the more risk-averse the outside investors are, the closer to zero δ would be. This is because if investors infer managers' skills from their performance, they would penalize the uncertainty coming from a pool of funds having the same ex post performance. Under the above general definition of performance rank, I show that if δ is smaller than some critical value depending only on the return distribution, the equilibrium risky investment must be: above x_0 and below D for almost every fund, without jump discontinuities, and strictly decreasing with default costs almost everywhere in the fund population. Moreover, in the limit of the highest default cost, the equilibrium risky investment is exactly x_0.

First, it is straightforward to show by substitution that for a given strategy profile $x : \Omega \to [0, D]$, the objective function of player c is

$$\begin{aligned} \upsilon_c(x) =& \gamma D \left\{a + F_R(R_f) + 2qF_X(x)\right\} - \left\{\gamma D \left[a + 1 - F_X(x)\right] + c\right\} F_R\left(R_0(x)\right) + \\ &+ \gamma D \left\{\delta \left[1 - F_R\left(R_0(x)\right)\right] - F_R(R_f) + F_R\left(R_0(x)\right)\right\} \lambda\left(C_x\right), \end{aligned}$$

where $q = 0.5 - F_R(R_f)$, $R_0(x) = R_f - (R_f - 1)\frac{D}{x}$ and $C_x = \{c \in \Omega : x(c) = x\}$. Note that $R_0(x)$ is continuous, strictly increasing, and $R_0(x_0) = \underline{R}$. Hence, $F_R(R_0(x)) = 0$ for all $x \leq x_0$.

Lemma 2. *Suppose there exists a NE $x : \Omega = (\underline{c}, \overline{c}) \to [0, D]$ s.t. $x(c) \in (x_0, D]$ for all $c \in C_1$, and $x(c) \in [0, x_0]$ for all $c \in \Omega \setminus C_1$. Then, C_1 cannot be divided into two disjoint positive measure closed subsets,* $\inf C_1 = \underline{c}$*, and $x(c)$ is weakly decreasing a.e. on C_1.*

Proof. By contradiction, suppose that there exist two positive measure sets $C_a \subseteq \Omega$ and $C_b \subseteq C_1$ s.t. $\sup C_a < \inf C_b$ and $\sup\limits_{c \in C_a} x(c) < \inf\limits_{c \in C_b} x(c)$. For notational simplicity, let $x_a = x(c_a)$ for any $c_a \in C_a$, and $x_b = x(c_b)$ for any $c_b \in C_b$. Since C_a is assumed to have positive measure, by definition of NE, there exist some $c_a \in C_a$ s.t. $\upsilon_{c_a}(x_a) \geq \upsilon_{c_a}(x)$ for all x. Then, for all $c_b \in C_b$,

$$\begin{aligned} \upsilon_{c_b}(x_a) &= \upsilon_{c_a}(x_a) - (c_b - c_a) F_R\left(R_0(x_a)\right) \geq \upsilon_{c_a}(x_b) - (c_b - c_a) F_R\left(R_0(x_a)\right) \\ &= \upsilon_{c_b}(x_b) + (c_b - c_a)\left[F_R\left(R_0(x_b)\right) - F_R\left(R_0(x_a)\right)\right] > \upsilon_{c_b}(x_b), \end{aligned}$$

which contradicts the optimality of the NE for a positive measure set of players. □

Proposition 8. *Suppose there exists a NE $x : \Omega = (\underline{c}, \overline{c}) \to [0, D]$ s.t. $x(c) = D$ for all $c \in C_0$, $x(c) \in (x_0, D)$ for all $c \in C_1$, and $x(c) \in [0, x_0]$ for all $c \in C_2 = \Omega \setminus \{C_0 \cup C_1\}$.*

If $\delta < 1 - F_R(R_f)$, then

(i) $x(c) \in (x_0, D]$ a.e. on Ω (i.e., C_2 has measure zero);

(ii) neither C_0 nor C_1 can be divided into two disjoint positive measure closed subsets, $\inf C_0 = \underline{c}$*, and* $\sup C_1 = \overline{c}$*;*

(iii) $x(c)$ is strictly decreasing and equal to a continuous function a.e. on C_1;

(iv) $\lim\limits_{c \to \overline{c}} x(c) = x_0$ *if* $\overline{c} > \gamma D \left[\delta\left(1 - F_R(1)\right) - F_R(R_f) - aF_R(1)\right] / F_R(1)$.

If $\delta < \frac{F_R(R_f) - F_R(1)}{1 - F_R(1)}$ ($< 1 - F_R(R_f)$ by Assumption 1), then

(v) $x(c) \in (x_0, D)$ a.e. on Ω (i.e., both C_0 and C_2 have measure zero);

(vi) $x(c)$ is strictly decreasing and equal to a continuous function a.e. on Ω;

(vii) $\lim\limits_{c \to \overline{c}} x(c) = x_0$.

Proof. (i) By contradiction, suppose that C_2 has positive measure, i.e. $\lambda(C_2) > 0$. First, let C_a and C_b be two positive measure subsets of C_2 s.t. $\sup_{c \in C_a} x(c) \leq \inf_{c \in C_b} x(c)$. For notational simplicity, let $x_a = x(c_a)$ and $\lambda_a = \lambda(\{c : x(c) = x_a\})$ for any $c_a \in C_a$. By construction, $\lambda(C_2) - F_x(x_a) \geq \lambda(C_b) > 0$ and $\lambda(C_2) - F_x(x_a) - \lambda_a \geq 0$ for all $c_a \in C_a$. Second, for sufficiently small $\varepsilon > 0$,

$$\begin{aligned} \upsilon_{c_a}(x_0 + \varepsilon) = & \gamma D \{a + F_R(R_f) + 2q\lambda(C_2)\} - \{\gamma D [a + 1 - \lambda(C_2)] + c_a\} F_R(R_0(x_0 + \varepsilon)) + \\ & + g(\varepsilon)\gamma D [2q + F_R(R_0(x_0 + \varepsilon))], \end{aligned}$$

where $g(\varepsilon) = \lambda(\{c \in C_1 : x(c) < x_0 + \varepsilon\}) \geq 0$. Hence, if $\delta < 1 - F_R(R_f)$, for all $c_a \in C_a$, there exists a sufficiently small $\varepsilon > 0$ s.t.

$$\begin{aligned} \upsilon_{c_a}(x_0 + \varepsilon) \geq & \upsilon_{c_a}(x_a) + \gamma D\{2q [\lambda(C_2) - F_X(x_a) - \lambda_a] + \lambda_a [1 - F_R(R_f) - \delta]\} + \\ & - \{\gamma D [a + 1 - \lambda(C_2)] + c_a\} F_R(R_0(x_0 + \varepsilon)) > \upsilon_{c_a}(x_a), \end{aligned}$$

which contradicts the optimality of the NE for a positive measure set of players.

(ii) It follows directly from (i) and Lemma 2.

(iii) *Monotonicity.* The proof is very similar to that of (i), and the details are thus omitted. The idea is that if the "premium" for pooling is sufficiently small ($\delta < 1 - F_R(R_f)$), pooling in the region (x_0, D) cannot be a best response for a positive measure set of players because each of the players playing the pooling strategy would be strictly better off by infinitesimally increasing her risky investment so that her expected performance rank (and therefore her expected payoff) increases by a finite amount (proportional to the measure of pooling players), while her default risk only increases by an infinitesimal amount (because of continuity of the return distribution).

(iii) *Continuity.* Since by the rules of the game (i.e., no-short-selling and no-borrowing) the NE can only take values in $[0, D]$, proving that it is equal to a continuous function a.e. amounts to prove that it cannot have jump discontinuities. The proof is similar to that of (i), and the details are thus omitted. The idea is that for any jump size, there is at least some player on the LHS of the jump that would be strictly better off by reducing her risky investment by a finite amount so that her default risk decreases by a finite amount, while her expected performance rank does not change (since the NE is strictly decreasing a.e. on C_1). By continuity of the payoff function w.r.t. player type, this is true for a positive measure set of players on the LHS of the jump.

(iv) The exact statement is that on a subset $C \subseteq \Omega$ s.t. $\lambda(\Omega \setminus C) = 0$, $\lim_{c \to \bar{c},\, c \in C} x(c) = x_0$. The proof is similar to that of (i), and the details are thus omitted. The idea is the following. First, since the NE is bounded in $[0, D]$ by the game rules and is weakly decreasing a.e. on Ω, there exists a subset C with $\lambda(\Omega \setminus C) = 0$ s.t. the limit exists. Second, the limit cannot be in (x_0, D) because the NE, and hence the expected performance rank, is strictly decreasing a.e. on C_1. Therefore, a positive measure set of players in a sufficiently small left-neighborhood of $\bar{c}$ would be strictly better off by reducing their risky investment to x_0 because the gain from lowering their

default risk to zero strictly offsets the small loss in expected performance rank. Finally, if the maximum cost of default among players (i.e., $\overline{c}$) is sufficiently high, it cannot be $\lim_{c \to \overline{c},\, c \in C} x(c) = D$ either. Since the NE is weakly decreasing a.e. on Ω, that limit would imply $x(c) = D$ a.e. on Ω. If $\overline{c} > \gamma D \left[\delta \left(1 - F_R(1)\right) - F_R(R_f) - aF_R(1)\right] / F_R(1)$, the gain from lowering the default risk to zero by investing exactly x_0 in the risky asset would strictly offset the loss due to deviating from the poling strategy for a positive measure set of players in a left-neighborhood of $\overline{c}$.

(v) From (i), we already know that $x(c) \in (x_0, D]$ a.e. on Ω. We only need to show that the pooling strategy $x(c) = D$ cannot be a best response for a positive measure set of players (i.e., $\lambda(C_0) = 0$). The proof is very similar to that of monotonicity in (iii) and is thus omitted.

(vi) It follows directly from (iii) and (v).

(vii) The proof is the same as the first part of the proof of (iv) and is thus omitted. □

Proof of the results in the main text

Here I derive the unique NE of the tournament under the definition of performance rank used in the main text ($\delta = 0$). Hereafter I drop the "a.e." notation. Statements on properties of the NE such as monotonicity and differentiability are to be interpreted as valid a.e. in the fund population.

Proof of Proposition 1. From Proposition 8, it follows that under $\delta = 0$, any NE is strictly decreasing and has no jumps. Let $x : \Omega = (\underline{c}, \overline{c}) \to (x_0, D)$ be a NE, and let $x[\Omega] \subseteq (x_0, D)$ be its image. From strict monotonicity, it follows that $F_X(y) = 1 - F_C(x^{-1}(y))$ for all $y \in x[\Omega]$, where $x^{-1}(\cdot)$ is the inverse of $x(\cdot)$. For any NE, fund c's payoff for investing $y \in x[\Omega]$ can be written as

$$\upsilon(y, c) = A(x^{-1}(y)) - B(x^{-1}(y), c)G(y),$$

where

$$\begin{aligned} A(x^{-1}(y)) &= \gamma D \left\{a + F_R(R_f) + \left[1 - 2F_R(R_f)\right]\left[1 - F_C(x^{-1}(y))\right]\right\}, \\ B(x^{-1}(y), c) &= \left\{\gamma D \left[a + F_C(x^{-1}(y))\right] + c\right\}, \\ G(y) &= F_R\left(R_0(y)\right). \end{aligned}$$

By optimality of the NE, for any Δc we have:

$$A(c) - B(c, c)G(x(c)) \geq A(c + \Delta c) - B(c + \Delta c, c)G(x(c + \Delta c)),$$

and

$$A(c + \Delta c) - B(c + \Delta c, c + \Delta c)G(x(c + \Delta c)) \geq A(c) - B(c, c + \Delta c)G(x(c)).$$

Since F_R is absolutely continuous by assumption, and $R_0(\cdot)$ is continuously differentiable on (x_0, D),

with strictly positive first derivative, by using the mean value theorem on $G(\cdot)$ we can write

$$\frac{[A(c+\Delta c)-A(c)]-[B(c+\Delta c,c)-B(c,c)]\,G(x(c))}{B(c+\Delta c,c)G'(x^*)} \leq x(c+\Delta c)-x(c)$$

and

$$\frac{[A(c+\Delta c)-A(c)]-[B(c+\Delta c,c+\Delta c)-B(c,c+\Delta c)]\,G(x(c))}{B(c+\Delta c,c+\Delta c)G'(x^*)} \geq x(c+\Delta c)-x(c),$$

where $G'(\cdot)$ is the strictly positive first derivative of $G(\cdot)$, and $x^* \in (x(c), x(c+\Delta c))$. Combining the last two inequalities and dividing by $\Delta c > 0$, we obtain

$$\begin{aligned}\frac{[A(c+\Delta c)-A(c)]-[B(c+\Delta c,c+\Delta c)-B(c,c+\Delta c)]\,G(x(c))}{\Delta c\,B(c+\Delta c,c+\Delta c)G'(x^*)} &\geq \frac{x(c+\Delta c)-x(c)}{\Delta c}\\ \geq \frac{[A(c+\Delta c)-A(c)]-[B(c+\Delta c,c)-B(c,c)]\,G(x(c))}{\Delta c\,B(c+\Delta c,c)G'(x^*)}&.\end{aligned}$$

Since $x(c)$ has no jumps, the left- and right-most terms of this double inequality converge to

$$\frac{A'(c)-B'(c,c)G(x(c))}{B(c,c)G'(x(c))}$$

as $\Delta c \to 0$, where $A'(\cdot)$ is the first derivative of $A(\cdot)$, and $B'(\cdot,\cdot)$ is the first derivative of $B(\cdot,\cdot)$ with respect to the first argument. By plugging the explicit expressions for A, B, and G, we obtain

$$\frac{\mathrm{d}x}{\mathrm{d}c} = -\frac{\gamma D f_C(c)\,[2q+F_R\,(R_0(x(c)))]\,x(c)^2}{\{\gamma D\,[a+F_C(c)]+c\}\,f_R(R_0(x(c)))(R_f-1)D} < 0\,.$$

Therefore, by continuity of f_C and f_R, $x(c)$ is continuously differentiable, strictly decreasing with strictly negative first derivative, and must satisfy the above ODE. The above ODE is the same ODE we would obtain by taking the first-order condition of the objective function under the assumption that the NE is continuously differentiable with strictly negative first derivative so that the objective function is continuously differentiable as well.

The boundary condition follows from Proposition 8 with $\delta = 0$. □

Proof of Proposition 2. From the proof of Proposition 1, we know that any NE is differentiable and must satisfy the following Dirichlet problem

$$\begin{cases} S(x)\mathrm{d}x + \widetilde{Q}(c)\mathrm{d}c = 0 \qquad \text{with } c \in \Omega = (\underline{c}, \overline{c}) \;\text{ and }\; x \in (x_0, D),\\ \lim\limits_{c\to\overline{c}} x(c) = x_0, \end{cases}$$

where

$$S(x) = \frac{(R_f - 1)Df_R(R_0(x))x^{-2}}{2q + F_R(R_0(x))} \qquad \text{and} \qquad \widetilde{Q}(c) = \frac{\gamma D f_C(c)}{\gamma D\left[a + F_C(c)\right] + c}.$$

$S(x)$ is integrable on (x_0, D), and $\widetilde{Q}(c)$ is integrable on Ω because $a > 0$ by assumption. (Alternatively, for $\widetilde{Q}(c)$ to be integrable, one can assume $\underline{c} > 0$.) By integrating the above ODE,

$$\int^c \widetilde{Q}(s)\mathrm{d}s = -\int^x \frac{(R_f - 1)Df_R(R_0(u))u^{-2}}{2q + F_R(R_0(u))}\mathrm{d}u + K = -\log\left[2q + F_R(R_0(x))\right] + K,$$

from which it follows

$$x(c) = \frac{(R_f - 1)D}{R_f - F_R^{-1}\left(\exp\left(-\int_{\underline{c}}^c \widetilde{Q}(s)\mathrm{d}s + K\right) - 2q\right)},$$

where F_R^{-1} is the quantile function of R (i.e., the inverse of the cumulative distribution function). By using the boundary condition $\lim_{c\to\overline{c}} x(c) = x_0$, we derive $K = \int_{\underline{c}}^{\overline{c}} \widetilde{Q}(s)\mathrm{d}s + \log(2q)$ and obtain the unique solution of the Dirichlet problem

$$x(c) = \frac{(R_f - 1)D}{R_f - F_R^{-1}\left(2qQ(c)\right)}, \tag{IA.1.1}$$

where $Q(c) = \exp\left(\int_c^{\overline{c}} \widetilde{Q}(s)\mathrm{d}s\right) - 1$. Therefore, if there exists a NE, it is unique and equal to (IA.1.1).

The next step is to check that $x(c) \in (x_0, D)$ for all c. From the boundary condition and the fact that $x(c)$ is continuous and strictly decreasing it follows that $x(c) > x_0$ for all $c \in \Omega$. It is easy to show that $x(c) < D$ for all $c \in \Omega$ if and only if $\int_{\underline{c}}^{\overline{c}} \widetilde{Q}(s)\mathrm{d}s = \mathbb{E}_C\left[\frac{\gamma D}{\gamma D[a+F_C(c)]+c}\right] < \log\left(1 + \frac{F_R(1)}{2q}\right)$.

The last step is to prove that the unique solution of the Dirichlet problem is indeed a NE. Under the strategy profile (IA.1.1), each player's objective function is continuous everywhere and continuously differentiable on $[0, x_0) \cup (x_0, x(\underline{c})) \cup (x(\underline{c}), D]$. For all c, it is straightforward to show that

$$\frac{\partial v_c}{\partial y}(y) = \begin{cases} 0 & \text{for } \ y \in [0, x_0), \\ -\left[\gamma Da + c\right] f_R\left(R_0(y)\right)(R_f - 1)Dy^{-2} < 0 & \text{for } \ y \in (x(\underline{c}), D], \end{cases}$$

while the first derivative of $v_c(y)$ on $(x_0, x(\underline{c}))$ is

$$\begin{aligned} \frac{\partial v_c}{\partial y}(y) = {} & \gamma D\left[2q + F_R(R_0(y))\right] f_C(x^{-1}(y))\left(\frac{\mathrm{d}x}{\mathrm{d}c}\left(x^{-1}(y)\right)\right)^{-1} \\ & - \left\{\gamma D\left[a + F_C(x^{-1}(y))\right] + c\right\} f_R\left(R_0(y)\right)(R_f - 1)Dy^{-2} \end{aligned}$$

By substituting the above ODE, we obtain $\frac{\partial v_c}{\partial y}(y) = \left(x^{-1}(y) - c\right) f_R\left(R_0(y)\right)(R_f - 1)Dy^{-2}$, which

is: positive for $y \in (x_0, x(c))$, negative for $y \in (x(c), x(\underline{c}))$, and equal to zero for $y = x(c)$. Since $\upsilon_c(y)$ is continuous everywhere, it follows that under the strategy profile (IA.1.1), $x(c)$ is a global maximum for all $c \in \Omega$. Therefore, $x(c)$ is the unique NE of the tournament. □

Proof of Lemma 1. By applying Taylor's theorem on $q(R_f) = 0.5 - F_R(R_f)$ around μ. □

Proof of Corollary 2. By applying Taylor's theorem on the NE (3) around $\overline{c}$. □

Proof of Corollary 3. Trivial. □

Proof of Proposition 4. Let $F^{(i)}$ denote the distribution function of risky returns when the left tail is $H^{(i)}$, and let $G^{(i)} = {F^{(i)}}^{-1}$ be the corresponding quantile function. Note that by construction, the mass in the left tail remains the same, i.e. $F^{(1)}(1) = F^{(2)}(1)$. Under $F^{(i)}$, the equilibrium critical return on the risky asset is $R_0^{(i)}(c) := G^{(i)}\left(2q^{(i)}Q(c)\right)$; in equilibrium, fund c breaks the buck if and only if $R < R_0^{(i)}(c)$. Since $Q(c) \in (0, F^{(i)}(1)/2q^{(i)})$ is strictly decreasing and $\lim_{c\to\overline{c}} Q(c) = 0$, $R_0^{(i)}(c) \in (\underline{R}, 1)$ is also strictly decreasing and $\lim_{c\to\overline{c}} R_0^{(i)}(c) = \underline{R}$. Moreover, being $F^{(i)}$ absolutely continuous, $R_0^{(i)}(c)$ is continuous. Finally, $f^{(i)}$ and $h^{(i)}$ denote the densities of $F^{(i)}$ and $H^{(i)}$, respectively, and $x_c^{(i)}$ is the unique NE (3) under $F^{(i)}$. Note that $R_0^{(i)}(c)$ strictly increases with $x_c^{(i)}$. Hereafter, for any functions f and g, the expression $\frac{f}{g}(x)$ stands for $f(x)/g(x)$.

(i) For every c, $2q^{(1)}Q(c) = F^{(1)}(R_0^{(1)}(c)) = F^{(1)}(1)H^{(1)}(R_0^{(1)}(c)) \geq \frac{q^{(1)}}{q^{(2)}}F^{(2)}(1)H^{(2)}(R_0^{(1)}(c))$. Hence, $2q^{(2)}Q(c) \geq F^{(2)}(R_0^{(1)}(c))$, and therefore $R_0^{(2)}(c) \geq R_0^{(1)}(c)$ and $x_c^{(2)} \geq x_c^{(1)}$ for all c.

(ii) First, it is easy to prove by contradiction that $\frac{q^{(2)}}{q^{(1)}} < \sup \frac{H^{(2)}}{H^{(1)}}$ implies $\frac{q^{(2)}}{q^{(1)}} < \sup \frac{h^{(2)}}{h^{(1)}}$. Second, likelihood ratio dominance (LRD) of $H^{(1)}$ implies $\inf \frac{h^{(2)}}{h^{(1)}} < 1$. Hence, since $\frac{q^{(2)}}{q^{(1)}} > 1$, we have $\inf \frac{h^{(2)}}{h^{(1)}} < \frac{q^{(2)}}{q^{(1)}} < \sup \frac{h^{(2)}}{h^{(1)}}$. Since $\frac{h^{(2)}}{h^{(1)}} = \frac{f^{(2)}}{f^{(1)}}$ is weakly decreasing by LRD, there exists $r^* \in (\underline{R}, 1)$ s.t. $\frac{f^{(2)}}{f^{(1)}}(r) > \frac{q^{(2)}}{q^{(1)}}$ for all $r \in (\underline{R}, r^*)$ and $\frac{f^{(2)}}{f^{(1)}}(r) \leq \frac{q^{(2)}}{q^{(1)}}$ for all $r \in [r^*, 1)$. Since $R_0^{(1)}(c)$ is continuous, strictly decreasing, and goes to $\underline{R}$ as $c \to \overline{c}$, there exists $c^* \in (\underline{c}, \overline{c})$ s.t. for all $c > c^*$, by the mean value theorem, $F^{(2)}\left(R_0^{(1)}(c)\right) = F^{(2)}\left(G^{(1)}\left(2q^{(1)}Q(c)\right)\right) = \frac{f^{(2)}}{f^{(1)}}(\widetilde{r}_c)2q^{(1)}Q(c)$ for some $\widetilde{r}_c \in (\underline{R}, r^*)$. Hence, $F^{(2)}\left(R_0^{(1)}(c)\right) > 2q^{(2)}Q(c)$ for all $c > c^*$, and therefore $R_0^{(1)}(c) > R_0^{(2)}(c)$ and $x_c^{(1)} > x_c^{(2)}$ for all $c > c^*$.

On the other hand, by the single crossing property of LRD, there exists $r^{**} \in (\underline{R}, 1)$ with $r^{**} > r^*$ s.t. $\frac{H^{(2)}}{H^{(1)}} = \frac{F^{(2)}}{F^{(1)}}$ is decreasing on $(r^{**}, 1)$. Since $\frac{q^{(2)}}{q^{(1)}} > 1 = \frac{F^{(2)}}{F^{(1)}}(1)$, there exists $Q(\underline{c})$ sufficiently large s.t. the NE exists but at the same time $R_0^{(1)}(\underline{c}) > r^{**}$ and $\frac{F^{(2)}}{F^{(1)}}(R_0^{(1)}(\underline{c})) < \frac{q^{(2)}}{q^{(1)}}$, which implies $2q^{(2)}Q(c) > F^{(2)}\left(R_0^{(1)}(\underline{c})\right)$ and hence $x^{(2)}(\underline{c}) > x^{(1)}(\underline{c})$. By continuity and monotonicity of the NE, for $Q(\underline{c})$ sufficiently large there exists $c_* \in (\underline{c}, c^*)$ s.t. $x^{(2)}(c) < x^{(1)}(c)$ for all $c < c_*$.

If $H^{(2)}/H^{(1)}$ is decreasing everywhere on $(\underline{R}, 1)$, then obviously $c_* = c^*$. □

Corollary 4. Trivial. □

Proof of Proposition 5. By differentiating the NE (3) w.r.t R_f holding $q = 0.5 - F_R(R_f)$ constant. □

Proof of Proposition 6. Let $x(c; R_f)$ be the unique NE (3), where the second argument indicates the explicit dependence on the risk-free rate, and $q(R_f) = 0.5 - F_R(R_f)$ be the tournament incentive. Since the density f_R is continuous and positive on $(\underline{R}, \overline{R})$, and F_R/f_R is weakly increasing on $(\underline{R}, 1)$, $x(c; R_f)$ is continuously differentiable w.r.t. R_f everywhere on $(\underline{c}, \overline{c})$, and

$$\frac{\mathrm{d}x(c;R_f)}{\mathrm{d}R_f} = \frac{f_R(R_f)(R_f-1)}{q(R_f)\left[R_f - R_0^{eq}(c)\right]^2}\left[\frac{q(R_f)\left(1-R_0^{eq}(c)\right)}{f_R(R_f)(R_f-1)} - \frac{F_R\left(R_0^{eq}(c)\right)}{f_R\left(R_0^{eq}(c)\right)}\right],$$

where $R_0^{eq}(c) = F_R^{-1}\left(2q(R_f)Q(c)\right) \in (\underline{R}, 1)$ is the equilibrium critical return on the risky asset for fund c (see proof of Proposition 4). Moreover, since $R_0^{eq}(c)$ is strictly decreasing, and F_R/f_R is weakly increasing on $(\underline{R}, 1)$, $\frac{\mathrm{d}x(c;R_f)}{\mathrm{d}R_f}$ is strictly increasing in c. From the weak monotonicity of F_R/f_R, it also follows that $\lim_{r\to\underline{R}} \frac{F_R}{f_R}(r) = 0$. Hence, since $\lim_{c\to\overline{c}} R_0^{eq}(c) = \underline{R}$, by continuity, $\frac{\mathrm{d}x(c;R_f)}{\mathrm{d}R_f}$ is positive on a left-neighborhood of $\overline{c}$.

It is easy to show that if $\mathbb{E}_C\left[\frac{\gamma D}{\gamma D(a+F_C(c))+c}\right] \leq \frac{1}{2q(R_f)} \lim_{c\to\underline{c}} \log\left(1 + F_R\left(1 - \frac{f_R(R_f)(R_f-1)}{q(R_f)}\frac{F_R\left(R_0^{eq}(c)\right)}{f_R\left(R_0^{eq}(c)\right)}\right)\right)$, then $\lim_{c\to\underline{c}} \frac{F_R\left(R_0^{eq}(c)\right)}{f_R\left(R_0^{eq}(c)\right)} \leq \lim_{c\to\underline{c}} \frac{q(R_f)(1-R_0^{eq}(c))}{f_R(R_f)(R_f-1)}$. Since $\frac{\mathrm{d}x(c;R_f)}{\mathrm{d}R_f}$ is strictly increasing in c, it follows that $\frac{\mathrm{d}x(c;R_f)}{\mathrm{d}R_f} > 0$ for all $c \in (\underline{c}, \overline{c})$.

On the other hand, if $\mathbb{E}_C\left[\frac{\gamma D}{\gamma D(a+F_C(c))+c}\right] > \frac{1}{2q(R_f)} \lim_{c\to\underline{c}} \log\left(1 + F_R\left(1 - \frac{f_R(R_f)(R_f-1)}{q(R_f)}\frac{F_R\left(R_0^{eq}(c)\right)}{f_R\left(R_0^{eq}(c)\right)}\right)\right)$, then $\lim_{c\to\underline{c}} \frac{F_R\left(R_0^{eq}(\underline{c})\right)}{f_R\left(R_0^{eq}(\underline{c})\right)} > \lim_{c\to\underline{c}} \frac{q(R_f)(1-R_0^{eq}(c))}{f_R(R_f)(R_f-1)}$, and it follows that $\frac{\mathrm{d}x(c;R_f)}{\mathrm{d}R_f} < 0$ in a neighborhood of $\underline{c}$. Since $\frac{\mathrm{d}x(c;R_f)}{\mathrm{d}R_f}$ is strictly increasing in c, there exists a unique $c^* \in (\underline{c}, \overline{c})$ s.t. $\frac{\mathrm{d}x(c;R_f)}{\mathrm{d}R_f} < 0$ for all $c < c^*$ and $\frac{\mathrm{d}x(c;R_f)}{\mathrm{d}R_f} > 0$ for all $c > c^*$. □

Proposition 7. If $F_C^{(2)} \succ_{LRD} F_C^{(1)}$, there exists c^* s.t. $f^{(2)}(c) > f^{(1)}(c)$ for all $c > c^*$. Since $F_C^{(2)}(c) < F_C^{(1)}(c)$ for all c,

$$\int_c^{\overline{c}} \frac{\gamma D f_C^{(2)}(u)\mathrm{d}u}{\gamma D\left[F_C^{(2)}(u) + a\right] + u} > \int_c^{\overline{c}} \frac{\gamma D f_C^{(1)}(u)\mathrm{d}u}{\gamma D\left[F_C^{(1)}(u) + a\right] + u} \qquad \text{for all } c > c^*,$$

from which it follows that $Q^{(2)}(c) > Q^{(1)}(c)$ and therefore $x^{(2)}(c) > x^{(1)}(c)$ for all $c > c^*$.

Using integration by parts, for any $i = 1, 2$,

$$Q^{(i)}(\underline{c}) = \int_{\underline{c}}^{\overline{c}} \frac{\gamma D f_C^{(i)}(u)\mathrm{d}u}{\gamma D\left[F_C^{(i)}(u) + a\right] + u} = \log\left(\frac{\gamma D(a+1) + \overline{c}}{\gamma D\, a + \underline{c}}\right) - \int_{\underline{c}}^{\overline{c}} \frac{\mathrm{d}u}{\gamma D(F_C^{(i)}(u) + a) + u},$$

and since $F_C^{(2)}(c) < F_C^{(1)}(c)$ everywhere by LRD, $Q^{(2)}(\underline{c}) < Q^{(1)}(\underline{c})$. By continuity and monotonicity

of the NE, there exists c_* s.t. $Q^{(2)}(c) < Q^{(1)}(c)$ and therefore $x^{(2)}(c) < x^{(1)}(c)$ for all $c < c_*$. $\square$

Appendix IA.2

Data Construction

Data on fund characteristics are from iMoneyNet. These data are the most comprehensive source of information on MMFs and are widely used for both academic research and investment decisions. KS check that the iMoneyNet database covers the universe of US MMFs by comparing it to the list of funds registered at the SEC, and Chodorow-Reich (2014) shows that the coverage of iMoneyNet data matches that of the Financial Accounts of the United States.

My sample is from January 5, 1999 to August 26, 2008. Data are at the weekly, share class level. In my sample, there are a total of $1,161$ share classes. I find that 23 of these share classes have some missing data for some week. Almost all missing data come from funds that report monthly for the first few months of their existence and later switch to weekly reporting. Following KS, I use linear interpolation to generate weekly data for these share classes. Since my analysis is at the fund level, I aggregate share classes at the fund level. To identify funds, I use information on the underlying portfolio, which is the same for all share classes belonging to the same fund. Share classes that have the same portfolio composition in terms of asset classes and the same weighted average maturity identify a unique fund. Over my period of analysis, consisting of 504 weeks, I identify 514 prime MMFs. I double-check the accuracy of my fund identifier by verifying that the assets for all share classes add up to total fund size. The difference between the two exceeds \$100,000 (data are reported in \$100,000 increments) only for 605 fund-week observations out of $142,787$, i.e., roughly 0.4% of the sample.

To construct fund level characteristics, I follow KS and average share class characteristics using share class assets as weights. Each fund can have both retail share classes, which are available only to retail investors, and institutional share classes, which are available only to institutional investors. In my empirical analysis, I label a fund as institutional if it has at least one institutional share class. A fund is labeled as retail if it has no institutional share class. KS use the same convention. Moreover, institutional share classes are typically much larger than retail share classes, which justifies this identification. In my sample, I identify 219 funds as institutional over the whole period 01/1999–08/2008 and 237 funds as retail over the whole period 01/1999–08/2008. 58 funds changed from "institutional" to "retail" or vice versa at some point in the sample. The total number of institutional fund-week observations is $69,529$, and the total number of retail fund-week observations is $73,258$. My empirical analysis focuses on institutional funds because it has been observed that they face a more sensitive flow-performance relation than retail funds.

To calculate sponsor reputation concerns as described in Section 6, I merge the iMoneyNet database with the CRSP Survivorship Bias Free Mutual Fund Database. KS also use CRSP data. CRSP data are at the quarterly level. Therefore, share classes in the two data sets are matched

at that frequency. (Any within-quarter variation at the sponsor level is assumed to be constant.) To match funds in the iMoneyNet database with sponsors in the CRSP database, I proceed as follows. First, I match share classes by using the NASDAQ ticker. If a share class is matched, I assign to it a sponsor based on the entry `mgmt_cd` in the corresponding CRSP match. If `mgmt_cd` is not available, I use `mgmt_name`. If there is no match in CRSP using the NASDAQ ticker, I use the 9-digit CUSIP number. For some share classes neither NASDAQ nor CUSIP have a match in the CRSP database. In those cases, I assign a match based on the other share classes in the same fund for which a match is available. (If share classes from the same fund are assigned to different sponsors in CRSP, I only use the largest share class.) If no other share class in the fund has a valid match in CRSP, I assign a match based on the other share classes in the same fund complex, as indicated by MoneyNet. (Again, if share classes from the same complex are assigned to different sponsors in CRSP, I only use the largest share class.) If no other share class in the complex has a valid match in CRSP, I match share classes by matching the name of the complex as reported by iMoneyNet with the fund name in the CRSP database. With this algorithm, 98 share classes out of $1,161$ are not matched with a unique sponsor in CRSP, corresponding to 70 funds out of 514. Most of the unmatched funds operated in the period 1999–2001 and exited the industry before 2002. Until December 2001, the fraction of MMFs matched with their sponsor is between 62% and 88% per week. After January 2002, the fraction of matched funds is always greater than 94% per week. For this reason, when I test my model's predictions on the effect of default costs (i.e., sponsor reputation concerns) on MMF risk-taking, I restrict my analysis to the period January 2002–August 2008. Finally, I manually match 65 of the 98 unmatched share classes with the corresponding fund sponsor in CRSP by using SEC filings in EDGAR, company sources, and press coverage. After this manual assignment, from January 2002 onward, at least 98.53% of funds are matched with their sponsors every week, corresponding to a coverage of at least 99.87% in terms of asset volume.

Summary statistics and distributional properties of *Fund Business*

Table IA.2.1 provides summary statistics for all institutional prime MMFs as of January 3, 2006. I choose this date to make my results comparable to those of KS. The sample includes 143 funds and 82 sponsors. Column (1) shows summary statistics for all funds, column (2) shows summary statistics for funds with *Fund Business* above the industry median, and column (3) shows summary statistics for funds with *Fund Business* below the industry median. As of January 3, 2006, the industry median of *Fund Business* is 0.82. Results are discussed in Section 6 of the main text. My findings are close to those of KS, confirming that my data set is consistent with theirs.

Table IA.2.2 shows summary statistics for both the time-series variation (i.e., within fund) and the cross-section variation (i.e., within month) of *Fund Business* at the monthly frequency. In both cases, the variation is significant, which supports the validity of a "continuum-of-funds" approach and helps the identification of the effect of default costs (i.e., sponsor's reputation concerns) on

				Kacperczyk & Schnabl (2013)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	High FB	Low FB	All	High FB	Low FB
Fund Characteristics						
Spread (bp)	7.54	7.27	7.70	6.93	6.60	7.28
	(6.46)	(6.22)	(6.64)	(6.44)	(7.54)	(5.00)
Expense Ratio (bp)	35.90	34.89	36.53	31.64	32.40	30.81
	(21.79)	(22.81)	(21.23)	(19.10)	(18.43)	(19.90)
Fund Size ($mil)	6,318	4,195	7,645**	4,886	2,981	6,951***
	(10,793)	(8,413)	(11,899)	(8,685)	(4,833)	(11,169)
Maturity (days)	33.27	33.93	32.85	34.32	35.12	33.45
	(10.65)	(10.90)	(10.54)	(11.02)	(12.48)	(9.17)
Age (years)	11.20	11.12	11.25	10.61	10.43	10.81
	(6.84)	(7.36)	(6.53)	(4.75)	(5.53)	(3.75)
Family Size ($bil)	73.3	99.1	47.5*	72.8	97.5	45.9**
	(157.1)	(211.7)	(61.8)	(149.1)	(200.9)	(39.2)
Fund Business	0.745	0.929	0.562***	0.764	0.897	0.619***
	(0.248)	(0.051)	(0.230)	(0.198)	(0.064)	(0.192)
Conglomerate	0.566	0.418	0.659***	0.601	0.558	0.648
	(0.497)	(0.498)	(0.477)	(0.491)	(0.500)	(0.481)
Portfolio Holdings						
U.S. treasuries & agency	0.059	0.065	0.055	0.060	0.072	0.048
	(0.096)	(0.092)	(0.099)	(0.109)	(0.120)	(0.095)
Repurchase Agreements	0.134	0.128	0.138	0.135	0.142	0.126
	(0.151)	(0.169)	(0.139)	(0.150)	(0.169)	(0.128)
Bank Deposits	0.034	0.016	0.045***	0.032	0.021	0.044**
	(0.058)	(0.034)	(0.067)	(0.057)	(0.039)	(0.069)
Bank Obligations	0.124	0.112	0.132	0.122	0.111	0.135
	(0.127)	(0.116)	(0.133)	(0.126)	(0.120)	(0.132)
Floating-Rate Notes	0.199	0.225	0.183	0.198	0.192	0.204
	(0.164)	(0.184)	(0.149)	(0.162)	(0.168)	(0.156)
Commercial Paper	0.314	0.305	0.319	0.320	0.356	0.280**
	(0.216)	(0.226)	(0.212)	(0.224)	(0.252)	(0.182)
Asset-Backed CP	0.136	0.149	0.128	0.134	0.106	0.164**
	(0.154)	(0.180)	(0.136)	(0.155)	(0.151)	(0.154)
Funds	143	55	88	148	77	71

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.2.1: Summary statistics for all U.S. institutional prime MMFs as of January 3, 2006. *Fund Business* (FB) is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. High (Low) FB includes all funds with *Fund Business* above (below) the median value of *Fund Business* in the sponsor population (i.e., 0.82). Fund characteristics are spread, expense ratio, fund size, average portfolio maturity, age, family size, and whether the fund sponsor is part of a conglomerate. Holdings are the share of assets invested in Treasuries and agency debt, repurchase agreements, bank deposits, bank obligations, floating-rate notes, commercial paper, and asset-backed commercial paper. Cross-sectional standard deviations of the given characteristics are in parentheses. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively.

MMF risk-taking. The left panel of Figure IA.2.1 shows the distribution of *Fund Business* in the population of MMFs on January 3, 2006. The distribution is widely spread on the interval

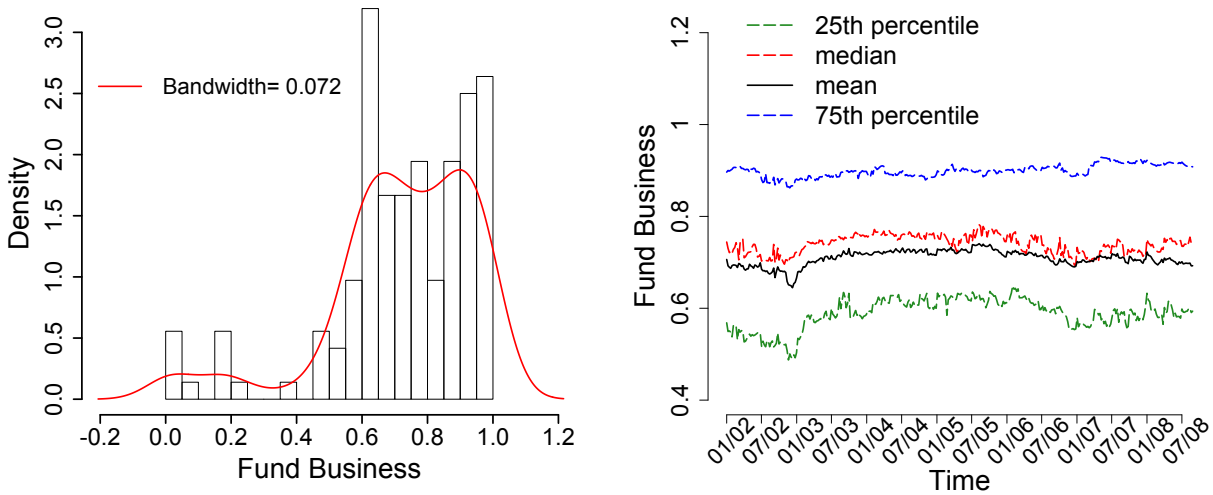
	$sd(Fund\ Business)/mean(Fund\ Business)$ (in %)					
	Min	1st Qu.	Median	Mean	3rd Qu.	Max.
Time-Series Variation	0.1	3.1	8.7	14.9	15.0	187.8
Cross-Section Variation	30.1	31.8	32.6	33.1	34.0	41.5

	$sd(FB\ Rank)$ (in percentiles)					
	Min	1st Qu.	Median	Mean	3rd Qu.	Max.
Time-Series Variation	0.6	4.5	9.4	11.9	17.4	46.7
Cross-Section Variation	27.3	28.3	28.7	28.7	29.1	30.0

Table IA.2.2: Top panel: percentage variation of *Fund Business* in the time series (i.e., within fund) and in the cross-section (i.e., within month). Bottom panel: variation of the percentile rank of *Fund Business* in the time series (i.e., within fund) and in the cross-section (i.e., within month). Data are at the monthly frequency for all US institutional prime MMFs active from January 2002 to August 2008. The rank is already a relative measure, and therefore it does not need to be normalized by its mean to make its variations comparable. Also, note that in each cross-section, *FB Rank* in percentiles is uniformly distributed over $[1, 100]$ by construction. Hence, its cross-section standard deviation is $99/\sqrt{12} \approx 28.6$.

$[0, 1]$, suggesting that a binary distribution would be a poor approximation of the actual one. The distribution shows some degree of multi-modality, with a small peak around zero (funds belonging to sponsors specialized in MMFs, e.g. City National Rochdale) and two pronounced peaks around 0.7 and 1 (funds belonging to diversified asset managers, e.g PIMCO). The right panel of Figure IA.2.1 shows the evolution of the mean and quartiles of *Fund Business* from January 2002 to August 2008. Even though *Fund Business* has sizable within-fund variation, its distribution is stable over the period of analysis. This is important because in Section 5, I show that stochastic shocks to the distribution of default costs (i.e., *Fund Business*) affect MMF risk-taking and have different effects on funds in different parts of the distribution. Since the empirical analysis aims to test the model's predictions on the effect of risk premia and risk-free rates on MMF risk-taking, and their different effects in the cross-section of funds, it is important that the distribution of default costs remains relatively stable over the period of analysis.

To check that my results are not driven by the same cross-sectional heterogeneity considered by Chodorow-Reich (2014) or Di Maggio and Kacperczyk (2015), I check that *Fund Business* does not covary in a statistically significant way with fund incurred expenses or affiliation to a financial conglomerate, respectively. Figure IA.2.2 shows the correlation between *Fund Business* and *Incurred Cost* (left panel) and between *Fund Business* and *Conglomerate* (right panel) in the cross-section of institutional prime MMFs at weekly frequency, from January 2002 to August 2008. *Fund Business* and *Incurred Cost* are almost never statistically significantly correlated. *Fund Business* and *Conglomerate* are negatively and statistically significantly correlated at the 10% level until December 2003 (and at the 1% level until December 2002) but almost never after



(a) Cross-section distribution of *Fund Business* (01/2006). (b) Time evolution of *Fund Business* distribution.

Figure IA.2.1: The sample is all U.S. institutional prime MMFs. Left panel: distribution of *Fund Business* as of January 3, 2006. The red line represents the density of *Fund Business* estimated using a Gaussian kernel. The bandwidth is determined according to Silverman's "rule of thumb" (Silverman, 1986). Right panel: time evolution of the mean and quartiles of *Fund Business* from January 2002 to August 2008.

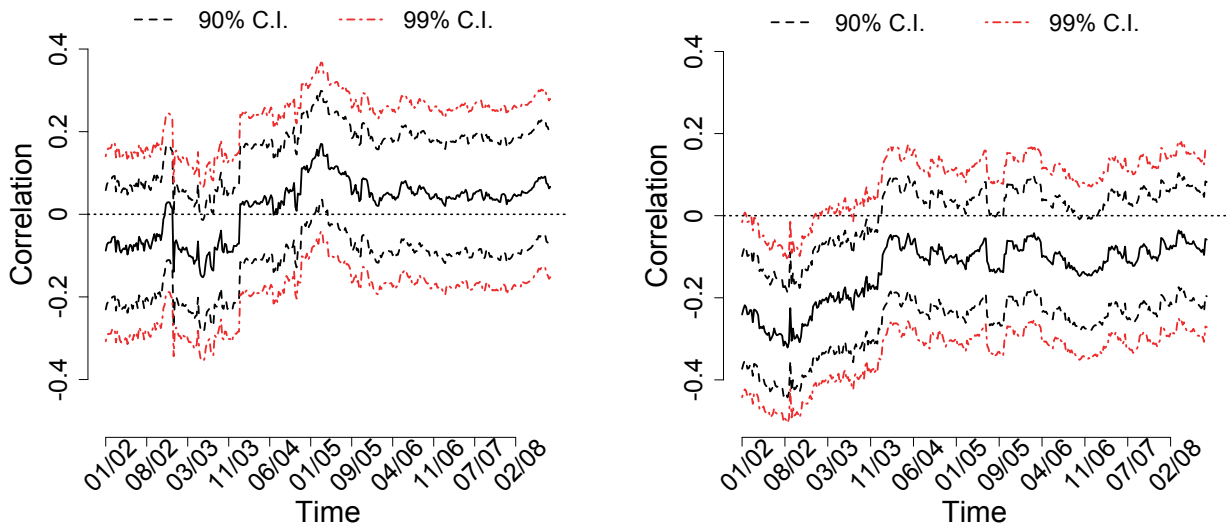
then. For robustness, I estimate the following regression at the weekly frequency:

$$Fund\ Business_{i,t} = \alpha_i + \mu_t + \beta X_{i,t} + \varepsilon_{i,t} \tag{IA.2.1}$$

where X is either *Incurred Cost* (i.e., incurred expense ratio in %) and *Conglomerate* (i.e., 1 if the fund belongs to a financial conglomerate and 0 otherwise). α_i and μ_t represent fund and week fixed effects, respectively. Since *Conglomerate* is constant over time for the vast majority of funds, I also estimate regression (IA.2.1) without fund fixed effects, i.e. with only week fixed effects. Results are in Table IA.2.3. Standard erros are HACSC robust to account for both within- and across-fund correlation. For both *Incurred Cost* and *Conglomerate*, and in all regression specifications, β is statistically insignificant at the 10% level, and the within R^2 is less than 2%.

Appendix IA.3 Flow-performance: robustness

Table IA.3.1 shows the results for the estimation of regression (7) using the rank of *Fund Flow* (*Fund Flow Rank*) as dependent variable. The rank is calculated in percentiles normalized to $[0, 1]$ (e.g., for a given week, a fund in the $98th$ percentile of that week's fund flow distribution has *Fund Flow Rank* $= 0.98$). Using the rank is an alternative to trimming to mitigate the effect of outliers. Results are qualitatively similar to those obtained using *Fund Flow* trimmed at the 0.5%. When the past *Spread Rank* is included in the RHS of regression (7), past *Spread* loses



(a) $cor(Fund\ Business, Incurred\ Cost)$ (b) $cor(Fund\ Business, Conglomerate)$

Figure IA.2.2: Correlation between *Fund Business* and *Incurred Cost* (left panel), and between *Fund Business* and *Conglomerate* (right panel) in the cross-section of MMFs at weekly frequency. The sample is all U.S. institutional prime MMFs from January 2002 and August 2008. For each week, I calculate the Pearson correlation coefficient between *Fund Business* and *Incurred Cost*, and between *Fund Business* and *Conglomerate*. Black dashed lines are 10% confidence intervals, and the dashed red lines are 1% confidence intervals.

	$Fund\ Business_{i,t}$ (decimals)			
	(1)	(2)	(3)	(4)
$Incurred\ Cost_{i,t}$ (%)	0.015	−0.145		
	(0.058)	(0.093)		
$Conglomerate_{i,t}$			−0.060	−0.007
			(0.038)	(0.014)
Time Fixed Effects	Y	Y	Y	Y
Fund Fixed Effects	N	Y	N	Y
Adj. R^2 (within)	0.000	0.014	0.018	0.000
R^2 (overall)	0.006	0.839	0.023	0.836
Observations	49,133	49,133	49,133	49,133

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.2.3: *Fund Business* vs. *Incurred Cost* and *Conglomerate*. Data are at the weekly frequency for all US institutional prime MMFs from January 2002 to August 2008. *Fund Business* is the share of mutual fund assets other than institutional prime MMF in the sponsor's total mutual fund assets. *Incurred Cost* is the incurred expense ratio in percentages. *Conglomerate* is an indicator variable equal to 1 if the fund sponsor is affiliated with a financial conglomerate and 0 otherwise. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 36-week lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics are roughly 3.05, 2.25, and 1.86, respectively.

all its statistical and economic significance as determinant of current fund flows. On the contrary, *Spread Rank* is always statistically and economically significant.

Table IA.3.2 shows the results for the estimation of regression (7) using only time fixed effects. Results are similar to those obtained when also including fund fixed effects. The effect of past performance rank on fund flows is always both statistically and economically significant, while the effect of past raw performance loses most of its statistical and economic significance when the performance rank is included in the RHS of the regression.

As a further robustness check, I run regression (7) using trimming conditions based on the interquartile range. Results are similar and omitted for brevity. This empirical evidence confirms that the performance rank is a better explanatory variable of money flows to MMFs than the raw performance and supports the choice of a pure tournament model.

IA.3.1 Exogeneity of the flow-performance relation

Here I test the assumption that the flow-performance relation can be taken as exogenous in the context of my model. That is, I test the hypothesis that the flow-performance relation is not explicitly affected by sponsor reputation concerns. This characteristic may affect the flow-performance relation if investors anticipate the effect of reputation concerns on fund risk-taking. KS have already checked that reputation concerns do not affect the flow-performance relation for the period January 2006–August 2008. Here I extend their analysis to the period January 2002–August 2008. Following KS, I estimate the flow-performance regression (7) including also the interaction of *Fund Business* with *Spread Rank*. To be consistent with KS, I also consider the interaction of *Conglomerate* with *Spread Rank*. Results are in Table IA.3.3. Standard errors are HAC robust.

I find that the interaction terms are statistically and economically insignificant for both measures of reputation concern over the whole period, consistent with KS. For robustness, I run the same regression using *Spread* instead of *Spread Rank* as the main explanatory variable, and using the rank of *Fund Flow* as the dependent variable. Results are similar and omitted for brevity. These findings suggest that investors do not risk-adjust fund performance based on sponsor reputation concerns and hence support the assumption of an exogenous flow-performance relation in my model.

Appendix IA.4 MMF risk-taking: robustness

IA.4.1 *Pre* and *Post* July 2007

Table IA.4.1 reports the results of regression (8) when *Fund Business* is used as the main explanatory variable instead of its rank. Standard errors are HACSC robust. Results are very similar to those of Table 3 of Section 6.5 and confirm the predictions of my model.

	$Fund\ Flow\ Rank_{i,t+1}$				
	(1)	(2)	(3)	(4)	(5)
$Spread\ Rank_{i,t}$		0.064^{***}	0.058^{***}		0.056^{***}
		(0.008)	(0.009)		(0.009)
$Spread_{i,t}$ (%)	0.097^{**}		0.025	0.092^{***}	0.024
	(0.039)		(0.019)	(0.028)	(0.015)
$Spread^2_{i,t}$				0.017^{**}	0.008
				(0.009)	(0.005)
$Log(Fund\ Size)_{i,t}$	-0.059^{***}	-0.061^{***}	-0.061^{***}	-0.059^{***}	-0.061^{***}
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$Expense\ Ratio_{i,t}$	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Age_{i,t}$	-0.006^{**}	-0.006^{**}	-0.006^{**}	-0.006^{**}	-0.006^{**}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$Flow\ Volatility_{i,t}$	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.003^{***}	-0.002^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Log(Family\ Size)_{i,t}$	0.000	0.000	0.000	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Week fixed effect	Y	Y	Y	Y	Y
Fund fixed effect	Y	Y	Y	Y	Y
Observations	48,543	48,543	48,543	48,543	48,543
Adj. R^2 (within)	0.006	0.008	0.008	0.007	0.008
R^2 (overall)	0.014	0.015	0.015	0.014	0.015

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.3.1: Flow-performance relation. The sample is all U.S. institutional prime MMFs from 1/1/2002 to 8/31/2008. The dependent variable is *Fund Flow Rank*, which is the rank of *Fund Flow*. *Fund Flow* is the percentage change in total net assets from week t to week $t+1$, adjusted for earned interests. The rank is computed in percentiles normalized to $[0, 1]$. Using the rank of *Fund Flow* mitigates the effect of possible outliers in the distribution of fund flows. Independent variables are the weekly annualized fund spread from $t-1$ to t, its rank in percentiles normalized to $[0, 1]$, logarithm of fund size, fund expense ratio, fund age, volatility of fund flows based on past 12-week fund flows, and logarithm of fund family size. All regressions are at the weekly frequency and include week and fund fixed effects. Standard errors are HAC robust. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively.

	$Fund\ Flow_{i,t+1}$				
	(1)	(2)	(3)	(4)	(5)
$Spread\ Rank_{i,t}$		0.743^{***}	0.640^{***}		0.623^{***}
		(0.098)	(0.108)		(0.109)
$Spread_{i,t}$ (%)	1.019^{**}		0.335^{*}	1.102^{***}	0.400^{**}
	(0.427)		(0.199)	(0.238)	(0.193)
$Spread^2_{i,t}$				0.266^{***}	0.085
				(0.098)	(0.080)
$Log(Fund\ Size)_{i,t}$	-0.065^{***}	-0.074^{***}	-0.076^{***}	-0.068^{***}	-0.076^{***}
	(0.022)	(0.023)	(0.024)	(0.022)	(0.024)
$Expense\ Ratio_{i,t}$	-0.005^{***}	-0.005^{***}	-0.005^{***}	-0.005^{***}	-0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Age_{i,t}$	-0.019^{***}	-0.019^{***}	-0.019^{***}	-0.019^{***}	-0.019^{***}
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)
$Flow\ Volatility_{i,t}$	-0.022^{**}	-0.017^{***}	-0.023^{***}	-0.038^{**}	-0.025^{**}
	(0.010)	(0.006)	(0.009)	(0.015)	(0.010)
$Log(Family\ Size)_{i,t}$	0.053^{***}	0.042^{**}	0.045^{**}	0.050^{**}	0.043^{**}
	(0.020)	(0.021)	(0.022)	(0.020)	(0.021)
Week fixed effect	Y	Y	Y	Y	Y
Fund fixed effect	N	N	N	N	N
Observations	48,543	48,543	48,543	48,543	48,543
Adj. R^2 (within)	0.002	0.003	0.003	0.002	0.003
R^2 (overall)	0.031	0.031	0.032	0.031	0.032

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.3.2: Flow-performance relation. The sample is all U.S. institutional prime MMFs from 1/1/2002 to 8/31/2008. The dependent variable is *Fund Flow*, computed as the percentage change in total net assets from week t to week $t+1$, adjusted for earned interests and trimmed at the 0.5%. Independent variables are the weekly annualized fund spread from $t-1$ to t, its percentile rank normalized to $[0, 1]$, logarithm of fund size, fund expense ratio, fund age, volatility of fund flows based on past 12-week fund flows, and logarithm of fund family size. All regressions are at the weekly frequency and include week fixed effects. Standard errors are HAC robust. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively.

	$Fund\ Flow_{i,t+1}$		
	(1)	(2)	(3)
$Spread\ Rank_{i,t}$	1.544^{***}	1.180^{***}	1.648^{***}
	(0.361)	(0.239)	(0.455)
$Fund\ Business_{i,t} * Spread\ Rank_{i,t}$	-0.608		-0.631
	(0.482)		(0.490)
$Conglomerate_{i,t} * Spread\ Rank_{i,t}$		-0.131	-0.158
		(0.272)	(0.274)
$Log(Fund\ Size)_{i,t}$	-1.261^{***}	-1.239^{***}	-1.261^{***}
	(0.186)	(0.180)	(0.187)
$Expense\ Ratio_{i,t}$	-0.001	-0.001	-0.001
	(0.006)	(0.006)	(0.006)
$Age_{i,t}$	-0.118^{**}	-0.121^{**}	-0.118^{**}
	(0.048)	(0.049)	(0.049)
$Flow\ Volatility_{i,t}$	-0.012	-0.011	-0.012
	(0.008)	(0.008)	(0.008)
$Log(Family\ Size)_{i,t}$	-0.013	-0.046	-0.011
	(0.068)	(0.061)	(0.068)
Week fixed effect	Y	Y	Y
Fund fixed effect	Y	Y	Y
Observations	48,543	48,543	48,543
Adj. R^2 (within)	0.009	0.009	0.009
R^2 (overall)	0.043	0.043	0.043

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.3.3: Flow-performance relation. The sample is all U.S. institutional prime MMFs from 1/1/2002 to 8/31/2008. The dependent variable is *Fund Flow*, computed as the percentage change in total net assets from week t to week $t+1$, adjusted for earned interests and trimmed at the 0.5%. Independent variables are the rank of weekly annualized fund spread from $t-1$ to t, logarithm of fund size, fund expense ratio, fund age, volatility of fund flows based on past 12-week flows, and logarithm of fund family size. The rank is computed in percentiles normalized to $[0, 1]$. Additional independent variables are the interactions of *Spread Rank* with *Fund Business* and *Conglomerate*. *Fund Business* is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. *Conglomerate* is an indicator variable equal to 1 if the fund sponsor is affiliated with a financial conglomerate and 0 otherwise. All regressions are at the weekly frequency and include week and fund fixed effects. Standard errors are HAC robust. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively.

	$Holdings\ Risk_{i,t}$		$Holdings\ Risk^{dyn}_{i,t}$		$Maturity\ Risk_{i,t}$		$Spread_{i,t}$		$Safe\ Holdings_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	k=4	k=8	k=4	k=8	k=4	k=8	k=4	k=8	k=4	k=8
$Fund\ Business_{i,t-k}$	-19.769^{***}	-18.577^{***}	-10.844^{*}	-8.769	-8.339^{***}	-7.217^{***}	-5.557	-7.123	4.962	3.295
	(4.445)	(4.247)	(5.849)	(5.011)	(2.309)	(2.393)	(5.318)	(4.796)	(3.153)	(3.312)
$Fund\ Business_{i,t-k} *$	-8.930^{***}	-8.230^{***}	-11.035^{**}	-10.823^{**}	-7.040^{***}	-7.082^{***}	-6.574^{***}	-6.751^{***}	7.643^{***}	7.143^{***}
$Post_t$	(2.160)	(2.139)	(4.003)	(3.846)	(1.394)	(1.481)	(1.382)	(1.387)	(1.893)	(1.796)
$Controls_{i,t-k}$	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
$Controls_{i,t-k} * Post_t$	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	16,470	15,982	16,470	15,982	16,470	15,982	16,470	15,982	16,470	15,982
Adj. R^2 (within)	0.033	0.030	0.014	0.014	0.041	0.038	0.010	0.010	0.027	0.026
R^2 (overall)	0.761	0.763	0.464	0.460	0.586	0.590	0.960	0.960	0.758	0.760

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.4.1: Cross-sectional risk-taking differential in the *Pre* and *Post* period. The sample is all U.S. institutional prime MMFs continuously active from 1/1/2006 to 8/31/2008 ($n = 122$). Data are weekly ($T = 139$). The dependent variables are: the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., US treasuries, GSE debt, and repos) in a fund's portfolio (*Holdings Risk*) in columns (1)–(2); the percentage of each week's riskiest asset class net of safe assets in a fund's portfolio ($Holdings\ Risk^{dyn}$) in columns (3)–(4); average portfolio maturity (*Maturity Risk*) in days in columns (5)–(6); the weekly annualized fund spread (*Spread*) in basis points in columns (7)–(8); and the percentage of safe assets in a fund's portfolio (*Safe Holdings*) in columns (9)–(10). For a detailed discussion of $Holdings\ Risk^{dyn}$, see Section 6.1 and Appendix A. *Fund Business* is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. *Post* is an indicator variable equal to 1 from 8/1/2007 to 8/31/2008, and 0 otherwise. The other independent variables (*Controls*) are fund assets, expense ratio, fund age, and fund family size. All regressions include week and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 12-week lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics are roughly 2.97, 2.20 1.82, respectively.

As a further robustness check, I estimate the exact same regression as KS:

$$\begin{aligned} Risk_{i,t+1} =& \alpha + \mu_t + \beta_1 Reputation\ Concerns_{i,2006} \\ &+ \beta_2 Post_t * Business\ Spillovers_{i,2006} + \gamma \cdot X_{i,2006} + \varepsilon_{i,t+1} \end{aligned} \tag{IA.4.1}$$

where *Reputation Concerns* is a generic name for either *Fund Business* or *Conglomerate*. *Post* is an indicator variable equal to 1 for the *Post* period and 0 for the *Pre* period. $X_{i,2006}$ is a vector of control variables similar to those in equation (8). Both sponsor's reputation concern and the controls are measured as of January 3, 2006 to mitigate possible endogeneity issues. Regression model (IA.4.1) also includes week fixed effects (μ_t) to account for any time differences in aggregate fund flows or macroeconomic conditions. As KS, I use three measures of risk (*Risk*): *Spread*, *Holdings Risk*, and *Maturity Risk*.

To be consistent with KS (see Table IV therein), Table IA.4.2 shows the results when both *Fund Business* and *Conglomerate* are included on the RHS of (IA.4.1). Reported standard errors are HACSC robust. My results are qualitatively similar to those of KS. Sponsor reputation concerns are negatively correlated with fund risk-taking in the *Post* period, and their effect is statistically significant at the 1% level for most measures of risk. In both my regressions and those of KS, sponsor reputation concerns tend to be negatively correlated with *Holdings Risk* also in the *Pre* period, with the effect being statistically significant at the 1% level in my regression but insignificant in that of KS. For robustness, I also run regression (IA.4.1) using *Safe Holdings* (U.S. treasuries + GSE debt + repos) as dependent variable (see column 4). In this case, my model predicts $\beta_2 > 0$ and $\beta_1 > 0$. In the data, I find that for *Fund Business* both $\widehat{\beta}_1$ and $\widehat{\beta}_2$ are positive and statistically significant at the 1% level, in agreement with the model and empirical results of Section 6.5.

In regression (IA.4.1), the sponsor's reputation concern is instrumented with its value as of January 3, 2006. While this eliminates possible endogenous correlations between the level of sponsor's reputation concern and the unobserved regression error, it also excludes all truly exogenous variations in sponsor's reputation concern coming from changes in other parts of a sponsor's business (e.g., shocks to the sponsor's equity mutual fund business). For these reasons, Section 6.5 extends the analysis of KS by using as the main explanatory variable the lagged value of sponsor's reputation concern, so to account for the exogenous variations in other parts of a sponsor's business.

IA.4.2 Risk-taking in the time series

This section presents several robustness checks of the results in Table 4, which test my model's predictions on the effect of risk premium and risk-free rate on the level of risky investment in the time series. First, Figure IA.4.1 shows the industry average *Holdings Risk*, i.e. the average percentage of risky assets (bank obligations) net of safe assets (treasuries, GSE debt, and repos) in MMF portfolios, over the January 2006–August 2008 period. The 1-month T-bill rate is superimposed (green line). The industry as a whole did not significantly "reach for yield" in the second half of

	$Holdings\ Risk_{i,t+1}$	$Holdings\ Risk^{dyn}_{i,t+1}$	$Maturity\ Risk_{i,t+1}$	$Spread_{i,t+1}$	$Safe\ Holdings_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)
$Fund\ Business_{i,2006}$	-15.022^{***}	-4.903^{***}	4.507	1.259	4.022^{**}
	(1.593)	(1.339)	(2.519)	(1.440)	(1.372)
$Fund\ Business_{i,2006} * Post_t$	-12.808^{***}	-13.892^{***}	-11.816^{***}	-10.671^{***}	7.626^{***}
	(2.517)	(3.940)	(1.660)	(2.446)	(1.765)
$Conglomerate_{i,2006}$	-1.608^{***}	0.264	1.312^{*}	-5.546^{***}	-0.530
	(0.287)	(0.721)	(0.619)	(0.269)	(0.330)
$Conglomerate_{i,2006} * Post_t$	-1.453^{***}	-3.976^{***}	-0.013	-1.304^{**}	2.474^{***}
	(0.434)	(0.884)	(0.711)	(0.525)	(0.412)
$Controls_{i,2006}$	Y	Y	Y	Y	Y
$Controls_{i,2006} * Post_t$	Y	Y	Y	Y	Y
Week fixed effect	Y	Y	Y	Y	Y
Fund fixed effect	N	N	N	N	N
Observations	16,836	16,836	16,836	16,836	16,836
R^2 (overall)	0.184	0.169	0.119	0.905	0.113

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.4.2: Cross-sectional risk-taking differential in the *Pre* and *Post* period. The sample is all U.S. institutional prime MMFs continuously active from 1/1/2006 to 8/31/2008 ($n = 122$). Data are weekly ($T = 139$). The dependent variables are: the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., US treasuries, GSE debt, and repos) in a fund's portfolio (*Holdings Risk*) in column (1); the percentage of each week's riskiest asset class net of safe assets in a fund's portfolio ($Holdings\ Risk^{dyn}$) in column (2); average portfolio maturity (*Maturity Risk*) in days in column (3); the weekly annualized fund spread (*Spread*) in basis points in column (4); and the percentage of safe assets in a fund's portfolio (*Safe Holdings*) in column (5). For a detailed discussion of $Holdings\ Risk^{dyn}$, see Section 6.1 and Appendix A. *Fund Business* is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. *Post* is an indicator variable equal to 1 from 8/1/2007 to 8/31/2008, and 0 otherwise. The other independent variables (*Controls*) are fund assets, expense ratio, fund age, and fund family size. All RHS variables are as of 1/3/2006. All regressions include week and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 12-week lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics are roughly 2.97, 2.20 1.82, respectively.

2007, when risk-free rates decreased and risk premia increased. This is consistent with the model's prediction that when the credit risk and hence the premium of the risky asset increases, the risk-taking of MMFs with low default costs and that of MMFs with high default costs go in opposite directions. If any, there was more "reach for yield" in the *Pre* period, when risk-free rates were higher and risk premia lower.

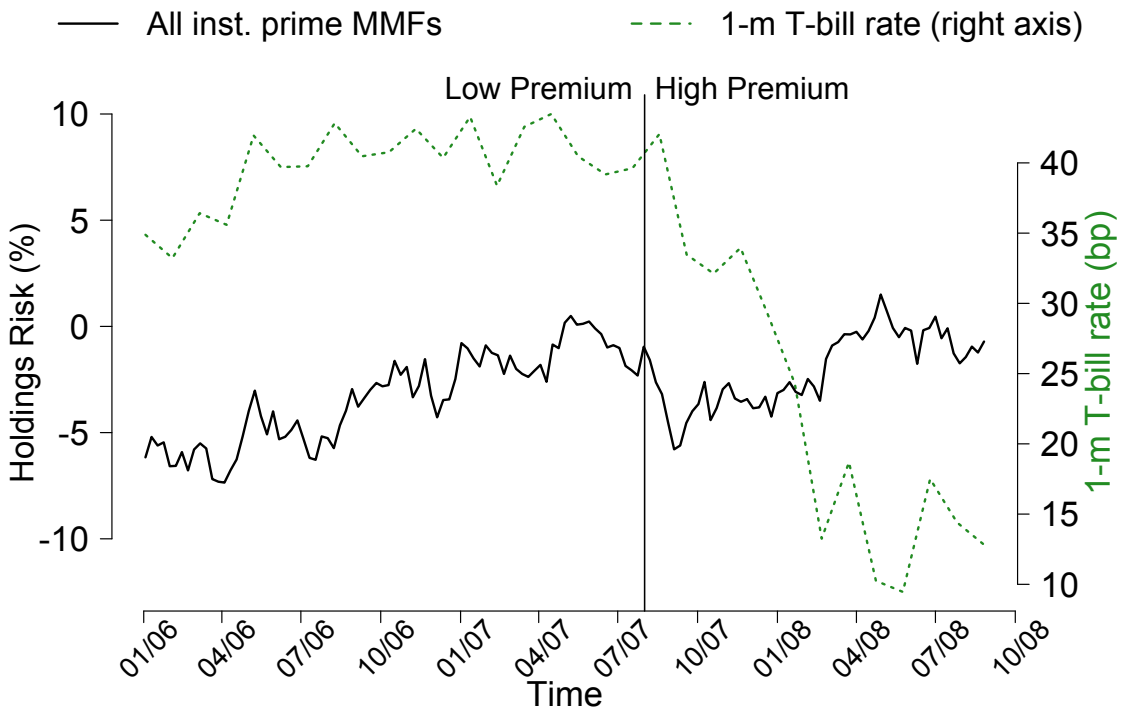


Figure IA.4.1: Industry average risk-taking in the time series. The sample is all U.S. institutional prime MMFs. The black line represents the industry average percentage of assets held in bank obligations (risky assets) net of U.S. treasuries, GSE debt, and repurchase agreements (safe assets). The vertical black line separates the sample in two sub-periods: one in which the risk premia available to MMFs are relatively low (before 08/2007) and one in which the risk premia available to MMFs are relatively high (after 08/2007). The dashed green line represents the 1-month T-bill rate. The scale for average net holdings is on the left y-axis. The scale for the T-bill rate is on the right y-axis.

To have a quantitative robustness check of the results in Table 4, I estimate regression (9) using the 3-month T-bill rate as a proxy for the risk-free rate (Table IA.4.3), and lagging all fund-specific time-varying controls by two lags (Table IA.4.4). Both robustness checks give results that are qualitatively and quantitatively similar to those in Table 4, confirming the model's predictions. An increase in the risk premium generates a bifurcation in the risk-taking of MMFs: funds with low default costs increase their risk-taking, while funds with low default costs decrease it, as predicted by the model. On the other hand, a decrease in the risk-free rate pushes all MMFs to tilt their portfolios toward safer asset classes (i.e., less bank obligations and ABCPs, and more treasuries, GSE debt, and repos). However, MMFs compensate this shift to safer asset classes by lengthening

the maturity of their portfolios, as observed also in Table 4.

As a further robustness check, I also estimate regression (9) changing the identification of high- and low-default-cost funds as follows: for each month t, I identify as high-default-cost funds those whose $Fund\ Business$ in month $t-1$ is above the $60th$ percentile of the cross-section distribution, and as low-default-cost funds those whose $Fund\ Business$ in month $t-1$ is below the $40th$ percentile. Under this specification, the indicator variables $High\ FB$ and $Low\ FB$ on the RHS of regression (9) vary over time and are lagged by one month w.r.t. the dependent variable to mitigate endogeneity issues. Results are in Table IA.4.5. Again, they are qualitatively similar to those in Table 4, confirming the model's predictions.

IA.4.3 Cross-sectionals risk-taking differential

I perform several robustness checks of the results in Table 6, which test my model's predictions on the different effect of risk premia and risk-free rates on the cross-sectional risk-taking differential. In my first robustness check, I estimate regression (10) using $Fund\ Business$ rather than its rank as the main explanatory variable. Results are in Table IA.4.6 and are qualitatively and quantitatively similar to those of Table 6, confirming the predictions of the model. The effect of the risk premium is statistically significant at the 1% level for all measures of fund risk-taking. The effect of the risk-free rate is statistically significant at the 5% level for all measures of fund risk-taking except *Spread*. Moreover, both effects are economically important.

As further robustness checks, I estimate regression (10) using the $GZ\ Premium$ as a proxy for the risk premium (Table IA.4.7), using the 3-month T-bill rate as a proxy for the risk-free rate (Table IA.4.8), and lagging all fund-specific RHS variables by two lags (Table IA.4.9). The results are qualitatively and quantitatively close to those of Table 6 and confirm the model's predictions. The effect of the risk premium is statistically significant at the 5% level for all measures of risk-taking, and in most cases at the 1% level. The effect of the risk-free rate is statistically significant at the 1% level for the measures of risk-taking based on the asset class composition of fund portfolios, while it is insignificant but consistent with the model's predictions for the measures of risk-taking based on portfolio maturity and spread. As in Table 6, all these effects are also economically important. The only noteworthy difference with respect to the main regression specification is that when the risk premium is proxied by the Gilchrist and Zakrajsek (2012) excess bond premium, the magnitude of the effect of the risk-free rate diminishes.

Appendix IA.5 Microfoundation of the tournament

This appendix presents a random utility model of fund investors that rationalizes the rank-based payoff function of the MMF tournament. The standard theoretical justification for the empirically observed positive relation between money flows and past performance is that investors assume that fund managers have idiosyncratic, unobservable skills and try to infer them from historical data.

	(1)	(2)	(3)	(4)
	$Holdings\ Risk_{i,t}$	$Holdings\ Risk^{dyn}_{i,t}$	$Maturity\ Risk_{i,t}$	$Safe\ Holdings_{i,t}$
$\widehat{rp}_t$	−0.275	−1.166	−0.786	0.160
	(0.835)	(1.415)	(1.282)	(1.110)
$\widehat{rp}_t * Low\ FB_i$	2.246*	6.336***	5.169***	−0.561
	(1.152)	(1.643)	(0.958)	(0.475)
$\widehat{rp}_t * High\ FB_i$	−3.701**	−2.257*	−2.615**	2.075***
	(1.309)	(1.006)	(1.028)	(0.661)
rf_t	19.210**	26.507***	−18.783***	−17.193***
	(6.955)	(5.982)	(4.614)	(3.747)
$rf_t * Low\ FB_i$	−3.075	11.354	−9.861*	0.576
	(3.290)	(7.738)	(4.858)	(2.845)
$rf_t * High\ FB_i$	2.815	8.776*	0.053	−4.836
	(4.918)	(4.410)	(5.379)	(3.929)
$Fund\ Business_{i,t-1}$	−10.061	−17.794**	2.106	3.458
	(6.202)	(6.884)	(4.583)	(1.799)
$Controls_{i,t-1}$	Y	Y	Y	Y
Fund Fixed Effects	Y	Y	Y	Y
Observations	6,715	6,715	6,715	6,715
Adj. R^2 (within)	0.083	0.071	0.173	0.091
R^2 (overall)	0.652	0.426	0.442	0.653
$\beta_{rp} + \beta^L_{rp}$	1.971	5.170*	4.383*	−0.401
$\beta_{rp} + \beta^H_{rp}$	−3.976***	−3.423**	−3.401	2.235**
$\beta_{rf} + \beta^L_{rf}$	16.135*	37.861***	−28.644***	−16.617***
$\beta_{rf} + \beta^H_{rf}$	22.025***	35.283***	−18.730*	−22.029***

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.4.3: Reach for yield: risk premium vs. risk-free rate. The sample is all U.S. institutional prime MMFs continuously active from 1/1/2002 to 8/31/2008 ($n = 85$). Data are monthly ($T = 80$). The dependent variables are: the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., US treasuries, GSE debt, and repos) in a fund's portfolio ($Holdings\ Risk$) in column (1); the percentage of each month's riskiest asset class net of safe assets in a fund's portfolio ($Holdings\ Risk^{dyn}$) in column (2); average portfolio maturity ($Maturity\ Risk$) in days in column (3); and the percentage of safe assets in a fund's portfolio ($Safe\ Holdings$) in column (4). For a detailed discussion of $Holdings\ Risk^{dyn}$, see Section 6.1 and Appendix A. The risk premium $\widehat{rp}$ is the index of spreads available to MMFs defined by equation (6). The risk-free rate rf_t is the return on 3-month T-bills. $High$ (Low) FB_i is a binary variable equal to 1 if fund i's $Fund\,Business$ is continuously above (below) the cross-sectional median throughout the whole period, and 0 otherwise. $Fund\ Business$ is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. $Controls$ are: fund assets, expense ratio, fund age, fund family size, and $Fund\ Business$. All regressions include fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 8-month lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85. For the Wald statistics they are roughly 9.31, 4.94, and 3.35.

	(1)	(2)	(3)	(4)
	$Holdings\ Risk_{i,t}$	$Holdings\ Risk^{dyn}_{i,t}$	$Maturity\ Risk_{i,t}$	$Safe\ Holdings_{i,t}$
$\widehat{rp}_t$	−0.329	0.682	−0.967	−0.924
	(0.874)	(1.199)	(1.275)	(1.051)
$\widehat{rp}_t * Low\ FB_i$	3.254**	6.493***	4.932***	0.324
	(1.156)	(2.015)	(0.887)	(0.479)
$\widehat{rp}_t * High\ FB_i$	−3.343**	−2.584**	−2.660**	1.802**
	(1.308)	(1.020)	(0.963)	(0.620)
rf_t	24.819***	33.630***	−21.926***	−21.298***
	(6.122)	(5.092)	(5.490)	(3.087)
$rf_t * Low\ FB_i$	−3.286	13.686	−11.190*	0.980
	(3.534)	(7.429)	(5.387)	(3.134)
$rf_t * High\ FB_i$	1.473	8.573*	−1.294	−4.948
	(4.799)	(4.529)	(6.256)	(4.291)
$Fund\ Business_{i,t-2}$	−9.859*	−16.833**	1.293	3.476
	(5.244)	(6.862)	(4.991)	(1.176)
$Controls_{i,t-2}$	Y	Y	Y	Y
Fund Fixed Effects	Y	Y	Y	Y
Observations	6,630	6,630	6,630	6,630
Adj. R^2 (within)	0.088	0.078	0.180	0.099
R^2 (overall)	0.654	0.430	0.447	0.657
$\beta_{rp} + \beta^L_{rp}$	2.925*	7.175**	3.965*	−0.600
$\beta_{rp} + \beta^H_{rp}$	−3.672***	−1.902*	−3.627	0.878
$\beta_{rf} + \beta^L_{rf}$	21.533**	47.316***	−33.116***	−20.318***
$\beta_{rf} + \beta^H_{rf}$	26.292***	42.203***	−23.220**	−26.246***

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.4.4: Reach for yield: risk premium vs. risk-free rate. The sample is all U.S. institutional prime MMFs continuously active from 1/1/2002 to 8/31/2008 ($n = 85$). Data are monthly ($T = 80$). The dependent variables are: the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., US treasuries, GSE debt, and repos) in a fund's portfolio ($Holdings\ Risk$) in column (1); the percentage of each month's riskiest asset class net of safe assets in a fund's portfolio ($Holdings\ Risk^{dyn}$) in column (2); average portfolio maturity ($Maturity\ Risk$) in days in column (3); and the percentage of safe assets in a fund's portfolio ($Safe\ Holdings$) in column (4). For a detailed discussion of $Holdings\ Risk^{dyn}$, see Section 6.1 and Appendix A. The risk premium $\widehat{rp}$ is the index of spreads available to MMFs defined by equation (6). The risk-free rate rf_t is the return on 1-month T-bills. $High$ (Low) FB_i is a binary variable equal to 1 if fund i's $Fund\,Business$ is continuously above (below) the cross-sectional median throughout the whole period, and 0 otherwise. $Fund\ Business$ is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. $Controls$ are: fund assets, expense ratio, fund age, fund family size, and $Fund\ Business$. All regressions include fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 8-month lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85. For the Wald statistics they are roughly 9.31, 4.94, and 3.35.

	(1)	(2)	(3)	(4)
	$Holdings\ Risk_{i,t}$	$Holdings\ Risk^{dyn}_{i,t}$	$Maturity\ Risk_{i,t}$	$Safe\ Holdings_{i,t}$
$\widehat{rp}_t$	1.129	4.131*	−0.253	−0.843
	(1.816)	(2.148)	(1.827)	(1.104)
$\widehat{rp}_t * Low\ FB_{i,t-1}$	5.874***	3.878**	2.996**	−1.500
	(1.229)	(1.673)	(1.253)	(0.998)
$\widehat{rp}_t * High\ FB_{i,t-1}$	−1.778	−7.294***	−0.248	2.457***
	(1.183)	(1.775)	(0.407)	(0.518)
rf_t	16.982**	36.046***	−30.896***	−18.298***
	(6.559)	(7.406)	(8.725)	(3.116)
$rf_t * Low\ FB_{i,t-1}$	−6.386	−3.443	2.883	8.557
	(8.191)	(10.964)	(4.654)	(6.301)
$rf_t * High\ FB_{i,t-1}$	19.850***	10.829**	9.844***	−13.671***
	(3.458)	(4.787)	(2.965)	(3.438)
$Fund\ Business_{i,t-1}$	−10.445*	−14.202**	2.740	4.844*
	(5.198)	(5.811)	(5.099)	(2.316)
$Controls_{i,t-1}$	Y	Y	Y	Y
Fund Fixed Effects	Y	Y	Y	Y
Observations	6,715	6,715	6,715	6,715
Adj. R^2 (within)	0.101	0.084	0.179	0.109
R^2 (overall)	0.659	0.434	0.447	0.660
$\beta_{rp} + \beta^L_{rp}$	7.003*	8.009**	2.743*	−2.343*
$\beta_{rp} + \beta^H_{rp}$	−0.649	−3.163*	−0.501*	1.614*
$\beta_{rf} + \beta^L_{rf}$	10.596	32.603**	−28.013***	−9.741
$\beta_{rf} + \beta^H_{rf}$	36.832***	46.875***	−21.052**	−31.969***

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.4.5: Reach for yield: risk premium vs. risk-free rate. The sample is all U.S. institutional prime MMFs continuously active from 1/1/2002 to 8/31/2008 ($n = 85$). Data are monthly ($T = 80$). The dependent variables are: the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., US treasuries, GSE debt, and repos) in a fund's portfolio ($Holdings\ Risk$) in column (1); the percentage of each month's riskiest asset class net of safe assets in a fund's portfolio ($Holdings\ Risk^{dyn}$) in column (2); average portfolio maturity ($Maturity\ Risk$) in days in column (3); and the percentage of safe assets in a fund's portfolio ($Safe\ Holdings$) in column (4). For a detailed discussion of $Holdings\ Risk^{dyn}$, see Section 6.1 and Appendix A. The risk premium $\widehat{rp}$ is the index of spreads available to MMFs defined by equation (6). The risk-free rate rf_t is the return on 1-month T-bills. $High$ (Low) $FB_{i,t}$ is a binary variable equal to 1 if fund i's $Fund\,Business$ is above (below) the $60th$ ($40th$) percentile in month t, and 0 otherwise. $Fund\ Business$ is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. $Controls$ are: fund assets, expense ratio, fund age, fund family size, and $Fund\ Business$. All regressions include fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 8-month lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85. For the Wald statistics they are roughly 9.31, 4.94, and 3.35.

	(1)	(2)	(3)	(4)	(5)
	$Holdings\ Risk_{i,t}$	$Holdings\ Risk^{dyn}_{i,t}$	$Maturity\ Risk_{i,t}$	$Spread_{i,t}$	$Safe\ Holdings_{i,t}$
$Fund\ Business_{i,t-1}$	-15.633^{**}	-5.939	2.916	1.019	5.347^{*}
	(5.912)	(5.429)	(3.106)	(1.884)	(2.561)
$FB_{i,t-1} * \widehat{rp}_t$	-12.326^{***}	-14.179^{***}	-4.030^{***}	-8.422^{***}	8.221^{***}
	(3.533)	(4.207)	(1.120)	(1.344)	(1.961)
$FB_{i,t-1} * rf_t$	43.642^{**}	52.530^{**}	16.499^{**}	4.694	-32.680^{**}
	(16.528)	(18.733)	(5.964)	(6.514)	(13.826)
$Controls_{i,t-1}$	Y	Y	Y	Y	Y
$Controls_{i,t-1} * \widehat{rp}_t$	Y	Y	Y	Y	Y
$Controls_{i,t-1} * rf_t$	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y
Fund Fixed Effects	Y	Y	Y	Y	Y
Observations	6,715	6,715	6,715	6,715	6,715
Adj. R^2 (within)	0.044	0.021	0.025	0.107	0.022
R^2 (overall)	0.665	0.513	0.557	0.953	0.660

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.4.6: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime MMFs continuously active from 1/1/2002 to 8/31/2008 ($n = 85$). Data are monthly ($T = 80$). The dependent variables are: the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., US treasuries, GSE debt, and repos) in a fund's portfolio (*Holdings Risk*) in column (1); the percentage of each month's riskiest asset class net of safe assets in a fund's portfolio ($Holdings\ Risk^{dyn}$) in column (2); average portfolio maturity (*Maturity Risk*) in days in column (3); the annualized fund spread (*Spread*) in basis points in column (4); and the percentage of safe assets in a fund's portfolio (*Safe Holdings*) in column (5). For a detailed discussion of $Holdings\ Risk^{dyn}$, see Section 6.1 and Appendix A. *FB* stands for *Fund Business*, which is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. The risk premium $\widehat{rp}$ is the index of spreads available to MMFs defined by equation (6). The risk-free rate rf_t is the return on 1-month T-bills. *Controls* are: fund assets, expense ratio, fund age, fund family size, and their interaction terms with $\widehat{rp}$ and rf. All regressions include month and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 8-month lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85.

	(1)	(2)	(3)	(4)	(5)
	$Holdings\ Risk_{i,t}$	$Holdings\ Risk^{dyn}_{i,t}$	$Maturity\ Risk_{i,t}$	$Spread_{i,t}$	$Safe\ Holdings_{i,t}$
$FB\ Rank_{i,t-1}$	-12.641^{***}	-5.261	3.939	-2.399	3.969^{*}
	(3.459)	(5.082)	(2.833)	(1.442)	(2.106)
$FB\ Rank_{i,t-1} * \widehat{rp}_t$	-8.301^{***}	-9.726^{***}	-2.753^{***}	-5.680^{***}	5.477^{***}
	(1.273)	(1.512)	(0.776)	(1.098)	(0.846)
$FB\ Rank_{i,t-1} * rf_t$	41.932^{***}	36.218^{***}	6.554	-0.561	-25.932^{***}
	(9.174)	(8.920)	(5.895)	(3.201)	(7.703)
$Controls_{i,t-1}$	Y	Y	Y	Y	Y
$Controls_{i,t-1} * \widehat{rp}_t$	Y	Y	Y	Y	Y
$Controls_{i,t-1} * rf_t$	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y
Fund Fixed Effects	Y	Y	Y	Y	Y
Observations	6,715	6,715	6,715	6,715	6,715
Adj. R^2 (within)	0.051	0.024	0.025	0.112	0.026
R^2 (overall)	0.664	0.512	0.558	0.953	0.659

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.4.7: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime MMFs continuously active from 1/1/2002 to 8/31/2008 ($n = 85$). Data are monthly ($T = 80$). The dependent variables are: the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., US treasuries, GSE debt, and repos) in a fund's portfolio (*Holdings Risk*) in column (1); the percentage of each month's riskiest asset class net of safe assets in a fund's portfolio ($Holdings\ Risk^{dyn}$) in column (2); average portfolio maturity (*Maturity Risk*) in days in column (3); the annualized fund spread (*Spread*) in basis points in column (4); and the percentage of safe assets in a fund's portfolio (*Safe Holdings*) in column (5). For a detailed discussion of $Holdings\ Risk^{dyn}$, see Section 6.1 and Appendix A. *FB Rank* is the rank of *Fund Business*, which is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. *FB Rank* is expressed in percentiles normalized to $[0, 1]$. The risk premium $\widehat{rp}$ is the excess bond premium for financial firms from Gilchrist and Zakrajsek (2012). The risk-free rate rf_t is the return on 1-month T-bills. *Controls* are: fund assets, expense ratio, fund age, fund family size, and their interaction terms with $\widehat{rp}$ and rf. All regressions include month and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 8-month lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85.

	(1)	(2)	(3)	(4)	(5)
	$Holdings\ Risk_{i,t}$	$Holdings\ Risk^{dyn}_{i,t}$	$Maturity\ Risk_{i,t}$	$Spread_{i,t}$	$Safe\ Holdings_{i,t}$
$FB\ Rank_{i,t-1}$	-10.430^{***}	-3.582	4.189	-0.804	3.595^{*}
	(3.302)	(5.247)	(2.966)	(1.901)	(1.888)
$FB\ Rank_{i,t-1} * \widehat{rp}_t$	-8.015^{***}	-9.801^{***}	-3.827^{***}	-6.964^{***}	5.415^{***}
	(2.493)	(2.969)	(1.108)	(1.048)	(1.242)
$FB\ Rank_{i,t-1} * rf_t$	45.905^{***}	45.179^{***}	9.952^{*}	7.502	-28.657^{***}
	(9.440)	(11.642)	(4.887)	(4.847)	(7.684)
$Controls_{i,t-1}$	Y	Y	Y	Y	Y
$Controls_{i,t-1} * \widehat{rp}_t$	Y	Y	Y	Y	Y
$Controls_{i,t-1} * rf_t$	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y
Fund Fixed Effects	Y	Y	Y	Y	Y
Observations	6,715	6,715	6,715	6,715	6,715
Adj. R^2 (within)	0.041	0.021	0.026	0.108	0.021
R^2 (overall)	0.660	0.510	0.557	0.953	0.657

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.4.8: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime MMFs continuously active from 1/1/2002 to 8/31/2008 ($n = 85$). Data are monthly ($T = 80$). The dependent variables are: the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., US treasuries, GSE debt, and repos) in a fund's portfolio (*Holdings Risk*) in column (1); the percentage of each month's riskiest asset class net of safe assets in a fund's portfolio ($Holdings\ Risk^{dyn}$) in column (2); average portfolio maturity (*Maturity Risk*) in days in column (3); the annualized fund spread (*Spread*) in basis points in column (4); and the percentage of safe assets in a fund's portfolio (*Safe Holdings*) in column (5). For a detailed discussion of $Holdings\ Risk^{dyn}$, see Section 6.1 and Appendix A. *FB Rank* is the rank of *Fund Business*, which is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. *FB Rank* is expressed in percentiles normalized to $[0, 1]$. The risk premium $\widehat{rp}$ is the index of spreads available to MMFs defined by equation (6). The risk-free rate rf_t is the return on 3-month T-bills. *Controls* are: fund assets, expense ratio, fund age, fund family size, and their interaction terms with $\widehat{rp}$ and rf. All regressions include month and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 8-month lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85.

	(1)	(2)	(3)	(4)	(5)
	$Holdings\ Risk_{i,t}$	$Holdings\ Risk^{dyn}_{i,t}$	$Maturity\ Risk_{i,t}$	$Spread_{i,t}$	$Safe\ Holdings_{i,t}$
$FB\ Rank_{i,t-2}$	-10.750^{**}	-4.427	4.031	-0.384	3.517
	(3.846)	(5.384)	(3.247)	(2.161)	(2.164)
$FB\ Rank_{i,t-2} * \widehat{rp}_t$	-6.571^{**}	-8.668^{**}	-3.394^{***}	-7.079^{***}	4.748^{***}
	(2.718)	(2.888)	(1.067)	(1.044)	(1.210)
$FB\ Rank_{i,t-2} * rf_t$	49.345^{***}	43.802^{***}	9.964	6.474	-31.283^{***}
	(10.383)	(12.755)	(5.631)	(4.776)	(8.659)
$Controls_{i,t-2}$	Y	Y	Y	Y	Y
$Controls_{i,t-2} * \widehat{rp}_t$	Y	Y	Y	Y	Y
$Controls_{i,t-2} * rf_t$	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y
Fund Fixed Effects	Y	Y	Y	Y	Y
Observations	6,630	6,630	6,630	6,630	6,630
Adj. R^2 (within)	0.043	0.020	0.026	0.110	0.023
R^2 (overall)	0.661	0.511	0.557	0.953	0.659

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IA.4.9: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime MMFs continuously active from 1/1/2002 to 8/31/2008 ($n = 85$). Data are monthly ($T = 80$). The dependent variables are: the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., US treasuries, GSE debt, and repos) in a fund's portfolio (*Holdings Risk*) in column (1); the percentage of each month's riskiest asset class net of safe assets in a fund's portfolio ($Holdings\ Risk^{dyn}$) in column (2); average portfolio maturity (*Maturity Risk*) in days in column (3); the annualized fund spread (*Spread*) in basis points in column (4); and the percentage of safe assets in a fund's portfolio (*Safe Holdings*) in column (5). For a detailed discussion of $Holdings\ Risk^{dyn}$, see Section 6.1 and Appendix A. *FB Rank* is the rank of *Fund Business*, which is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. *FB Rank* is expressed in percentiles normalized to $[0, 1]$. The risk premium $\widehat{rp}$ is the index of spreads available to MMFs defined by equation (6). The risk-free rate rf_t is the return on 1-month T-bills. *Controls* are: fund assets, expense ratio, fund age, fund family size, and their interaction terms with $\widehat{rp}$ and rf. All regressions include month and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 8-month lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85.

Higher past performance is perceived as a signal of higher ability and generates money inflows.

Assume there is a continuum of investors. Each investor is associated with a single fund and endowed with a wealth $D > 0$. I refer to the investor associated with fund c as "investor c." I assume that investor c has only two options: she can either put her money into her idiosyncratic fund c or invest in an alternative technology outside the MMF industry. The investor demand for delegated management satisfies the following random utility model:

$$\text{investor } c \text{ invests in } \begin{cases} \text{fund } c & \text{with probability} \quad p = Rk_\pi(c) \\ \text{alternative technology} & \text{with probability} \quad 1 - p \end{cases}$$

This model can be motivated by arguing that investors have limited information, or limited capacity of processing information, on the management industry and market structure. Each investor has accumulated some information on a given fund, which she prefers to the others for some idiosyncratic reason. Investor c uses the ex post rank of fund c's performance as an indication of its manager's skill. The acquisition of ex post information on other funds is too costly. Hence, each investor only decides whether to invest in the idiosyncratic fund or in the alternative technology.

There are other ways to endogeneize the rank-based flow-performance relation observed in the data as the outcome of an optimal investment strategy of rational investors. Huang, Wei, and Yan (2007) formally show that rank-based reward functions arise in equilibrium due to information acquisition and participation costs faced by retail investors. Matejka and McKay (2015) show that the logit model (closely related to the above random utility model) is the optimal decision rule for a rationally inattentive agent who is uncertain on the fundamental value of her investment possibilities but faces a cost of acquiring information. In the context of my model, the unobservable, fundamental value of investment opportunities would be a fund's underlying quality, and the logit model would represent the endogenous rank-based flow-performance relation. Frankel (2014) shows that ranking is the optimal delegated alignment contract when a principal delegates multiple decisions to an agent, who has private information relevant to each decision, but the principal is uncertain about the agent's preferences. In the case of the mutual fund industry, we can think of the principal as the investor and the agent as a financial adviser. Finally, the normative literature on tournament theory (e.g., Lazaer and Rosen, 1981) shows that a tournament reward structure is optimal for a principal-agent problem in presence of moral hazard.

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