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Abstract

Do asset managers reach for yield because of competitive pressures in a low interest 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 riskfree 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 2002–2008 period.

"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](#page-2-0)} U.S. prime money market funds $(MMFs)$, in particular, are seen as a leading example of asset managers reaching for yield because of competitive forces.[2](#page-2-1) 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](#page-2-2)} 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.

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

² Stein (2013): "[\ldots] 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. $[\dots]$ "

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

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 more risk. The fund with the highest default cost anticipates that in equilibrium, it will have the lowest expected 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 optimally 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, since they optimally choose to outperform a larger fraction of competitors, and 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 is 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 in the 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 asset 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 have to cut risky investment to keep the default probability sufficiently close to zero. Conversely, funds with lower default costs face 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 risky investment despite the increase in risk. This bifurcation comes from the heterogeneity of equilibrium competitive pressure.

Importantly, the equilibrium default probability does not depend on the level of the riskfree rate. This is because, absent default, funds only care about relative performance, and in case of default, they pay a fixed idiosyncratic cost. The equilibrium risky investment, however, does depend on the level of the risk-free rate because the safe assets in a fund's portfolio work as a buffer against default risk. If the return on safe assets 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 reduces 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 risky investment differential increases as 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 risk-free rate level from that of the risk premium. Risk premia trigger risktaking 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."

My empirical analysis shows that these predictions are consistent with the risk-taking of institutional prime MMFs over January 2002–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 for a possible "reach for yield" of financial intermediaries, and particularly MMFs, in a low interest rate environment emerged for the first time precisely in 2003–2004 (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), which is 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](#page-5-0) 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 the results in Table [3,](#page-45-0) in which I disentangle the

Figure 1: MMF risk-taking in the time series: high- vs. low-default-cost funds. The sample is U.S. institutional prime MMFs. 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 always 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 [5](#page-26-0) for details.

effect of risk-free rates from that of risk premia over the 2002–2008 period.^{[4](#page-5-1)} After an increase of 1% in the premium, there is a clear bifurcation in MMF risk-taking: funds with default

⁴My 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 [5](#page-26-0) for details.

costs always 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 always 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 across time. I 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 yield.

The reminder of the paper is organized as follows. The next section reviews the literature. Section [1](#page-8-0) describes prime MMFs and their institutional setting. Section [2](#page-9-0) introduces the model. Section [3](#page-13-0) characterizes and discusses the equilibrium. Section [4](#page-19-0) contains comparative statics with respect to asset returns. Section [5](#page-26-0) presents the empirical analysis and tests the model's predictions. Section [6](#page-37-0) concludes. Appendices [A–](#page-48-0)[C](#page-51-0) contain further theoretical results and in-depth analyses of the flow-performance relation for MMFs and of their risk-taking opportunities. The Internet Appendix (IA) contains comparative statics with respect to the distribution of default costs, model extensions, proofs, data descriptions, and robustness checks.

Related literature

This paper belongs to the recent growing literature on the risk-taking and systemic im-portance of MMFs.^{[5](#page-7-0)} 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 more risk than funds whose sponsors have higher reputation 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 going 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](#page-7-1) 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 reached for higher returns in 2009–2011 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. I consider a different type of MMF heterogeneity and add to these works by providing a model that explains how relative performance competition affects 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 rates but without runs or 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 net asset value (NAV)

 ${}^{5}E.g.,$ 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. (2016).

⁶This is also a form of sponsor's reputation concerns but is significantly different from the one I use in my empirical analysis. See Section [5](#page-26-0) for details.

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, 2014). In this paper, in contrast, heterogeneity comes from the cost of default, which is an intrinsic property of each fund. From a technical perspective, most theoretical papers consider fund 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 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.

Finally, this paper contributes to the literature on the transmission of monetary policy to financial intermediaries (Adrian and Shin, 2009; Borio and Zhu, 2012; Landier et al., 2015) by studying how the level of risk-free rates affects the risk-taking of important non-bank financial institutions such as prime MMFs.

1 Prime Money Market Funds: Institutional Features

U.S. 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 2014, they had roughly \$1.5 trillion in assets under management and held approximately 35% of the global outstanding volume of commercial papers (ICI, 2015). 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, prime MMFs can only hold commercial papers that carry either the highest or secondhighest rating from at least two of the nationally recognized credit rating agencies. During the January 2002–August 2008 period, prime MMFs were not permitted to hold more than 5% of investments in second tier (A2-P2) paper or 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 prime MMFs to invest in even higher-quality assets with 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 prime MMFs (SEC Release No. IC-31166). The main pillar of these rules is that from October 2016, institutional prime MMFs have to sell and redeem shares based on the current market-based value of the securities in their underlying portfolios. That is, they 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 has encountered the strong opposition of the industry (ICI, 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. R is 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](#page-10-0) 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 c's portfolio is

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

Hereafter, when it causes no confusion, $\pi(x_c)$ is simply denoted as π_c and 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 π is

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

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.^{[7](#page-11-0)} Then, the ex post payoff of fund c is

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

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 $x : [c, \bar{c}] \to [0, D]$, the expected payoff of fund c is

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

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 deposit rate 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 fixed costs include reputation costs and negative spillovers to other parts of sponsor's business. A default, however, might also have a variable cost depending on how large the shortfall is. The internet Appendix [IA.2](#page-58-0) contains two model extensions that also include variable default costs and shows that the results of the model above are robust to such extensions.

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,](#page-10-0) 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 the median return because in a tournament context, fund payoffs depend only on relative performance. As I discuss in more

⁷Under 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.

detail below, 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, 2015). The assumption that a fund's AUM at the end of the tournament depend on the fund's net return only via the flowperformance 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 a vast empirical literature (Chevalier and Ellison, 1997). In Appendix [B,](#page-49-0) 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 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 study the incentives generated by the tournament nature of fund competition alone.[8](#page-12-0) However, the qualitative predictions of the model hold under any payoff (convex or concave) that increases with the performance rank. Moreover, Appendix [B](#page-49-0) shows that when we control for performance rank, any convexity in the flow-performance relation of MMFs disappears.

In the above model, the flow-performance relation is exogenously given. In mapping the model to the data, this amounts to assuming 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. The internet Appendix [IA.5](#page-86-0) show that this assumption is satisfied in the data.

Under specification [\(1\)](#page-10-1), the rank of a fund's performance is equal to the measure of funds with strictly lower performance. In Appendix [IA.3,](#page-69-0) I consider the more general specification in which the rank of a fund's performance is equal to the measure of funds with strictly

⁸Moreover, Spiegel and Zhang (2013) argue that the empirically observed convexity of the flowperformance relation in the mutual fund industry is due solely to misspecification of the empirical model.

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.

The assumption that fund flows also depend on factors unrelated 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 model's primitives. However, the model can be solved and gives the same results if that assumption is relaxed and substituted with a regularity condition on the distribution of default costs.

Finally, the above model abstracts from investor heterogeneity within the same MMF. Schmidt *et al.* (2016) show that the likelihood and size of a run on a MMF due to a negative shock to its portfolio fundamentals depend on the fraction of institutional vs. retail investors. Such within-fund heterogeneity, which may impact equilibrium risk-taking, is not considered here. The model also abstracts 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:

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

 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 $x \le x_0$ 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 $x : [\underline{c}, \overline{c}] \rightarrow [0, D]$ is a Nash equilibrium of the tournament defined by [\(2\)](#page-11-1) if and only if $v_c(x_c, x_{-c}) \ge v_c(z, x_{-c})$ for all $z \in [0, D]$ almost everywhere $(a.e.)$ on $[\underline{c}, \overline{c}]$.

Hereafter, I omit the "a.e." qualification. All the following results are true a.e. on $[\underline{c}, \overline{c}]$.

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](#page-14-0) 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.^{[9](#page-14-1)} The second part of Proposition [1](#page-14-0) 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 were 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 would strictly increase with its risky investment. Hence, each fund has an incentive to invest at least x_0 in the risky asset. Since equilibrium risky investment decreases with default costs, the expected performance rank also decreases with default costs from Assumption [1.](#page-10-0) 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 that with highest default costs) not perfectly safe ex ante. Since investors have historically perceived MMFs as safe as insured deposits, Corollary [1](#page-14-2) can be regarded as the most basic form of excessive risk-taking by MMFs. Importantly, it holds regardless of the scale of default costs in the industry, i.e., even if all funds have extremely large default costs. This result would not hold if fund payoffs depended on absolute performance. In fact, in that case, all funds whose default costs are sufficiently large in absolute terms would invest x_0 in the risky asset and have zero default probability.

⁹Similar results are obtained in auction theory (Krishna, 2010).

To explicitly determine the equilibrium, I proceed as follows. Under Assumption [1,](#page-10-0) 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 profile $x(c)$, the rank of a risky investment y is $1 - F_C(x^{-1}(y))$. Since any equilibrium is continuously differentiable, I take the first-order condition of the objective function (2) with respect to x and obtain an ordinary differential equation (ODE) in $dx(c)/dc$. The ODE, together with the boundary condition given by Proposition [1,](#page-14-0) provides a well-defined Dirichlet problem, which can be solved exactly and has a unique solution. Finally, I prove that the solution of the Dirichlet problem is indeed the equilibrium of the tournament by checking a second-order condition.

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

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

and the equilibrium risky investment is

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

where

$$
q := 0.5 - F_R(R_f) > 0,
$$

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

 F_R^{-1} $R_R^{-1}(\cdot)$ 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 and strictly positive under Assumption [1.](#page-10-0) q is referred to as the *tournament* incentive because it fully captures the model's risk-taking motive. To see this, note that the ex post rank of fund c's performance, $Rk(\pi_c)$, depends on the ex ante rank of 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. Hence, within the debate on a competition-driven reach for yield of MMFs, q represents the incentive to reach for yield. A larger q means a larger default probability and more risky investment for all funds.

Roughly speaking, q is a spread between risky and safe returns in terms of probabilities. Appendix [A](#page-48-0) shows that under mild and realistic conditions on the risky return distribution, q is linearly proportional to the standard risk premium. Hence, in the empirical analysis, I proxy q with a measure of the risk premium available to MMFs.

 $Q(c)$ is fund-specific, positive, strictly decreasing in the cost of default, and goes to zero as c goes to \bar{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 on the fund in equilibrium. To see this, consider the fund with the highest cost of default, \bar{c} . As discussed above, \bar{c} anticipates that in equilibrium its expected performance will have the lowest rank and hence decides to keep its default probability at zero by investing x_0 in the risky asset, regardless of other players' actions. That is, \bar{c} is not affected by fund competition, and in fact $Q(\bar{c}) = 0$. Funds with slightly lower default costs anticipate \bar{c} 's move and, in order to outperform it in expectation, choose a default probability slightly greater than zero by investing a 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 funds with higher default costs. Figure [2](#page-17-0) shows the equilibrium risky investment and incentive multiplier as functions of the cost of default.

More specifically, the competitive pressure on a fund \tilde{c} in the MMF tournament depends on: (1) how many competitors the fund has, and (2) how competitive they are. The multiplier $Q(\tilde{c})$ captures both effects through the interaction term:

Figure 2: Equilibrium risky investment and competitive pressure. The solid black line (left yaxis) 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.

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

 $1-F_C(\tilde{c})$ measures the mass of \tilde{c} 's competitors: the mass of funds with higher default costs; $\mathbb{E}_C \left[(\gamma D (F_C(c) + a) + c)^{-1} | c > \tilde{c} \right]$ measures their competitiveness: the average of their inverse marginal cost of increasing the default probability by buying more risky assets. An extra unit of risky asset increases the ex post performance rank if the realized return is above the risk-free rate but decreases it if the realized return is below the risk-free rate. Hence, for a competitor c, increasing the default probability by buying more risky assets has both a *direct cost* (its own default cost) and an *opportunity cost* (the AUM it will receive at the end of the tournament if it does not default and $R < R_f$). Since equilibrium risky investment decreases with default costs, the opportunity cost is $\gamma D(F_C(c) + a)$. The economic intuition is: the lower the competitors' marginal cost of risky investment is, the more competitive they are. Figure [3](#page-18-0) shows the two components of competitive pressure at work. This in-depth analysis of $Q(c)$ shows that in the MMF tournament, competitive pressure is

 $Q(\widetilde{c}) \uparrow$ with $E_C[(\gamma D(a + F_C(c)) + c)^{-1} | c > \widetilde{c}] \times (1 - F_C(\widetilde{c}))$

Figure 3: Components of the equilibrium competitive pressure. The solid green line (left yaxis) is the density of the distribution of default costs in the fund population, f_C . The green shaded area is the mass of funds with default costs larger 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 larger than \tilde{c} as a function of \tilde{c} and represents their average 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.

fund-specific and depends only on the distribution of default costs in the industry, and not on the risk-free rate or the return distribution.

For some comparative statics, it is more convenient to work with an approximate version of the equilibrium risky investment. Appendix [A](#page-48-0) shows that under mild and realistic conditions on the return distribution, the equilibrium risky investment is approximately

$$
x_{app}(c) := [1 + 2\tilde{q}Q(c)]x_0,
$$
\n⁽⁴⁾

where $\widetilde{q} :=$ \overline{q} $f_R(\underline{R})(R_f-\underline{R})$. In Section [4,](#page-19-0) I use [\(4\)](#page-18-1) to study how the cross-sectional risktaking differential reacts to changes in the risk premium and riskiness of the risky asset.

Finally, Appendix [A](#page-48-0) provides two sufficient conditions for the existence of the equilibrium,

each with a clear economic interpretation and likely to hold in the MMF industry.

4 Shocks to Asset Returns

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

The equilibrium default probability depends on asset returns only via the tournament incentive q , i.e., the model's risk premium. 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 fixed cost independent of the amount of the shortfall.

Proposition 3. The equilibrium default probability increases with the tournament incentive for all funds, with the effect being stronger for funds with lower default costs.

Proposition [3](#page-19-1) 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 $Q(\bar{c}) = 0$). 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} $R^{-1}(p(c))$. Importantly, only the left tail of the distribution matters. This is because the no-short-selling constraint implies $x(c) \leq D$, and hence the equilibrium default probability must be weakly smaller than the probability that $R < 1$, i.e., $p(c) \leq F_R(1)$. The risk-free rate affects the equilibrium risky investment both explicitly via its level, R_f , and implicitly via the tournament incentive, $q = 0.5 - F_R(R_f)$. The following section studies the effects of these variables on equilibrium risky investment both separately and jointly, so as 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, I consider an increase in the tournament incentive, which is the model's risk premium, accompanied by an increase in the left tail of the return distribution, which is the only other part of the distribution affecting equilibrium risky investment. In real-world terms, the increase in the left tail of the return distribution represents an increase in the default risk of the securities held by MMFs.

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. The shift to the left of the return distribution, on the other hand, mechanically reduces the amount of risky investment corresponding to any given default probability level. In equilibrium, the heterogeneous competitive pressure determines which effect dominates, generating a bifurcation in the fund population.

Let $H := \frac{F_R(r)}{F_R(1)}$ 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 [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 $\frac{q^{(2)}}{q^{(1)}}$ $\frac{q^{(2)}}{q^{(1)}} > (\ge) \sup \frac{H^{(2)}}{H^{(1)}}$, all funds (weakly) increase their risky investment.

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

- (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 $\frac{H^{(2)}}{H^{(1)}}$ $\frac{H(1)}{H^{(1)}}$ 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 risk, 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 that 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, $q^{(2)}$ $\frac{q^{(2)}}{q^{(1)}}$ < 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.[10](#page-21-0) 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 also occurs 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 R . 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 low- c funds is high, this intuition is formalized by Proposition 4 (ii). To have a formal result when competitive pressure on those funds is low, I use the approximate equilibrium [\(4\)](#page-18-1). As discussed in Appendix [A,](#page-48-0) that approximation is valid for all funds when the competitive pressure on low-c funds is low. Since \tilde{q} in [\(4\)](#page-18-1) incorporates both the tournament incentive and the risk of low returns, I differentiate [\(4\)](#page-18-1) with respect to (w.r.t.) \tilde{q} to capture the effect of a simultaneous change in both variables.

Corollary 2.
$$
\frac{d}{d\widetilde{q}} \left| \frac{dx_{app}(c)}{dc} \right| > 0
$$
 for all c.

¹⁰Except 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.

Corollary [2](#page-21-1) confirms that the cross-sectional risky investment differential also increases with the risk premium when the 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 constant. Since q is proportional to the standard risk premium, this amounts to assume that the risk premium remains constant when the risk-free rate changes.

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 constant, the equilibrium risky investment strictly increases with the risk-free rate for all funds.

The effect is stronger for funds with relatively higher default costs. To see this, suppose that the competitive pressure on the fund with the lowest default cost, c , is sufficiently high so that its equilibrium default probability is equal to $F_R(1)$. That is, 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, \bar{c} , 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 c and \bar{c} increases. This intuition is summarized by the following corollary.

Corollary 3. Suppose $\underline{R} > 2 - R_f$. Holding q constant, the cross-sectional risky investment differential increases as R_f decreases, i.e., $\frac{\partial}{\partial I}$ ∂R_f $\begin{array}{c} \hline \end{array}$ $dx(c)$ $\mathrm{d}c$ $\begin{array}{c} \hline \end{array}$ < 0 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, 11 11 11 since MMFs can only invest in securities of the highest credit quality and short maturity. Moreover, for the approximate equilibrium [\(4\)](#page-18-1), the result of Corollary [3](#page-22-1) holds without any assumption on \underline{R} , confirming the above economic intuition.

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

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, $q = 0.5 - F_R(R_f)$, i.e. the model's risk premium.^{[12](#page-23-0)} In this section, I denote the tournament incentive by $q(R_f)$ to make its dependence on the risk-free rate explicit. In the following proposition, the symbol of total derivative w.r.t. R_f indicates that q is allowed to vary with R_f , while the return distribution is held constant.

ASSUMPTION 2. The reverse hazard rate of the risky return is non-increasing on $[\underline{R}, 1)$.^{[13](#page-23-1)}

Proposition 6. Under Assumption [2,](#page-23-2) there exists $c^* \in (\underline{c}, \overline{c})$ s.t.

- i) $\frac{dx(c)}{dR}$ $\mathrm{d}R_f$ > 0 for all $c > c^*$;
- $ii) \frac{dx(c)}{dR}$ $\mathrm{d}R_f$ < 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 all funds (except \bar{c}), 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 competition. To see this, take the fund with the highest cost of default, \bar{c} . \bar{c} is unaffected by competition $(Q(\bar{c}) = 0)$ and always keeps its equilibrium default probability equal to zero by investing x_0 in the risky asset. Since x_0 increases with R_f , a decrease in R_f leads \bar{c} to cut its risky investment despite the increase in $q(R_f)$. In contrast, low-c funds face a higher competitive pressure, captured by higher $Q(c)$. If $Q(c)$ is sufficiently large, the effect on the default probability via the increase in $q(R_f)$ dominates (see Figure [4\)](#page-24-0).

 12 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 .

¹³This assumption is very weak. Many common distributions with support in \mathbb{R}_+ have a decreasing reverse hazard rate in the left tail, including uniform, log-normal, Beta, chi-squared, and exponential (Shaked and Shanthikumar, 1994). Even more importantly, Assumption [2](#page-23-2) is not necessary for part (i) of Proposition [6.](#page-23-3)

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.

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 these predictions.

The model also predicts that: (1) all funds have a strictly positive probability of "breaking the buck," which decreases with fund's cost of default; (2) the probability of "breaking the buck" is independent of the risk-free rate and increases with the risk premium, with the effect being stronger for funds with lower default costs. My data do not allow me to test these predictions, but they are consistent with the empirical findings of Moody's (2010) and Brady et al. (2012).[14](#page-25-0)

Further predictions and robustenss

Appendix [IA.1](#page-56-0) presents comparative statics with respect to changes in the distribution of default costs across funds (which represents the industry's competitive landscape). When the distribution of default costs shifts to the right, funds with lower costs decrease their risk-taking, while funds with higher costs increase it. This is because when the fraction of high-cost funds increases, competition becomes relatively stronger among those funds and relatively weaker for funds with lower default costs.

In Appendix [IA.2,](#page-58-0) I show that Predictions 1, 2, and 3 are robust to the inclusion of variable costs of default (i.e., costs that depend on the amount of the shortfall) in addition to fixed ones. I do this under two modeling strategies: (i) the fund pays both the fixed and the variable cost, (ii) the fund pays either the fixed or the variable cost, with a given probability. The robusteness stems from three ingredients of the model: (1) the strategic nature of the tournament, which generates an "arms race" among all funds except the one with the highest fixed cost; (2) the fact that the buffer of safe assets necessary to eliminate the risk of default increases as the return on safe assets decreases; and (3) the heterogeneity of equilibrium competitive pressure due to the heterogeneous fixed costs, which determines the cross-sectional response of MMF risk-taking to changes in asset returns.

Note that the second variable-cost specification described above can be seen as a reducedform model for the effect of sponsor's support on MMF risk-taking; the probability of paying the variable cost can be interpreted as the sponsor's capacity to subsidize the fund. When this probability decreases, all funds reduce risky investment, and the effect is stronger for funds with lower fixed costs. This is because low-fixed-cost funds take on more risk in equilibrium; as a result, their default is more likely, their expected shortfall is larger, and hence they are more sensitive to sponsor's support.

 14 They find that between 2007 and 2011, 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 became more frequent and significant.

5 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 this period experienced significant variations in both the risk premia and the risk-free rates available to MMFs.^{[15](#page-26-1)} Those variations help identify the differential effects of risk premia and risk-free rates on MMF risk-taking and test the model's predictions.

An empirical study of the flow-performance relation for MMFs is in Appendix [B.](#page-49-0) I show that the rank of fund performance, and not the raw performance, determines money flows in the MMF industry, which supports the choice of a tournament model. In the internet Appendix [IA.5,](#page-86-0) I also show that my empirical proxy for a fund's cost of default does not affect the sensitivity of the fund's flow-performance relation, which supports the model's assumption that all funds face the same, exogenously given, flow-performance relation.

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 the sponsor's other mutual funds or losses in the sponsor's other business and franchise value due to reputation damages.

As KS, I focus on prime institutional MMFs 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

¹⁵I 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 the 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.

prime MMFs. Another plausible measure of sponsor's reputation concern is affiliation to a financial conglomerate (e.g., a bank or insurance company). However, such proxy would be a binary variable, while the cost of default in my model is continuous. Fund Business is continuous by construction and is therefore 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 U.S.treasuries. This index is defined and discussed below. For robustness, I also use 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 can only invest in high-quality, short-term securities, and U.S.treasuries are 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-bill rate.

Summary statistics of the proxies for the model's key variables are in Table [1.](#page-43-0)

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 here, iMoneyNet data are the most comprehensive source of information on MMF holdings (see also KS; Chodorow-Reich, 2014; Di Maggio and Kacperczyk, 2015). iMoneyNet data are at the weekly share-class level and contain information on yield, AUM, expense ratio, age, portfolio composition by instrument type, and weighted average portfolio maturity. Since my model is at the fund level, I aggregate share classes by fund and compute fund characteristics as weighted average of the share class values, with share class assets as weights. Details are in the internet Appendix [IA.4.](#page-81-0)

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

Summary statistics of fund characteristics

The internet Appendix [IA.4](#page-81-0) contains summary statistics for all U.S. institutional prime MMFs. Table [IA.4.1](#page-97-0) shows fund characteristics as of January 3, 2006, so as to compare my results with those of KS, also reported in Table [IA.4.1.](#page-97-0) The results are very similar, confirming that my data are 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 1-month T-bill yield) is 7.5 basis points; the average expense ratio is 35.9 basis points. The average size of the fund family is \$73.3 billion, and the average F und Business is 74.5% .

The internet Appendix [IA.4](#page-81-0) also shows that funds with different levels of sponsor's reputation concern do not significantly differ along other observable dimensions. In particular, Figure [IA.4.2](#page-86-1) 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.

The internet Appendix [IA.4](#page-81-0) also analyzes the distributional properties of $Fund~Business$. Figure [IA.4.1](#page-85-0) and Table [IA.4.2](#page-98-0) 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. Importantly, they also show that while the cross-sectional distribution of Fund Business is relatively stable over time, there is significant time-series variation within fund.

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

Prime MMFs can invest only in U.S. treasuries, GSE debt, repurchase agreements, certificates of deposit (CDs, i.e., time deposits and bank obligations), floating-rate notes (FRNs), commercial papers (CPs), and asset-backed commercial papers (ABCPs).[16](#page-28-0) E.g., as of January 3, 2016, prime institutional MMFs hold 31.4% in CPs, 19.9% in FRNs, 15.8% in CDs,

¹⁶MMFs can also invest in other MMFs, in particular via master-feeder relations. Consistent with the literature (Chernenko and Sunderam, 2014), I exclude feeder funds from my analysis.

13.6% in ABCPs, 13.4% in repos, and 5.9% in treasuries and agency-backed debt. Among these asset categories, treasuries, GSE debt, and repos are the safest ones.

To capture 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 monthly from FRED. The index is

$$
Spread Index_t = (a_{2002}^{CD} r_t^{CD} + a_{2002}^{FRNS} r_t^{LIBOR} + a_{2002}^{CP} r_t^{CP} + a_{2002}^{ABCP} r_t^{ABCP}) - GS3M_t
$$
 (5)

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. a_{2002}^K is the average relative weight of category K in the portfolio 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](#page-30-0) 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 of 0.2%. From July 2007, Spread Index started to rise, reaching a maximum of 1.9% in August 2008, with an average of 1.3% from August 2007 to August 2008.

 $Spread Index$ is an expost measure of the premia available to MMFs and reflects default risk. Figure [5](#page-30-0) 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 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 of more than 1% from August 2007 to August 2008.

Figure [5](#page-30-0) also shows the 1-month T-bill monthly return (green line). The 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 low until June 2004, reaching a minimum of 6 bp in May 2004, with an average of 8 bp from January 2003 to June 2004.[17](#page-29-0)

¹⁷Interestingly, 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).

It increased steadily from July 2004 to May 2006, remaining 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 of 22 bp from September 2007 to August 2008.

Importantly, the fact that during the period considered, the proxies for risk premium and risk-free rate vary significantly and do not comove systematically helps identify and disentangle their differential effects on MMF risk-taking.

Figure 5: Risk premium & risk-free rate. *Spread Index* (solid red line) is an index of realized spreads of the risky securities available to prime MMFs relative to Treasuries (see equation [\(5\)](#page-26-2)). GZ EBP (dot-dashed blue line) is the Gilchrist-Zakrajsek excess bond premium for financial firms. The dashed green line (right y -axis) is the monthly return on the 1-month T-bill. The black vertical line is August 2007. Data are monthly.

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 category with the largest coefficient as the riskiest one.^{[18](#page-31-0)} Details on the regression specification are in Appendix [C,](#page-51-0) and results are in Table [C.2.](#page-55-0) According to this operational 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 nonoverlapping time windows and again find that bank obligations were the riskiest asset class on average (see Appendix [C](#page-51-0) for details). In view of these results, I define Holdings Risk as the percentage holdings of bank obligations net of treasuries, GSE debt, and repos in a fund's portfolio; $Holdings$ Risk is the main proxy for fund risk-taking.

To have a finer risk-taking proxy that might capture changes in investment opportunities over time, I also introduce Holdings Risk^{dyn}. For each month, Holdings Risk^{dyn} is the percentage holdings of that month's riskiest asset class (identified using the above method) net of treasuries, GSE debt, and repos.

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.^{[19](#page-31-1)} 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 the most robust measure of MMF risk-taking. Summary statistics are in Table [1.](#page-43-0)

5.2 Risk-taking Pre and Post July 2007

This section shows that funds with lower default costs always take on more risk (Prediction 1) and that the cross-sectional risk-taking differential increases if either the risk premium increases or the risk-free rate decreases (Predictions 2c and 3b). Here I follow KS and do not disentangle the effect of risk premia from that of risk-free rates. To make my results comparable to theirs, I consider the January 2006–August 2008 period and divide it into two sub-periods: the Pre period, January 2006–July 2007, characterized by high risk-free rates and low risk premia, and the *Post* period, August 2007–August 2008, characterized by low

¹⁸KS and Chodorow-Reich (2014) use the same method and obtain similar results.

 19As 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.

risk-free rates and high risk premia.

On the balanced panel of MMFs active throughout January 2006–August 2008 ($n = 122$), I run the following weekly regression:

$$
Risk_{i,t} = \alpha_i + \mu_t + \beta_1 FB\ Rank_{i,t-k} + \beta_2 Post_t * FB\ Rank_{i,t-k} + \gamma \cdot (X_{i,t-k}, Post_t * X_{i,t-k}) + \varepsilon_{i,t}
$$
\n
$$
(6)
$$

where $Risk$ is either Holdings Risk, Holdings Risk dyn , Maturity Risk, Spread, or Safe Holdings defined in Section [5.1.](#page-28-1) FB Rank is the rank of Fund Business in percentiles normalized to [0, 1], i.e., FB Rank = 0 for funds whose sponsor has the lowest reputation concern, and FB Rank $= 1$ for funds whose sponsor has the highest reputation concern. Post is a dummy equal to 1 for the *Post* period and 0 for the *Pre* period. X is the following set of fund-specific controls: natural logarithm of size, expense ratio, age, and natural logarithm of the fund family size. FB Rank and X are lagged by k weeks to mitigate endogeneity issues. For robustness, I use different values of k, ranging from 1 week $(k = 1)$ to 3 months $(k = 12)$. μ_t and α_i are week and fund fixed effects, respectively.

The coefficients of interest are β_1 and β_2 . β_1 measures the effect of default costs on fund risk-taking in the Pre period, β_2 measures how this effect changes from the Pre to the Post period. Since the Post period experienced significantly higher risk premia and lower risk-free rates, the model predicts: $\beta_1 < 0$ and $\beta_2 < 0$. Obviously, when Safe Holdings is the dependent variable, the inequalities are reversed.

Table [2](#page-44-0) 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. For both β_1 and β_2 , results are consistent with the model's predictions, and the effects are both statistically and economically significant. E.g., going from the highest to the lowest rank of Fund Business increases Holdings Risk by roughly 7 percentage points (pp) in the P re period and 14 pp in the P ost period, and portfolio maturity by roughly 5 days in the Pre period and 12 days in the Post period.^{[20](#page-32-0)} Robustness checks and a detailed comparison of my results with those of KS are in the internet Appendix [IA.6.](#page-88-0)

²⁰At 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, of Spread is 68 bp, and of Safe Holdings is 18 pp.

5.3 Risky investment in the time series

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 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 3a). This section disentangles these two effects and shows evidence in support of the model's predictions.

I consider the January 2002–August 2008 period and only MMFs active throughout that period $(n = 85)$. On this balanced panel, I run the following regression:

$$
Risk_{i,t} = \alpha_i + \beta_{rp}rp_t + \beta_{rp}^Hrp_t * High FB_i + \beta_{rp}^Lrp_t * Low FB_i ++ \beta_{rf}rf_t + \beta_{rf}^Hrf_t * High FB_i + \beta_{rf}^Lrf_t * Low FB_i + \gamma \cdot X_{i,t-1} + \varepsilon_{i,t}
$$
 (7)

Risk is either Holdings Risk, Holdings Risk^{dyn}, Maturity Risk, or Safe Holdings.^{[21](#page-33-0)} rp is a proxy for the risk premium: S *pread Index* in the main specification. rf is the return on 1-month T-bills. Since data on rp are monthly, weekly fund-specific data are averaged over months, and regression [\(7\)](#page-33-1) is at the monthly level. High FB_i (Low FB_i) is a dummy equal to 1 if fund is Fund Business is always above (below) the industry median, and 0 otherwise. X is the set of fund-specific controls in regression (6) with the addition of Fund Business. Controls are lagged to mitigate endogeneity issues. α_i are fund fixed effects.

In terms of the model, High $FB_i = 1$ represents high-c funds, and Low $FB_i = 1$ represents low-c funds. $\beta_{rp} + \beta_{rp}^H$ and $\beta_{rf} + \beta_{rf}^H$ measure how the risky investment of high-c funds responds to changes in the risk premium and risk-free rate, respectively. $\beta_{rp} + \beta_{rp}^L$ and $\beta_{rf} + \beta_{rf}^L$ measure the corresponding sensitivities for low-c funds. The model predicts: $\beta_{rp} + \beta_{rp}^H < 0 < \beta_{rp} + \beta_{rp}^L$, and $\beta_{rf} + \beta_{rf}^H > \beta_{rf} > \beta_{rf} + \beta_{rf}^L > 0$. Obviously, when Safe Holdings is the dependent variable, the inequalities are reversed.

Table [3](#page-45-0) 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. First, funds with lower Fund Business always tend to take more risk (Prediction 1), with the effect

²¹Since *Spread* mechanically covaries with the risk-free rate, I do not use it as risk-taking measure in (7) .

being statistically and economically significant for Holdings Risk, Holdings Risk^{dyn}, and Safe Holdings. 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 always below the median increase Holdings Risk by 3.1 pp and Holdings Risk^{dyn} by 6.9 pp, while funds whose sponsors have $Fund~Business$ always above the median decrease Holdings Risk by 3.8 pp and Holdings Risk^{dyn} by 2.2 pp. These results are statis-tically and economically significant.^{[22](#page-34-0)} A qualitatively similar bifurcation occurs also for the other risk-taking measures; e.g., funds with low default costs increase *Maturity Risk* by 3.8 days (statistically significantly), while funds with high default costs decrease it by 3.2 days.

Changes in the risk-free rate have different effects depending on whether risk-taking is measured in terms of portfolio composition 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.^{[23](#page-34-1)} The effects on funds with low default costs have the same sign but are smaller in magnitude for *Holdings Risk* and *Safe Holdings*, as predicted. On the other hand, 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.

As first robustness check, I proxy the risk premium with the Gilchrist-Zakrajsek excess bond premium. In the model, the bifurcation between low-c and high-c funds occurs when the increase in the premium of the risky asset is accompanied by an increase in its default

 22 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 $\frac{dyn}{s}$ is 26%, of Maturity Risk is 14 days, and of *Safe Holdings* is [1](#page-43-0)8%. See Table 1 for more summary statistics.

²³Over the period of analysis, the standard deviation of the 1-month T-bill rate is 0.12%.

risk; absent the increase in default risk, all funds take more risk after an increase in the premium, with the effect being stronger for low-c funds (see Section [4.1\)](#page-20-1). Table [4](#page-46-0) shows the results of regression (7) when the risk premium is proxied with GZ *Premium*, which by construction does not reflect default risk. In agreement with the model, an increase of GZ Premium increases the risk-taking of all MMFs, with the effect being more statistically and economically significant for funds with lower Fund Business. As for the effect of the risk-free rate, results are similar to those in Table [3,](#page-45-0) confirming the model's predictions.

Other robustness checks are in the internet Appendix [IA.6.](#page-88-0) I run regression [\(7\)](#page-33-1): on separate subperiods, using the 3-month T-bill rate as a proxy for the risk-free rate, lagging fund-specific time-varying RHS variables by 2 months, and using various different cutoffs to identify high-c and low-c funds. Results are in Tables [IA.6.3](#page-109-0)[–IA.6.10](#page-116-0) and in most cases are similar to those in Table [3,](#page-45-0) confirming the model's predictions.

5.4 Cross-sectional risk-taking differential

The previous section tests the model's predicted effects of risk premia and risk-free rates on the overall level of risky investment by high-c and low-c MMFs across time. However, identification of these effects is challenging because other macroeconomic conditions might affect both the level of MMF risk-taking and the risk premia and risk-free rates, thereby confounding the results. To overcome this issue, I focus on the model's cross-sectional predictions, which allows me to control for time fixed effects, removing all time-varying macroeconomic conditions. Moreover, to fully exploit all cross-sectional variation in default costs, I substitute the dummies for funds with high and low default costs with the whole distribution of Fund Business.

My model predicts that the cross-sectional risky investment differential increases if either the risk premium goes up (Prediction 2c) or the risk-free rate goes down (Prediction 3b). To test both predictions and disentangle the two effects, I run the following regression on the balanced panel of MMFs active throughout January 2002–August 2008:

$$
Risk_{i,t} = \alpha_i + \mu_t + \beta_1 FB \ Rank_{i,t-1} * rp_t + \beta_2 FB \ Rank_{i,t-1} * rf_t + \gamma \cdot X_{i,t-1} + \varepsilon_{i,t} \tag{8}
$$
where Risk is either Holdings Risk, Holdings Risk^{dyn}, Maturity Risk, Spread, or Safe Holdings. FB Rank is the rank of Fund Business in percentiles normalized over [0, 1]. rp is a proxy for the risk premium: *Spread Index* in the main specification. rf is the 1-month T-bill rate. Since data on rp are at the monthly level, weekly fund-specific data are averaged over months, and regression (8) is at the monthly level. X is the same set of fund-specific controls as in (7) , with FB Rank instead of Fund Business and including their interactions with rp and rf . All RHS fund-specific variables are lagged by 1 month to mitigate endogeneity issues. μ_t and α_i are time and fund fixed effects, respectively.

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: $\beta_1 < 0$ and $\beta_2 > 0$. Obviously, when Safe Holdings is the dependent variable, the inequalities are reversed.

Results are in Table [5](#page-47-0) 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 more risk in terms of Holdings Risk, Holdings Risk^{dyn}, and Safe Holdings, as predicted by the model and observed also in Table [3.](#page-45-0) 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 *Maturity Risk*, 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.^{[24](#page-37-0)} 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.

Robustness checks are in the internet Appendix [IA.6.](#page-88-0) I run regression (8) using Fund Business instead of its rank as the main explanatory variable, using GZ P remium as a proxy for rp , using the 3-month T-bill rate as a proxy for rf , and lagging all fund-specific RHS variables by two months instead of one. Results are in Tables [IA.6.11–](#page-117-0)[IA.6.14](#page-120-0) and are always similar.

6 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 riskfree 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 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, in the MMF tournament a decrease in the

²⁴The results for *Spread* may be insignificant because *Spread* does not necessarily reflect active risk-taking.

risk-free rate reduces 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 January 2002–August 2008 period 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 risky investment, while funds whose sponsors had high reputation concerns decreased it. 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 choice of a tournament model and confirming that relative performance competition is a key incentive for MMFs.

These results shed light on the transmission of monetary policy to MMFs and contribute to the recent debate on their new regulation. The risk-free rate, intended as the return on treasuries, affects MMF risk-taking through the risk of "breaking the buck" that comes from the use of a stable NAV. This channel of monetary policy, peculiar to MMFs and contrary to the conventional "reach for yield" argument, reduces risk-taking when risk-free rates are low. The new regulation, taking effect in October 2016, requires institutional prime MMFs to adopt a floating NAV; such regulatory change, while possibly eliminating the risk of runs, may actually lead institutional prime MMFs to take more risk.

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Table 1: 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 U.S. institutional prime MMFs from $1/1/2002$ to $8/31/2008$. 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 U.S.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 (identified via regression [\(C.1\)](#page-52-0) in Appendix [C\)](#page-51-0) 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 equation (5) . GZ Premium is the excess bond premium for financial firms from Gilchrist and Zakrajsek (2012).

Table 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 fund size, expense ratio, fund age, and fund family size. All regressions include week and fund fixed effects. Standard errors are percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., U.S.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 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 5.1 and Appendix C. FB Rank is the rank of Fund Business, which is the share of mutual fund assets other than Post is a dummy equal to 1 from $8/1/2007$ to $8/31/2008$, and 0 otherwise. The other independent variables (*Controls*) are: Table 2: Cross-sectional risk-taking differential in the P re and P ost 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., U.S.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 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 [5.1](#page-28-0) and Appendix [C.](#page-51-0) 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 $[0,1]$. institutional prime MMFs in the sponsor's total mutual fund assets. FB Rank is expressed in percentiles normalized to $[0, 1]$. Post is a dummy equal to 1 from 8/1/2007 to 8/31/2008, and 0 otherwise. The other independent variables (Controls) are: fund size, 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, 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. respectively. The corresponding critical values from fixed-b asymptotics are roughly 2.97 , 2.20 1.82, respectively

∗∗∗p < 0.01, ∗∗p < 0.05, [∗]p < 0.1

Table 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., U.S.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 [5.1](#page-28-0) and Appendix [C.](#page-51-0) The risk premium rp is the index of spreads available to MMFs defined by equation [\(5\)](#page-26-0) in percentage points. The risk-free rate rf_t is the 1-month T-bill rate in percentage points. High (Low) FB_i is a dummy equal to 1 if fund is Fund Business is always above (below) the cross-sectional median throughout the 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 size, 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.

∗∗∗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., U.S.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 [5.1](#page-28-0) and Appendix [C.](#page-51-0) The risk premium rp is the excess bond premium for financial firms from Gilchrist and Zakrajsek (2012) in percentage points. The risk-free rate rf_t is the 1-month T-bill rate in percentage points. High (Low) FB_i is a dummy equal to 1 if fund is Fund Business is always above (below) the cross-sectional median throughout the 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 size, 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.

column (3); the monthly annualized fund spread (Spread) in basis points in column (4); and the percentage of safe assets in a Table 5: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime GSE debt, and repos) in a fund's portfolio (H oldings Risk) in column (1); the percentage of each month's riskiest asset class column (3); the monthly annualized fund spread (Spread) in basis points in column (4) ; and the percentage of safe assets in a FB Rank is the rank of Fund Business, which is the share of mutual fund assets other than institutional prime MMFs in the net of safe assets in a fund's portfolio (Holdings Risk^{dyn}) in column (2); average portfolio maturity (Maturity Risk) in days in fund's portfolio (Safe Holdings) in column (5). For a detailed discussion of Holdings Risk^{dyn}, see Section 5.1 and Appendix C. sponsor's total mutual fund assets. FB Rank is expressed in percentiles normalized to $[0,1]$. The risk premium rp is the index All regressions include month and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with Table 5: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., U.S.treasuries, GSE debt, and repos) in a fund's portfolio (H oldings 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 fund's portfolio (Safe Holdings) in column (5). For a detailed discussion of Holdings Riskdyn, see Section [5.1](#page-28-0) and Appendix [C.](#page-51-0) F B Rank is the rank of F und Business, which is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. F B Rank is expressed in percentiles normalized to $[0,1]$. The risk premium rp is the index f_1 and f_2 and f_3 is the index of $[0,1]$. The risk premium rp is the index f_2 an of spreads available to MMFs defined by equation (5) in percentage points. The risk-free rate rf_t is the 1-month T-bill rate in of spreads available to MMFs defined by equation [\(5\)](#page-26-0) in percentage points. The risk-free rate $r f_t$ is the 1-month T-bill rate in percentage points. Controls are: fund size, expense ratio, fund age, fund family size, and their interactions with rp and rf . percentage points. *Controls* are: fund size, expense ratio, fund age, fund family size, and their interactions with rp and r*f*.
All regressions include month and fund fixed effects. Standard errors are HACSC robust from 8-month lag. ***, * $*$ represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from 8-month lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from $T = 80$). 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., U.S.treasuries, $\overline{}$ $n = 85$). Data are monthly (7) fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85. fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85 \mathcal{C} MMFs continuously active from $1/1/2002$ to $8/31/2008$ (*n*

Appendix A Further theoretical results

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.[25](#page-48-0)

Lemma 1. Suppose F_R is twice differentiable at $\mu := \mathbb{E}[R]$ and $|F_R(\mu) - 0.5|$ is small. Then, $q \approx f_R(\mu) (\mu - R_f)$ for small $\mu - R_f > 0$.

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 premium is small. Since the spread on the risky securities available to MMFs is typically very small, the approximation provided by Lemma [1](#page-48-1) is likely to hold in the data. This suggests using a measure of risk premium as proxy for the tournament incentive in the empirical analysis.

For some comparative statics, the equilibrium risky investment [\(3\)](#page-15-0) is not easily tractable. However, under mild regularity conditions, it can be written in a more tractable form.

Corollary 4. Suppose F_R is twice differentiable on $[\underline{R}, 1]$ and $f_R(\underline{R}) > 0$. Then, for small equilibrium default probability, the equilibrium risky investment is

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

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 default risk and scaled by the fund-specific multiplier. Approximation [\(A.1\)](#page-48-2) 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,](#page-19-0) I use [\(A.1\)](#page-48-2) 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.

²⁵Hereafter, $f \approx g(x)$ for small x means $f = g(x) + o(x)$ in the standard small $o(\cdot)$ notation.

Corollary 5. The equilibrium exists if either $(e^{1/a}-1)^{-1} \geq \frac{2q}{F_R(1)}$ or $(e^{\gamma D/c}-1)^{-1} \geq \frac{2q}{F_R(1)}$ $\frac{2q}{F_R(1)}$.

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 (i.e., 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\)](#page-48-1). 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 the funds with relatively low default costs.

Appendix B Flow-performance relation and tournament

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:

$$
Fund\ Flow_{i,t+1} = \alpha_i + \mu_t + \beta Performance_{i,t} + \gamma \cdot X_{it} + \varepsilon_{i,t+1}
$$
\n(B.1)

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 interest 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 the following set of fund-specific controls: natural logarithm of fund size in millions of dollars, fund expenses in basis points, fund age in years, natural logarithm of the fund family size in billions of dollars, and volatility of fund flows measured as the standard deviation of weekly fund flows over the previous quarter. μ_t are week fixed effects, which account for variations in the macroeconomic environment, and α_i are 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 [C.1.](#page-54-0) 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. Results are in Column (2). Again, when the spread rank is the main explanatory variable, the flow-performance relation is positive and statistically significant. Moreover, the adjusted R^2 increases by 0.2%.

These results suggest that the rank of fund performance might be more important than raw performance in explaining fund flows to MMFs. To test this hypothesis, I estimate model [\(B.1\)](#page-49-0) including both measures of performance. Results are in Column (3) of Table [C.1.](#page-54-0) When both raw spreads and spread ranks are included, the spread rank remains positive and statistically significant, while the raw spread becomes statistically insignificant and less economically important. These results indicate that performance rank, not raw performance, determines fund flows in the MMF industry.^{[26](#page-50-0)} 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.^{[27](#page-50-1)}

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

 26 Massa (1998) and Patel, Zeckhauser, and Hendricks (1994) obtained similar results for equity mutual funds. Moreover, since regression [\(B.1\)](#page-49-0) 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.

²⁷An increase equal to the cross-sectional average of the within-fund standard deviation of S_{pread} Rank, i.e. roughly 0.22, increases future fund flows by 0.23% per week, i.e. by 13% per year. A standard-deviation shock to $Spread$, i.e. roughly 40 bp, would increase fund flows only by 10% per week, i.e. by 5% per year.

relation is convex in raw performance (Chevalier and Ellison, 1997). To check that convexity is not driving my results, I run regression $(B.1)$ including also $Spread^2$ on the RHS to capture possible convexity effects. When only $Spread$ and $Spread²$ 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 $Spread²$ 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.

Other robustness checks are in the internet Appendix [IA.5.](#page-86-0) I run regression [\(B.1\)](#page-49-0): using the rank of Fund Flow as the dependent variable to mitigate the effect of outliers without resorting to trimming, using only time fixed effects, and normalizing fund flows by each week's or month's mean or median flow. Results are in Tables [IA.5.1](#page-99-0)[–IA.5.4](#page-102-0) and are always very similar. As further robustness checks, I also run regression [\(B.1\)](#page-49-0) trimming the distribution of fund flows at either 1% or multiples of the interquartile range, and on separate time windows. Results are always similar and omitted for brevity.

In Appendix [IA.5,](#page-86-0) I also show that over the January 2002–August 2008 period, the flowperformance 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 (as also observed by KS for the January 2006–August 2008 period). This evidence indicates that the flow-performance relation can be taken as exogenous in the context of my model.

Appendix C 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, I follow KS and infer the spread of each instrument via the regression

$$
Spread_{i,t+1} = \alpha_i + \mu_t + \sum_j \beta_j Holdings_{i,j,t} + \gamma \cdot X_{i,t} + \varepsilon_{i,t+1}
$$
\n(C.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, $Holdings_{i,j,t}$ is fund i's fractional holdings of instrument type j in week t, α_i and μ_t are 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 in $(B.1)$ without Flow V olatility, which is not relevant to this analysis.^{[28](#page-52-1)} The coefficients of interest are β_j , which measure the return on instrument category j in week $t + 1$ relative to that of treasuries and GSE debt.

Table [C.2](#page-55-0) 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 $(C.1)$ 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 into monthly and quarterly sub-periods and estimate regression [\(C.1\)](#page-52-0) 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_i). Then, I take the average rank over the whole period. Column (5) shows the results when regression $(C.1)$ is run on monthly sub-panels, and column (6) shows the

²⁸However, my results are robust to the inclusion of $Flow Volatility$ on the RHS of [\(C.1\)](#page-52-0).

results when regression $(C.1)$ is run on quarterly sub-panels. *Bank Obligations* have the largest average rank, followed by $ABCPs$.

In light of these results, 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 motivates the use of Holdings Risk, i.e, the percentage of assets held in bank obligations net of U.S. treasuries, GSE debt, and repos, as the main proxy for MMF risk-taking.

∗∗∗p < 0.01, ∗∗p < 0.05, [∗]p < 0.1

Table C.1: Flow-performance relation: performance rank vs. raw performance. 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 interest and trimmed at the 0.5%. Independent variables are the weekly annualized spread from $t - 1$ to t in percentage points, its rank in percentiles normalized to [0, 1], log of fund size in millions of dollars, fund expense ratio in basis points, fund age in years, volatility of fund flows based on past 12-week fund flows, and log of fund family size in billions of dollars. 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.

 $\frac{1}{x^{n*}p}$ < 0.01, $\frac{1}{x^{n}}$ < 0.05, $\frac{1}{x^{n}}$ < 0.1

Table C.2: 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, time 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: log of fund size in millions of dollars, fund expense ratio in basis points, fund age in years, and log of fund family size in billions of dollars. 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 [C\)](#page-51-0).

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

This appendix contains supplemental material to the paper "Competition, Reach for Yield, and Money Market Funds." Appendix [IA.1](#page-56-0) studies the comparative statics of the equilibrium risky investment with respect to the distribution of default costs in the industry. Appendix [IA.2](#page-58-0) presents extensions of the model that also include variable costs of default. Appendix [IA.3](#page-69-0) contains the proofs of the theoretical results. Appendix [IA.4](#page-81-0) describes the data set and analyzes the distributional properties of the proxy for sponsor's reputation concerns (i.e., Fund Business). Appendix [IA.5](#page-86-0) presents robustness checks for the empirical results on the flow-performance relation. Appendix [IA.6](#page-88-0) presents robustness checks for the empirical results on fund risk-taking, in both the time series and the cross-section. Appendix [IA.7](#page-94-0) presents a random utility model that rationalizes a purely rank-based flowperformance 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 Shocks to the competitive environment

This section studies how fund risky investment responds to changes in the competitive environment. As discussed in Section [3,](#page-13-0) the competitive environment (i.e., the profile of fundspecific competitive pressures in equilibrium) is uniquely determined by the distribution of default costs. Suppose the distribution of default costs shifts from $F_C^{(1)}$ $\bar{C}^{(1)}$ to $F_C^{(2)}$ $C^{(2)}$, both with support $[c, \bar{c}]$, where $F_C^{(2)}$ dominates $F_C^{(1)}$ $\mathcal{C}^{(1)}$ in the likelihood ratio order.

Proposition 7. If $F_C^{(2)} \succ_{LRD} F_C^{(1)}$ $C^{(1)}$, 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 $c \in (c^*, \overline{c})$.

The intuition is as follows. The shift in the likelihood ratio order means that the mass of the distribution moves to the right. Fund \tilde{c} 's equilibrium risk-taking depends on the distribution of default costs only through its incentive multiplier $Q(\tilde{c})$, which increases with

$$
\mathbb{E}_C \left[\left(\gamma D(F_C(c) + a) + c \right)^{-1} \left| c > \tilde{c} \right] (1 - F_C(\tilde{c})) = \int_{\tilde{c}}^{\bar{c}} \frac{f_C(u) \mathrm{d}u}{\gamma D(F_C(u) + a) + u} \,. \tag{IA.1.1}
$$

The fund with the highest default cost, \bar{c} , is unaffected by shocks to the distribution of default costs because it is unaffected by competition. That is, $Q(\bar{c}) = 0$ under any F_C . For the funds in a left-neighborhood of \bar{c} , the LRD shift increases both the mass of competitors $(f_C^{(2)}$ $C^{(2)}(u) > f_C^{(1)}(u)$ in the upper tail) and their competitiveness by lowering the opportunity cost of risky investment $(F_C^{(2)})$ $C^{(2)}(u) < F_C^{(1)}(u)$ everywhere). As a result, for large \tilde{c} , the righthand side of $(IA.1.1)$ 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 $\cot \phi$, the mass of competitors remains equal to 1, and their average opportunity cost of risky investment does not change.[29](#page-57-1) 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.^{[30](#page-57-2)}

Intuitively, if the mass of the default cost distribution 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 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](#page-56-1) suggests that shocks to the competitive landscape might have surprising effects in the aggregate. E.g., 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 of high-c funds could more than offset the decrease in risk-taking of low-c funds.

²⁹Specifically, $\int_{\underline{c}}^{\overline{c}}$ $\frac{f(u)du}{\gamma D(F(u)+a)} = \frac{1}{\gamma D} \log (1 + a^{-1})$ for any CDF F on $[\underline{c}, \overline{c}]$.

 30 The assumption of LRD is made for simplicity. For Proposition [7](#page-56-1) 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.

Appendix IA.2 Model extensions: variable default costs

In the paper, I assume that the default of a MMF only has a fixed (idiosyncratic) cost. However, a default might also have a variable cost according to how large the shortfall is. To address this concern, here I present two extensions of the model that also include variable default costs equal to the amount of the shortfall. The first extension assumes that in case of default, a fund pays both the fixed and the variable cost. The second extension assumes that in case of default, a fund pays either the fixed or the variable cost, depending on the realization of an exogenous random variable that represents the sponsor's ex post capacity to subsidize the fund. The second extension can be seen as a reduced form model to study the effect of sponsor's support on MMF risk-taking.

For both model extensions, I show that the main features of the equilibrium and results of the model in the paper carry through also under these specifications. The robustness of the model comes from three fundamental ingredients: (1) the strategic nature of the tournament, which generates an "arms race" among all funds except that with the highest fixed cost; (2) the fact that the buffer of safe assets necessary to insure a fund against the risk of default increases as the return on safe assets decreases; and (3) the heterogeneity of equilibrium competitive pressure due to heterogeneous fixed costs of default, which determines how the cross-sectional risk-taking differential responds to changes in asset returns.

All variables are defined as in the paper. For notational simplicity, I drop the subscript from CDFs, PDFs, and expectations when it is clear what variable they refer to. E.g., $f(c)$ is the PDF of the fixed default cost c, and the expectation of the profit π is taken over the risky return R . Finally, the assumptions of the paper are maintained, and as in the paper, all statements on fund behavior are true up to a zero-measure set of funds.

IA.2.1 Extension 1: variable default cost

Suppose that in case of default (i.e., $\pi < 0$), a fund pays both a fixed idiosyncratic cost c and a variable cost equal to the shortfall $|\pi|$. Then, under a strategy profile $x : [c, \bar{c}] \to [0, D],$ the expected payoff of fund c becomes

$$
v_c(x_c, x_{-c}) = \underbrace{\gamma D \mathbb{E}[Rk(\pi_c) + a | \pi_c \ge 0] \mathbb{P}(\pi_c \ge 0)}_{\text{expected tournament reward}} - \underbrace{\left(\underbrace{c}_{\text{fixed cost}} + \underbrace{\mathbb{E}[|\pi_c| \mid \pi_c < 0]}_{\text{variable cost}}\right) \mathbb{P}(\pi_c < 0)}_{\text{expected cost of default}}
$$
\n
$$
= v_c^{(0)}(x_c, x_{-c}) - \mathbb{E}[|\pi_c| \mid \pi_c < 0] \mathbb{P}(\pi_c < 0), \tag{IA.2.1}
$$

where $v^{(0)}$ is the expected payoff when only fixed costs are incurred. The fundamental features of the equilibrium carry through under specification [\(IA.2.1\)](#page-59-0).

Proposition [1](#page-14-1)a. Proposition 1 and Corollary 1 hold unchanged under model [\(IA.2.1\)](#page-59-0).

Proposition [1a](#page-59-1) says that the first testable prediction of the model in the paper (Prediction 1 therein) remains unchanged by the inclusion of variable costs: funds with lower fixed costs of default always hold more risky assets. Moreover, as in the model with only fixed costs, all funds have a strictly positive probability of "breaking the buck," which decreases with the fund's fixed cost of default.

Importantly, Proposition [1a](#page-59-1) implies that the behavior of high-c funds in the model with variable costs is identical to that in the model with only fixed costs. This is because in both models, the fund with the highest fixed cost \bar{c} optimally decides to always keep its probability of "breaking the buck" at zero. Therefore, by continuity of the equilibrium, the comparative statics for the funds with relatively high fixed costs (i.e., in a left-neighborhood of \bar{c}) remain unchanged by the inclusion of variable default costs.

In general, for the model that includes variable costs, it is not possible to solve for an equilibrium in closed form. However, I can find sufficient conditions for the existence of an equilibrium, show that it must be unique, and fully characterize it as the solution of a Dirichlet problem. To this purpose, let $R_0(x) := R_f - (R_f - 1)\frac{D}{x}$ be the critical risky return such that a fund investing x in the risky asset would default if and only if the realized risky return falls below $R_0(x)$, i.e., $R < R_0(x)$.

Proposition 2a. If an equilibrium exists, it is unique and satisfies:

$$
\frac{dx}{dc} = -\frac{\gamma Df(c) [2q + F(R_0(x))] x^2}{[c + \gamma D (a + F(c))] (R_f - 1) Df(R_0(x)) + \mathbb{E}[R_f - R | R < R_0(x)] F(R_0(x)) x^2}
$$

\n
$$
\lim_{c \to \overline{c}} x(c) = x_0,
$$
\n(IA.2.2)

with
$$
c \in [\underline{c}, \overline{c}]
$$
 and $x \in [x_0, D]$.
Moreover, if $\mathbb{E}\left[\frac{\gamma D}{\gamma D\left[F(c) + a\right] + c}\right] \le \log\left(1 + \frac{F_R(1)}{2q}\right)$, the equilibrium exists.

Proposition [2a](#page-60-0) is the equivalent of Proposition [2](#page-15-1) in the paper. The existence of the equilibrium risky investment in $[x_0,\infty)$ is guaranteed by the Picard-Linderhöf theorem, which applies because the PDFs of c and R are continuous and strictly positive by assumption. The existence condition in Proposition [2a](#page-60-0) is to ensure that the no-short-sales constraint is satisfied. It is the same condition as in Proposition [2;](#page-15-1) the difference is that here the condition is only sufficient, while it is also necessary for the model without variable costs. This means that in the model with variable costs, the equilibrium exists for a larger set of primitive parameters than in the model with only fixed costs. This is because the inclusion of variable default costs on top of the fixed ones reduces the equilibrium risk-taking of all funds.

In the following, I use characterization [\(IA.2.2\)](#page-60-1) to study the comparative statics of the equilibrium risky investment with respect to (w.r.t.) the distribution of risky returns and the risk-free rate. Since there is no closed-form expression for the equilibrium risky investment, I have to impose a few additional conditions to derive some of the results in the paper. However, as discussed below, the conditions are mild, realistic, and only sufficient.

IA.2.1.1 Shocks to risk premium and default risk

Under economically reasonable sufficient conditions, the comparative statics w.r.t. the risky return distribution are robust to the inclusion of variable default costs. As in the model without variable costs, the return distribution affects the equilibrium risky investment only through its left tail, which represents the default risk of the risky asset, and the tournament incentive, which is the model's risk premium. Under realistic conditions, I show that: (1) an increase in the premium and riskiness of the risky asset generates a "bifurcation" between low-c funds and high-c funds (Predictions 2a, b in the paper), and (2) the cross-sectional risky investment differential always increases with the risk premium (Prediction 2c).

First, I consider an increase in the tournament incentive holding the left tail fixed.

Proposition 3a. Ceteris paribus, the equilibrium default probability and risky investment of all funds increase with the tournament incentive q, with the effect being stronger for funds with lower fixed costs of default.

Absent an increase in the riskiness of the risky asset, an increase in the premium increases the default probability and risky investment of all funds (except the one with the highest fixed cost, which always keeps its default probability at zero by investing x_0 in the risky asset). Moreover, the response of funds with lower fixed costs is stronger, which implies that, ceteris paribus, the cross-sectional risky investment differential increases with the premium. The same predictions hold for the model with only fixed costs (see Proposition [4](#page-20-0) and Corollary [2](#page-21-0) in the paper). My empirical analysis provides evidence supporting these predictions in Tables [4](#page-46-0) and [IA.6.12,](#page-118-0) which show the results of regressions [\(7\)](#page-33-0) and [\(8\)](#page-35-0) when q is proxied by Gilchrist-Zakrajsek's excess bond premium.

Next I consider a change in the risk premium accompanied by an increase in the left tail of the return distribution. An increase in the left tail means an increase in the probability of lower returns and can be interpreted as an increase in the default risk of the risky asset. As in the paper, the left tail is over $[\underline{R}, 1]$, and I renormalize it by $F_R(1)$ to have a proper distribution function for the comparative statics exercise. Let H and h be the CDF and PDF of R over the left tail, respectively. As in the paper, I assume that the tail shifts to the left in the likelihood ratio order: $H^{(1)} \succ_{LRD} H^{(2)}$. For each tail *i*, let $G_1^{(i)}$ $f_1^{(i)}(x) = \frac{h^{(i)}(R_0(x))}{H^{(i)}(R_0(x))}$ $H^{(i)}(R_0(x))$ be the reverse hazard rate calculated at $R_0(x)$, and $G_2^{(i)}$ $a_2^{(i)}(x) = \mathbb{E} [R_f - R | R < R_0(x)]$ be the marginal expected shortfall per unit of risky investment conditional on default. Finally, let $G := \sup$ $x \in [x_0,D]$ $G_2^{(2)}$ $Q_2^{(2)}(x) - G_2^{(1)}$ $2^{(1)}(x)$ $G_1^{(1)}$ $a_1^{(1)}(x) - G_1^{(2)}$ $1^{(2)}(x)$ $< \infty$. \overline{G} is well-defined and bounded since R has a positive and continuous PDF.

Proposition 4a. Let $H^{(1)} \succ_{LRD} H^{(2)}$ and $q^{(1)} < q^{(2)}$. Suppose $\frac{c}{L}$ \boldsymbol{D} $+ \gamma a >$ \overline{G} R_f-1

(i) If
$$
\frac{q^{(2)}}{q^{(1)}} \ge \sup \frac{H^{(2)}}{H^{(1)}}
$$
, all funds increase their risky investment.

.

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

(a) funds with higher fixed costs of default decrease their risky investment;

(b) funds with lower fixed costs of default increase their risky investment if $\frac{q^{(2)}}{q^{(1)}}$ $\frac{q}{q^{(1)}}$ is sufficiently close to sup $H^{(2)}$ $\frac{H^{(1)}}{H^{(1)}}$

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

Proposition [4a](#page-61-0) is analogous to the bifurcation result presented in Proposition [4](#page-20-0) of the paper. The economic intuition is the same: low-c funds are more sensitive to the increase in the premium, while high-c funds are more sensitive to the increase in risk. Hence, if the increase in the premium and that in risk are of comparable size, low-c funds increase their risky investment, while high-c funds decrease it. My empirical analysis provides evidence supporting this prediction in Table [3,](#page-45-0) which shows the results of regression (7) when q is proxied by Spread Index, i.e., by the index of realized spreads on the risky asset classes available to MMFs (see equation [\(5\)](#page-26-0) of the paper).

However, with respect to the bifurcation result presented in the paper, there are two differences. First, I assume that the minimum fixed cost of default in the fund population is sufficiently high. The reason is the following. In the model without variable costs, funds only care about the probability of default and not the extent of their shortfall. As a consequence, an increase in the riskiness of the risky asset always has a stronger effect on high- c funds because: (1) they are more sensitive to the probability of very low returns since they keep their default probability closer to zero, and (2) the shift to the left of the return distribution increases the probability of very low returns relatively more. In the model with variable costs, on the other hand, funds also pay the shortfall in case of default. As a consequence, an increase in the riskiness of the risky asset can have an ambiguous effect across funds, depending on the form of the return distribution, the extent of the shift, and the initial equilibrium position. However, if the minimum fixed cost of default in the industry is sufficiently high, the effect of an increase in default probability dominates the effect of a change in expected shortfall for all funds. Hence, in this case, the overall effect of an increase in risk is stronger on high-c funds also when variable costs are included, and the bifurcation of equilibrium risky investments occurs.

Importantly, the condition of Proposition [4a](#page-61-0) is economically reasonable and likely to hold in the real world. In fact, as discussed in the paper, the fixed costs of "breaking the buck" in the MMF industry are very large for any fund sponsor, as shown by the cases of Reserve Primary Fund in 2008 and Community Bankers US Government Fund in 1994.

Second, in the model without variable costs, the response of low-c funds is fully characterized by the competitive pressure they face in equilibrium, i.e., by the distribution of fixed costs of default in the fund population. In that model, an increase in the premium leads low-c funds to increase their risky investment if and only if they face sufficiently high competitive pressure, regardless of any increase in the riskiness of the risky asset. In the model with variable costs, on the other hand, this is not necessarily true because in case of default funds also pay a variable cost proportional to their risky investment. However, if the increase in the premium is not too low compared to the increase in risk, low-c funds will still increase their risky investment, generating a bifurcation.

Finally, note that these additional assumptions for the bifurcation between low-c and high-c funds are needed only to characterize the behavior of low-c funds. As mentioned above, the behavior of high-c funds in the model with variable costs is exactly the same as in the model with only fixed costs.

As Proposition [4](#page-20-0) of the paper, Proposition [4a](#page-61-0) suggests that the cross-sectional risky investment differential always increases after a simultaneous increase in the premium and riskiness of the risky asset.

Corollary 4a. Under the conditions of Proposition $4a$, the cross-sectional risky investment differential increases in both case (i) and case (ii) .

Corollary [4a](#page-63-0) is the analogous of Corollary [2](#page-21-0) in the paper, and the intuition is the same: regardless of the relative importance of the increase in the premium vis- λ -vis the increase in the riskiness of the risky asset, low-c funds are always more affected by the former, while highc funds are always more affected by the latter. The result of Corollary [4a](#page-63-0) is particularly important because, together with Proposition [3a,](#page-61-1) it implies that an increase in the risk premium always increases the cross-sectional risky investment differential, regardless of what happens to the tail of the return distribution. My empirical analysis tests this prediction in regression [\(8\)](#page-35-0) when the premium q is proxied by either S *pread Index* or GZ P remium (see Tables [5](#page-47-0) and [IA.6.12\)](#page-118-0).

IA.2.1.2 Risk-free rate

The comparative statics w.r.t. the risk-free rate R_f are unchanged by the inclusion of variable default costs. Namely, I show that: (1) the equilibrium risky investment increases with riskfree rate for all funds (Prediction 2a in the paper), and (2) under economically reasonable conditions, the cross-sectional risky investment differential increases when the risky-free rate decreases (Prediction 2b).

Proposition [5](#page-22-0)a. Proposition 5 holds unchanged under model [\(IA.2.1\)](#page-59-0).

Proposition [5a](#page-64-0) says that when the risk-free rate decreases, all funds decrease their risky investment, exactly as in the model without variable costs. This is because of two reasons. First, as in the model without variable costs, the fund with the highest fixed cost \bar{c} optimally decides to keep its default probability at zero, and the buffer of safe assets necessary to do so increases as the risk-free rate decreases. Second, if a fund's default probability is positive, the marginal expected shortfall per unit of risky investment increases as the risk-free rate decreases. This implies that relative to the model with only fixed costs, all funds (except \bar{c}) have a further incentive to cut their risky investment after a decrease in the risk-free rate.

Moreover, as in the model without variable costs, a change in the risk-free rate has a stronger effect on the equilibrium risky investment of funds with higher fixed costs. This implies that the risky investment differential between low- c and high- c funds increases when the risk-free rate decreases. The intuition behind this result is the same as in the model of the paper: the risky investment of high-c funds is closer to the critical risky investment x_0 , which decreases as R_f decreases, and is therefore more sensitive to changes in R_f . To prove this result for the model with variable costs, I assume that the PDF of the risky return is continuously differentiable^{[31](#page-64-1)} and define $J := \sup$ $R \in [R,1]$ $f'(R)$ $f(R)$ $< \infty$.

³¹This is done for technical reasons, since the equilibrium risky investment does not have a closed-form

Corollary 5a. If $\frac{c}{L}$ \boldsymbol{D} $+\gamma a > \frac{(R_f-1)(1-R)}{(B-1)(1+M)}$ $\sqrt{\frac{(R_f - R)\left[1 - J(1 - R)\right]}{R_f}}$, the cross-sectional risky investment differential increases when the risk-free rate decreases.

Corollary [5a](#page-65-0) is the equivalent of Corollary [3](#page-22-1) in the paper. As the condition of Corollary [3,](#page-22-1) the condition of Corollary [5a](#page-65-0) is mild and likely to hold in the real world. It is satisfied if either the minimum fixed cost of default in the fund population ϵ is sufficiently high, or the lowest possible return on the risky asset \underline{R} is not too low (exactly as in Corollary [3\)](#page-22-1). As discussed above and in the paper, both conditions are realistic in the MMF industry. Moreover, the condition can actually be weakened significantly by assuming: $\frac{R_f - R_f}{R_f - 1}$ R_f-1 $\begin{pmatrix} 1 \end{pmatrix}$ $1 - R$ $-\frac{f'(R)}{f(R)}$ $f(R)$ \setminus > 1 $\underline{c}/D + \gamma a$ for all $R \in [\underline{R}, 1]$, which is even milder. Importantly, my empirical analysis tests the prediction of Corollary [5a](#page-65-0) in regression [\(8\)](#page-35-0), using either the 1-month or the 3-month T-bill rate as proxy for the risk-free rate (see Tables [5](#page-47-0) and [IA.6.13\)](#page-119-0).

IA.2.2 Extension 2: the role of sponsor's support

In this section, I present a variation of the model that can be seen as a reduced form to study the effects of sponsor support on MMF risk-taking. Empirical evidence (Brady et al., 2012; Moody's, 2010) shows that when a MMF suffers a loss, the sponsor typically provides support by covering the shortfall, so as to prevent the fund from "breaking the buck." However, it can happen that after the loss occurs, the sponsor does not have the resources to cover the shortfall, and the MMF is forced to "break the buck." This was the case for Reserve Primary Fund in 2008 and Community Bankers US Government Fund in 1994. Such evidence suggests that sponsors will always subsidize their MMFs if they are ex post able to do so. Under this assumption, the MMF portfolio problem can be analyzed by treating fund and sponsor as a unique entity and allowing for the possibility that this entity is ex post unable to cover a loss, in which case it would have to incur a fixed default cost. The extension presented here is a reduced-form model to study such a scenario.

I assume that if a fund suffers a loss, it pays either the amount of the shortfall or its idiosyncratic fixed cost of default, depending on the realization of an exogenous random variable. This random variable represents the possibility that the sponsor is ex post cashsolution.

poor and therefore unable to subsidize the fund. Under economically reasonable sufficient conditions, I show that: (1) the main features of the equilibrium and results of the model in the paper carry though, (2) an increase in the likelihood of being ex post cash-poor reduces the risky investment of all funds, and (3) the effect is stronger for funds with lower fixed costs of default.

IA.2.2.1 Model and assumptions

Suppose that if $\pi_c < 0$, with probability θ the fund pays its idiosyncratic fixed cost of default c, and with probability $1-\theta$ the fund pays the shortfall $|\pi_c|$. Given a strategy profile $x:[\underline{c},\overline{c}]\rightarrow[0,D],$ the expected payoff of fund c under this specification is

$$
v_c(x_c, x_{-c}) = \gamma D \mathbb{E}[Rk(\pi_c) + a | \pi_c \ge 0] \mathbb{P}(\pi_c \ge 0) - \{ \theta c + (1 - \theta) \mathbb{E} [|\pi_c| | \pi_c < 0] \} \mathbb{P}(\pi_c < 0)
$$
\n(IA.2.3)

 θ represents the probability that the sponsor is ex post cash-poor and unable to subsidize the fund in case of a loss. For simplicity, I assume that θ does not depend on the extent of the shortfall and is common to all sponsors. These assumption greatly simplifies the analysis without affecting the qualitative results and insights of the model, as discussed below.

IA.2.2.2 Shocks to asset returns

The main features of the equilibrium and results of the model in the paper carry through also under specification [\(IA.2.3\)](#page-66-0). In fact, the above results for the model with both fixed and variable costs hold practically unchanged for the model with either fixed or variable costs.[32](#page-66-1)

Proposition 1b. Under model [\(IA.2.3\)](#page-66-0),

- i) Propositio[n1](#page-14-0) and Corollary [1](#page-14-1) hold unchanged;
- ii) Proposition [2a](#page-60-0) holds unchanged except that

$$
\frac{dx}{dc} = -\frac{\gamma Df(c) [2q + F(R_0(x))] x^2}{[\theta c + \gamma D (a + F(c))] (R_f - 1) Df(R_0(x)) + (1 - \theta) \mathbb{E}[R_f - R | R < R_0(x)] F(R_0(x)) x^2}
$$

,

³²Obviously, the particular algebraic expressions of some sufficient conditions differ in the two extensions.

and the condition for the existence of the equilibrium (i.e., no-short-selling condition) becomes $\mathbb{E}\left[\frac{\gamma D}{\sum_{i} \sum_{j} (\gamma_i)}\right]$ $\gamma D\left[F(c) + a \right] + c$ 1 ≤ $(1 - \underline{R})(R_f - 1)^2 f$ $\frac{1}{(2q+F_R(1))(R_f-\underline{R})^2};$

- iii) Propositions [3a](#page-61-1) and [4a](#page-61-0) hold unchanged except that the condition for the bifurcation becomes $\frac{c}{\overline{b}}$ D $+$ γa θ > $(1 - \theta)G$ $\frac{(1-\sigma)\sigma}{\theta(R_f-1)};$
- iv) Proposition [5a](#page-64-0) and Corollary [5a](#page-65-0) hold unchanged except that the condition in the corollary becomes $\frac{c}{c}$ \boldsymbol{D} $+\gamma a > \frac{(1-\theta)(R_f-1)(1-\underline{R})}{\frac{O(P_1-P_1)(1-\underline{R})}{P_1-\underline{R}}$ $\frac{\frac{(1-\theta)(1\theta)^{2}}{(1-\theta)(1-\theta)^{2}}}{\theta(R_f-\underline{R})\left[1-J(1-\underline{R})\right]}.$

The intuition for these results is the same as before: (1) funds with lower fixed costs are more sensitive to changes in the risk premium, while funds with higher fixed costs are more sensitive to changes in default risk; (2) funds with higher fixed costs are more sensitive to changes in the risk-free rate because they keep their default probability closer to zero, and the buffer of safe assets necessary to avoid default with certainty increases as the risk-free rate decreases. As for the model without variable costs, the existence condition of Proposition [1b](#page-66-2) (*ii*) comes from the no-short-sales constraint.

IA.2.2.3 Shocks to the probability of being ex post cash-poor

Here I study how the equilibrium responds to changes in the probability that the sponsor is ex post cash-poor θ .

Proposition 2b. Suppose $\frac{c}{L}$ D $\geq \frac{\mathbb{E}\left[R_f - R\middle| R < 1\right]}{R}$ R_f-1 $F_R(1)$ $\frac{f_{R}(1)}{f_{R}(1)}$. Then, the equilibrium risky investment of all funds decreases with θ , and the effect is stronger for funds with lower fixed costs of default.

Proposition [2b](#page-67-0) provides a predictable result: if the minimum fixed cost of default in the fund population is sufficiently high, all funds decrease their risky investment as the probability of the sponsor being ex post cash-poor increases. The only exception is the fund with the highest fixed cost \bar{c} , which always keeps its default probability at zero and is therefore unaffected by any change in θ . For all other funds, an increase in the probability of being ex post cash-poor has two competing effects: increasing the expected fixed cost of default, while decreasing the expected variable one. The first effect decreases the equilibrium marginal risky investment per unit decrease in fixed cost $\begin{array}{c} \hline \rule{0pt}{2.5ex} \\ \rule{0pt}{2.5ex} \end{array}$ dx $\mathrm{d}c$ $\begin{array}{c} \hline \rule{0pt}{2.5ex} \\ \rule{0pt}{2.5ex} \end{array}$, while the second effect increases it. The

relative weights of these two effects are: the marginal expected fixed cost per unit of risky investment and the marginal expected shortfall, respectively. If the minimum fixed cost of default is sufficiently high, the marginal expected fixed cost is greater than the marginal expected variable cost for all funds $c < \overline{c}$, and therefore $\begin{array}{c} \hline \end{array}$ dx $\mathrm{d}c$ $\begin{array}{c} \hline \end{array}$ decrease as θ increases for all $c < \overline{c}$. Since \overline{c} invests x_0 in the risky asset regardless of θ , it follows that the risky investment $x(c)$ of all other funds decreases after an increase in θ . As discussed above, it is realistic to assume that the fixed costs of default in the MMF industry are large, given the negative spillovers and reputation damages that sponsors would incur if their funds were to "break the buck."

Importantly, Proposition [2b](#page-67-0) implies that if the probability of being ex post cash-poor increases, the cross-sectional risky investment differential decreases, as summarized by the following corollary.

Corollary 2b. Under the condition of Proposition [2b,](#page-67-0) an increase in θ reduces the crosssectional risky investment differential.

The intuition behind this heterogeneous effect is that, even though low-c funds have lower fixed costs, they have a larger probability of "breaking the buck" in equilibrium. Therefore, if the fixed costs are sufficiently high compared to the variable ones, low-c funds are more sensitive to an increase in the probability of being ex post unable to cover the shortfall. On the contrary, the fund with the highest fixed cost always keeps its equilibrium default probability at zero and is therefore unaffected by any change in θ .

IA.2.2.4 Discussion of model assumptions

First, the assumption that θ does not depend on the amount of the shortfall is made only to simplify the derivation of the equilibrium. In principle, the probability of being ex post unable to cover the loss might increase with the amount of the shortfall. That is, θ should not only depend on the probability distribution of the sponsor's ex post cash-on-hand but also increase with $|\pi|$ for negative π . However, this generalization would only amplify the effect of sponsor's ex post liquidity on funds that ceteris paribus take more risk, i.e., the funds with lower fixed costs. The model above already shows that an increase in the probability of being ex post cash-poor has a stronger effect on funds with lower fixed costs (see Proposition [2b](#page-67-0) and Corollary [2b](#page-68-0) above).

Second, the assumption that θ is common to all funds rules out multiplicity of equilibria. If θ were fund-specific, there would be a continuum of different equilibrium strategies due to the presence of an additional dimension of heterogeneity. This continuum of equilibria may be reduced to a unique equilibrium by assuming a specific functional relation between the fixed cost of default and the probability of being ex post cash-poor. However, there is no clear economic rationale for any such relation, and including it would only complicate the analysis without adding any important insight.

Appendix IA.3 Proofs

Let $\Omega = (\underline{c}, \overline{c}) \subseteq \mathbb{R}_+$ and $\lambda(\cdot)$ be 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 paper and previous appendices, I prove some general properties of any NE of the tournament under the following, more general definition of ex post rank of fund performance:

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

Under this more general definition of performance rank, the money flow from outside investors 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 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 a.e. in the fund population. Moreover, in the limit of the highest default cost, the equilibrium risky investment is exactly x_0 .

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

$$
v_c(x) = \gamma D \{a + F_R(R_f) + 2qF_X(x)\} - \{\gamma D [a + 1 - F_X(x)] + c\} F_R(R_0(x)) +
$$

+ $\gamma D \{\delta [1 - F_R(R_0(x))] - F_R(R_f) + F_R(R_0(x))\} \lambda(C_x),$

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

Lemma 2. Suppose there exists a NE $x : \Omega = (c, \overline{c}) \rightarrow [0, D]$ 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 $c \in C_a$ $x(c) < \inf_{c \in C_b} x(c)$. 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. $v_{c_a}(x_a) \ge v_{c_a}(x)$ for all x. Then, for all $c_b \in C_b$,

$$
v_{c_b}(x_a) = v_{c_a}(x_a) - (c_b - c_a)F_R(R_0(x_a)) \ge v_{c_a}(x_b) - (c_b - c_a)F_R(R_0(x_a))
$$

= $v_{c_b}(x_b) + (c_b - c_a)[F_R(R_0(x_b)) - F_R(R_0(x_a))] > v_{c_b}(x_b),$

 \Box

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

Proposition 8. Suppose there exists a NE $x : \Omega = (\underline{c}, \overline{c}) \rightarrow [0, D]$ 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 ;

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

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 ;

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

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 $c \in C_a$ $x(c) \leq \inf_{c \in C_b} x(c)$. 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 $\lambda(C_2) - F_x(x_a) - \lambda_a \ge 0$ for all $c_a \in C_a$. Second, for sufficiently small $\varepsilon > 0$,

$$
v_{c_a}(x_0 + \varepsilon) = \gamma D \{ a + F_R(R_f) + 2q\lambda(C_2) \} - \{ \gamma D \left[a + 1 - \lambda(C_2) \right] + c_a \} F_R(R_0(x_0 + \varepsilon)) +
$$

+ $g(\varepsilon) \gamma D \left[2q + F_R(R_0(x_0 + \varepsilon)) \right],$

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

$$
v_{c_a}(x_0 + \varepsilon) \ge v_{c_a}(x_a) + \gamma D\{2q [\lambda(C_2) - F_X(x_a) - \lambda_a] + \lambda_a [1 - F_R(R_f) - \delta] \} +
$$

- $\{ \gamma D [a + 1 - \lambda(C_2)] + c_a \} F_R(R_0(x_0 + \varepsilon)) > v_{c_a}(x_a),$

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

 (ii) It follows directly from (i) and Lemma [2.](#page-70-0)

(*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; this is 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 payoff increase 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 funds can neither no-short-sell nor borrow, the NE can only take values in $[0, D]$; hence, 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 left 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. the player type, this is true for a positive measure set of players.

(iv) The exact statement is that on a subset $C \subseteq \Omega$ s.t. $\lambda(\Omega \setminus C) = 0$, $\lim_{c \to \overline{c}, c \in C} x(c) = x_0$. 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 $[0, D]$ 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 are 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 \bar{c} is sufficiently high, it cannot be $\lim_{c\to\bar{c}, c\in C} x(c) = D$ either. Since the NE is weakly decreasing a.e. on Ω , that limit would imply $x(c) = D$ a.e. on $Ω.$ If $\bar{c} > \gamma D \left[\delta (1 - F_R(1)) - F_R(R_f) - aF_R(1) \right] / F_R(1)$, 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 on the left of \bar{c} .

(v) From (i), we 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 thus omitted. \Box

Proofs

Here I derive the unique NE of the tournament under the definition of performance rank used in the paper $(\delta = 0)$. Hereafter I omit the "a.e." qualification. 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.](#page-14-0) From Proposition [8,](#page-70-0) it follows that if $\delta = 0$, 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

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

where

$$
A(x^{-1}(y)) = \gamma D \{a + F_R(R_f) + [1 - 2F_R(R_f)] [1 - F_C(x^{-1}(y))] \},
$$

\n
$$
B(x^{-1}(y), c) = \{ \gamma D [a + F_C(x^{-1}(y))] + c \},
$$

\n
$$
G(y) = F_R(R_0(y)).
$$

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

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

and

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

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

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

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

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

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

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

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

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 one 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](#page-70-0) with $\delta = 0$.

Proof of Proposition [2.](#page-15-0) From the proof of Proposition [1,](#page-14-0) we know that any NE is differentiable and must satisfy the following Dirichlet problem

 \Box

$$
\begin{cases}\nS(x)dx + \tilde{Q}(c)dc = 0 & \text{with } c \in \Omega = (\underline{c}, \overline{c}) \text{ and } x \in (x_0, D), \\
\lim_{c \to \overline{c}} x(c) = x_0,\n\end{cases}
$$

where

$$
S(x) = \frac{(R_f - 1)Df_R(R_0(x))x^{-2}}{2q + F_R(R_0(x))} \quad \text{and} \quad \tilde{Q}(c) = \frac{\gamma Df_C(c)}{\gamma D[a + F_C(c)] + c}.
$$

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

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

from which it follows

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

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

$$
x(c) = \frac{(R_f - 1)D}{R_f - F_R^{-1}(2qQ(c))},
$$
\n(IA.3.1)

where $Q(c) = \exp\left(\int_c^{\overline{c}} \widetilde{Q}(s)ds\right) - 1$. Hence, if a NE exists, it is unique and equal to [\(IA.3.1\)](#page-75-0).

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 $\int_{c}^{\overline{c}}$ $\int\limits_{\mathcal{C}}^{\mathcal{C}}\tilde{Q}(s)\mathrm{d}s=\mathbb{E}_{C}\left[\frac{\gamma D}{\gamma D[a+F_{C}]} \right]$ $\gamma D[a+F_C(c)]+c$ \vert $<$ $\log\left(1+\frac{F_R(1)}{2q}\right)$.

The last step is to prove that the solution of the Dirichlet problem is indeed a NE. Under the strategy profile [\(IA.3.1\)](#page-75-0), each player's objective function is continuous everywhere and continuously differentiable on $[0, x_0) \cup (x_0, x(\underline{c})) \cup (x(\underline{c}), D]$. It is easy to show that for all c,

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

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

$$
\frac{\partial v_c}{\partial y}(y) = \gamma D \left[2q + F_R(R_0(y)) \right] f_C(x^{-1}(y)) \left(\frac{dx}{dc} (x^{-1}(y)) \right)^{-1} - \left\{ \gamma D \left[a + F_C(x^{-1}(y)) \right] + c \right\} f_R(R_0(y)) (R_f - 1) D y^{-2}
$$

By substituting the above ODE, we obtain $\frac{\partial v_c}{\partial y}(y) = (x^{-1}(y) - c) f_R(R_0(y)) (R_f - 1) D y^{-2}$, which is: positive for $y \in (x_0, x(c))$, negative for $y \in (x(c), x(c))$, and equal to zero for $y = x(c)$. Since $v_c(y)$ is continuous everywhere, $x(c)$ is a global maximum for all $c \in \Omega$ under the strategy profile [\(IA.3.1\)](#page-75-0) and hence is the unique NE of the tournament. \Box

Proof of Proposition [4.](#page-20-0) Let $F^{(i)}$ be the risky return distribution when the left tail is $H^{(i)}$, and $G^{(i)} = F^{(i)-1}$ the corresponding quantile function. Note that by construction, the mass in the left tail remains the same, i.e., $F^{(1)}(1) = F^{(2)}(1)$. Let $R_0^{(i)}$ $Q_0^{(i)}(c) := G^{(i)}(2q^{(i)}Q(c));$ 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 $\lim_{c \to \overline{c}} Q(c) = 0$, $R_0^{(i)}$ $\binom{N}{0}(c) \in (\underline{R}, 1)$ is also strictly decreasing and $\lim_{c\to\overline{c}}R_0^{(i)}$ $Q_0^{(i)}(c) = \underline{R}$. Moreover, being $F^{(i)}$ absolutely continuous, $R_0^{(i)}$ $\binom{v}{0}(c)$ is continuous. Finally, let $f^{(i)}$ and $h^{(i)}$ be the densities of $F^{(i)}$ and $H^{(i)}$, respectively, and let $x_c^{(i)}$ be the NE under $F^{(i)}$. Obviously, larger $R_0^{(i)}$ $\binom{0}{0}(c)$ means larger $x_c^{(i)}$. Hereafter, for any functions f and g, the expression $\frac{f}{g}(x)$ stands for $f(x)/g(x)$.

(*i*) For every $c, 2q^{(1)}Q(c) = F^{(1)}(R_0^{(1)})$ $\binom{1}{0}(c) = F^{(1)}(1)H^{(1)}(R_0^{(1)})$ $\binom{1}{0}(c) \geq \frac{q^{(1)}}{q^{(2)}}$ $\frac{q^{(1)}}{q^{(2)}}F^{(2)}(1)H^{(2)}(R_0^{(1)}$ $\binom{1}{0}(c)$. Hence, $2q^{(2)}Q(c) \geq F^{(2)}(R_0^{(1)})$ $0^{(1)}(c)$, and therefore $R_0^{(2)}$ $b_0^{(2)}(c) \ge R_0^{(1)}$ $y_0^{(1)}(c)$ and $x_c^{(2)} \ge x_c^{(1)}$ for all c.

(*ii*) First, it is easy to prove by contradiction that $\frac{q^{(2)}}{q^{(1)}}$ $\frac{q^{(2)}}{q^{(1)}} < \sup \frac{H^{(2)}}{H^{(1)}}$ implies $\frac{q^{(2)}}{q^{(1)}}$ $\frac{q^{(2)}}{q^{(1)}} < \sup \frac{h^{(2)}}{h^{(1)}}.$ Second, $H^{(1)} \succ_{LRD} H^{(2)}$ implies inf $\frac{h^{(2)}}{h^{(1)}} < 1$. Hence, since $\frac{q^{(2)}}{q^{(1)}}$ $\frac{q^{(2)}}{q^{(1)}} > 1$, we have inf $\frac{h^{(2)}}{h^{(1)}} <$

 $q^{(2)}$ $\frac{q^{(2)}}{q^{(1)}} < \sup_{h^{(1)}} \frac{h^{(2)}}{h^{(1)}}$. Since $\frac{h^{(2)}}{h^{(1)}} = \frac{f^{(2)}}{f^{(1)}}$ $\frac{f^{(2)}}{f^{(1)}}$ is weakly decreasing by LRD, there exists $r^* \in (\underline{R}, 1)$ s.t. $f^{(2)}$ $\frac{f^{(2)}}{f^{(1)}}(r) > \frac{q^{(2)}}{q^{(1)}}$ $\frac{q^{(2)}}{q^{(1)}}$ for all $r \in (\underline{R}, r^*)$ and $\frac{f^{(2)}}{f^{(1)}}$ $\frac{f^{(2)}}{f^{(1)}}(r) \leq \frac{q^{(2)}}{q^{(1)}}$ $\frac{q^{(2)}}{q^{(1)}}$ for all $r \in [r^*, 1)$. Since $R_0^{(1)}$ $\binom{1}{0}(c)$ is continuous, strictly decreasing, and goes to <u>R</u> as $c \to \overline{c}$, there exists $c^* \in (\underline{c}, \overline{c})$ s.t. for all $c > c^*$, by the mean value theorem, $F^{(2)}\left(R_0^{(1)}\right)$ $\binom{10}{0}(c)$ = $F^{(2)}(G^{(1)}(2q^{(1)}Q(c))) = \frac{f^{(2)}}{f^{(1)}}$ $\frac{f^{(2)}}{f^{(1)}}(\widetilde{r}_c)2q^{(1)}Q(c)$ for some $\widetilde{r}_c \in (\underline{R}, r^*)$. Hence, $F^{(2)}\left(R_0^{(1)}\right)$ $\binom{10}{0}(c) > 2q^{(2)}Q(c)$ for all $c > c^*$; therefore, $R_0^{(1)}$ $Q_0^{(1)}(c) > R_0^{(2)}(c)$ 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 $\frac{q^{(2)}}{q^{(1)}}$ $\frac{q^{(2)}}{q^{(1)}} > 1 = \frac{F^{(2)}}{F^{(1)}}(1)$, there exists $Q(\underline{c})$ sufficiently large s.t. the NE exists but at the same time $R_0^{(1)}$ $v_0^{(1)}(\underline{c}) > r^{**}$ and $\frac{F^{(2)}}{F^{(1)}}(R_0^{(1)}$ $\binom{1}{0}(\underline{c}) < \frac{q^{(2)}}{q^{(1)}}$ $\frac{q^{(2)}}{q^{(1)}}$, which implies $2q^{(2)}Q(c) > F^{(2)}\left(R_0^{(1)}\right)$ $\binom{1}{0}(\underline{c})$ 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 $c_* = c^*$. \Box

Corollary [2.](#page-21-0) Trivial.

Proof of Proposition [5.](#page-22-0) By differentiating the NE [\(3\)](#page-15-1) w.r.t R_f , holding q constant.

Corollary [3.](#page-22-1) Trivial.

Proof of Proposition [6.](#page-23-0) Let $x(c; R_f)$ be the NE [\(3\)](#page-15-1), 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, 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

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

where $R_0(c) = F_R^{-1}$ $R_R^{-1}(2q(R_f)Q(c)) \in (\underline{R},1)$. Since $R_0(c)$ is strictly decreasing, and F_R/f_R is weakly increasing on $(\underline{R}, 1)$, $\frac{dx(c;R_f)}{dR_f}$ is strictly increasing in c. From the weak monotonicity of F_R/f_R , it also follows that $\lim_{r \to R}$ F_R $\frac{F_R}{f_R}(r) = 0$. Hence, since $\lim_{c \to \overline{c}} R_0(c) = \underline{R}, \frac{dx(c;R_f)}{dR_f}$ $\frac{dR_f}{dR_f}$ is positive on the left of \bar{c} by continuity.

 \Box

 \Box

 \Box

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

Proof of Lemma [1.](#page-48-0) By applying Taylor's theorem on $q(R_f) = 0.5 - F_R(R_f)$ around μ . \Box *Proof of Corollary [4.](#page-48-1)* By applying Taylor's theorem on the NE [\(3\)](#page-15-1) around \bar{c} for small $qQ(c)$. \Box

Proof of Corollary [5.](#page-49-0) Trivial.

Proposition [7.](#page-56-0) If $F_C^{(2)} \succ_{LRD} F_C^{(1)}$ $C^{(1)}$, there exists $c^* \in (c, \bar{c})$ s.t. $f^{(2)}(c) > f^{(1)}(c)$ for all $c > c^*$. Since $F_C^{(2)}$ $C^{(2)}(c) < F_C^{(1)}(c)$ for all c,

$$
\int_{c}^{\overline{c}} \frac{\gamma Df_C^{(2)}(u)du}{\gamma D\left[F_C^{(2)}(u) + a\right] + u} > \int_{c}^{\overline{c}} \frac{\gamma Df_C^{(1)}(u)du}{\gamma D\left[F_C^{(1)}(u) + a\right] + u} \quad \text{for all } c > c^*.
$$

Hence, $Q^{(2)}(c) > Q^{(1)}(c)$ and therefore $x^{(2)}(c) > x^{(1)}(c)$ for all $c > c^*$. On the other hand, using integration by parts,

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

Since $F_C^{(2)}$ $C^{(2)}(c) < F_C^{(1)}(c)$ everywhere by LRD, $Q^{(2)}(\underline{c}) < Q^{(1)}(\underline{c})$. By continuity and monotonicity of the NE, there exists $c_* \in (c, c^*)$ s.t. $Q^{(2)}(c) < Q^{(1)}(c)$ and therefore $x^{(2)}(c) < x^{(1)}(c)$ for all $c < c_*$. \Box

Proof of Proposition [1a.](#page-59-0) Since the additional variable cost of default is continuously differ-entiable with respect to c and x, Proposition [8](#page-70-0) holds also for model $(IA.2.1)$. The only

 \Box

difference is that the sufficient condition of part (iv) becomes $\bar{c} + \mathbb{E}[R_f - R | R < 1] F_R(1)$ $\gamma D \{\delta [1 - F_R(1)] - F(R_f) - aF_R(1)\} / F_R(1)$. This condition is even weaker than that for the model in the paper. Hence, we can conclude that $x(c)$ is decreasing, continuous, and $\lim_{c \to \overline{c}} x(c) = x_0$. The rest of the proof is along the same lines as that of Proposition [1](#page-14-0) in the paper. In fact, from optimality of the equilibrium, I can show that:

$$
\frac{dx}{dc} = -\frac{\gamma Df(c) [2q + F(R_0(x))] x^2}{[c + \gamma D(a + F(c))] (R_f - 1) Df(R_0(x)) + \mathbb{E}[R_f - R | R < R_0(x)] F(R_0(x)) x^2} < 0.
$$

Therefore, since $f(c)$ and $f(R)$ are positive and continuous by assumption, $x(c)$ is continuously differentiable with negative first derivative. Hence, Proposition [1](#page-14-0) holds unchanged. Corollary [1](#page-14-1) holds unchanged because $x(c) > x_0$ for all $c \in [c, \overline{c})$ and decreases with c. \Box

Proof of Proposition [2a.](#page-60-0) From the proof of Proposition [1a,](#page-59-0) we already know that any NE is differentiable and must satisfy the Dirichlet problem [\(IA.2.2\)](#page-60-1). It is straightforward to show that, under the assumption that F_C and F_R are continuously differentiable with positive density, $\frac{dx}{1}$ is continuous in $c \in [\underline{c}, \overline{c}]$ and uniformly Lipschitz continuous in $x \in [0, \infty)$. $\mathrm{d}c$ Hence, by the Picard-Lindelöf theorem, there exists a unique solution of [\(IA.2.2\)](#page-60-1) in $[\underline{c}, \overline{c}] \times$ $[x_0, \infty)$. The next step is to prove that the unique solution of the Dirichlet problem is indeed a NE equilibrium. For that, we can check that under the strategy defined by $(IA.2.2)$, $x(c)$ is a global maximum for every $c \in [\underline{c}, \overline{c}]$. The proof is identical to that of Proposition [2](#page-15-0) in the paper (i.e., take $\frac{\partial v_c(y, x_{-c})}{\partial y}$ and by substituting the expression for $\frac{dx}{dc}$ show that it is positive for all $y < x(c)$ and negative for all $y > x(c)$ and is therefore omitted. The final step is to provide conditions under which the solution of [\(IA.2.2\)](#page-60-1) satisfies the no-short-selling dx condition $x(c) \leq D$. Since is smaller for all (c, x) when variable costs of default are $\mathrm{d}c$ included, while the boundary condition $\lim_{c \to \overline{c}} = x_0$ does not change, the condition for the model without variable default costs suffices. \Box

Proof of Proposition [3a.](#page-61-0) $\begin{array}{c} \hline \end{array}$ dx $\mathrm{d}c$ $\begin{array}{c} \hline \end{array}$ strictly increases with q for all $x \in (x_0, D)$, while x_0 does not depend on q. Hence, since $x(c) = x_0 +$ $\int^{\overline{c}}$ c $\begin{array}{c} \begin{array}{c} \begin{array}{c} \begin{array}{c} \end{array} \\ \end{array} \\ \begin{array}{c} \end{array} \end{array} \end{array}$ dx $\mathrm{d}c$ $\begin{array}{c} \begin{array}{c} \begin{array}{c} \begin{array}{c} \end{array} \\ \end{array} \\ \begin{array}{c} \end{array} \end{array} \end{array}$ dc for all $c \in (\underline{c}, \overline{c})$, $x(c)$ strictly increases with q for all c, and the effect is stronger for low-c funds. Since the PDF of R is absolutely continuous by assumption, the same conclusion holds for the equilibrium default probability.

$$
\left| \frac{dx}{dc} \right| = \left[1 + \frac{2q}{F_R(1)H(R_0(x))} \right] \frac{\gamma Df(c)x^2}{[c + \gamma D(a + F(c))] G_1(x)(R_f - 1)D + G_2(x)x^2} . \quad \text{(IA.3.2)}
$$

It is easy to show that if $\frac{c}{L}$ D $+ \gamma a >$ G R_f-1 , the second term on the right-hand side of [\(IA.3.2\)](#page-80-0) increases after the LRD shift to the left for all $(c, x) \in [c, \bar{c}] \times [x_0, D]$. Hence, if $q^{(2)}$ $\frac{q}{q^{(1)}} \geq \sup$ $H^{(2)}$ $\frac{H^{(1)}}{H^{(1)}}$ \vert ac \vert dx dc increases for all c. Since x_0 is affected neither by the LRD shift nor by the increase in the premium, it follows that $x^{(2)}(c) > x^{(1)}(c)$ for all $c \in [c, \overline{c})$.

Part (*ii*): First, $\lim_{c \to \overline{c}}$ $\overline{}$ dx $\mathrm{d}c$ $\Big| =$ $\int \frac{2\gamma Df(c)x_0^2}{2\gamma^2}$ $[\overline{c} + \gamma D(a+1)] (R_f - 1)D$ $\setminus q$ $f(\underline{R})$. Under likelihood ratio dominance, sup $\frac{H^{(2)}}{H^{(1)}}$ $\frac{H}{H^{(1)}} =$ $f^{(2)}(\underline{R})$ $f^{(1)}(\underline{R})$. Hence, if $\frac{q^{(2)}}{q^{(1)}}$ $\frac{q}{q^{(1)}} < \sup$ $H^{(2)}$ $\frac{H}{H^{(1)}},$ $\begin{array}{c} \begin{array}{c} \begin{array}{c} \end{array} \\ \begin{array}{c} \end{array} \end{array} \end{array}$ dx $\mathrm{d}c$ $\begin{array}{c} \begin{array}{c} \begin{array}{c} \begin{array}{c} \end{array} \\ \end{array} \\ \begin{array}{c} \end{array} \end{array} \end{array} \end{array}$ decreases for all funds in a left-neighborhood of \bar{c} . Since x_0 does not change, there exists c^* such that $x^{(2)}(c) < x^{(1)}(c)$ for all $c \in [c^*, \bar{c})$. Second, from (i), we know that if $q^{(2)}/q^{(1)} = \sup H^{(2)}/H^{(1)}, x^{(2)}(\underline{c}) >$ $x^{(1)}(\underline{c})$. Hence, by continuity of $\frac{dx}{dx}$ $\mathrm{d}c$ with respect to q and c, if $q^{(2)}/q^{(1)}$ is sufficiently close to $\sup H^{(2)}/H^{(1)}$, there exists c_* such that $x^{(2)}(c) > x^{(1)}(c)$ for all $c \in [c, c_*)$.

 $dx^{(2)}$ $\mathrm{d}x^{(1)}$ $\begin{array}{c} \begin{array}{c} \begin{array}{c} \begin{array}{c} \end{array} \\ \end{array} \\ \begin{array}{c} \end{array} \end{array} \end{array} \end{array}$ $\begin{array}{c} \hline \end{array}$ $\begin{array}{c} \begin{array}{c} \begin{array}{c} \begin{array}{c} \end{array} \\ \end{array} \\ \begin{array}{c} \end{array} \end{array} \end{array} \end{array}$ Finally, when $q^{(2)}/q^{(1)} = \sup H^{(2)}/H^{(1)}$, $>$ for all c , which implies that the $\mathrm{d}c$ $\mathrm{d}c$ difference between $x^{(2)}(c)$ and $x^{(1)}(c)$ is maximized at c and monotonically decreases with c. Therefore, since $R_0(x(c))$ decreases with c, if $\frac{H^{(2)}}{H^{(1)}}$ is decreasing, the cutting point between high-c funds and low-c funds must be unique, i.e., $c^* = c_*$. \Box

Proof of Proposition [4a.](#page-63-0) Obvious from the proof of Proposition [4a.](#page-61-1)

Proof of Proposition [5a.](#page-64-0) First, the boundary condition $\lim_{c \to \overline{c}} x(c) = x_0 =$ R_f-1 $R_f - \underline{R}$ D strictly decreases after a decrease in R_f , exactly as in the model without variable costs. Second, the only difference in the marginal risky investment $\begin{array}{c} \hline \end{array}$ dx $\mathrm{d}c$ between the model with variable costs and that without variable costs is the presence at the denominator of the marginal expected shortfall per unit of risky investment, $\mathbb{E}[R_f - R | R < R_0(x; R_f)] F(R_0(x; R_f))$, which increases as R_f decreases. This means that as R_f decreases, $\begin{array}{c} \begin{array}{c} \begin{array}{c} \begin{array}{c} \end{array} \\ \end{array} \\ \begin{array}{c} \end{array} \end{array} \end{array}$ dx $\mathrm{d}c$ $\begin{array}{c} \begin{array}{c} \begin{array}{c} \begin{array}{c} \end{array} \\ \end{array} \\ \begin{array}{c} \end{array} \end{array} \end{array}$ increases relatively less (or decreases relatively more) than in the model without variable costs, for all x and c . Hence,

 \Box

since in the model without variable costs $x(c) = x_0 + \int_c^{\overline{c}} \left| \frac{dx}{dc} \right|$ $\frac{dx}{dc}$ dc decreases after a decrease in R_f for all c , it must be the same in the model with variable costs. \Box

Proof of Corollary [5a.](#page-65-0) It is straightforward to show that under the conditions of the corol- $\begin{array}{c} \begin{array}{c} \begin{array}{c} \begin{array}{c} \end{array}\\ \begin{array}{c}$ $\begin{array}{c} \begin{array}{c} \begin{array}{c} \begin{array}{c} \end{array}\\ \begin{array}{c}$ lary, $\frac{\partial}{\partial x}$ dx < 0 for all $(c, x) \in [\underline{c}, \overline{c}] \times [x_0, D].$ \Box ∂R_f dc

Proof of Proposition [1b.](#page-66-0) The proofs are almost identical to those for the model with both \Box fixed costs and variable costs and are therefore omitted.

Proof of Proposition [2b.](#page-67-0) Under the payoff function $(IA.2.3)$, the equilibrium risky investment must satisfy the following Dirichlet problem:

$$
\frac{dx}{dc} = -\frac{\gamma Df(c) [2q + F(R_0(x))] x^2}{[\theta c + \gamma D (a + F(c))] (R_f - 1) Df(R_0(x)) + (1 - \theta) \mathbb{E} [R_f - R | R < R_0(x)] F(R_0(x)) x^2},
$$
\n
$$
\lim_{c \to \overline{c}} x(c) = x_0.
$$

First, $\lim_{c\to\overline{c}}$ dx $\mathrm{d}c$ $\Big| =$ $\gamma D f(c) [2q + F(R_0(x))] x^2$ $\frac{[\theta c + \gamma D] (c) [\frac{1}{2} + 1] (\frac{1}{2} \alpha c)^{1/2}}{[\theta c + \gamma D] (a + F(c))] (R_f - 1) D_f(R_0(x))}$, which decreases with θ . Hence, since x_0 does not change with θ , after an increase in the probability of being ex post cashpoor θ , funds in a left-neighborhood of \bar{c} (i.e., with relatively high fixed costs of default) decrease their risky investment.

 $\mathbb{E}\left[R_f - R | R < R_0(x)\right]$ x^2 Second, $\frac{\partial}{\partial x}$ $\begin{array}{c} \hline \end{array}$ dx $\begin{array}{c} \hline \end{array}$ $F(R_0(x))$ < 0 for all $(c, x) \in [\underline{c}, \overline{c}] \times [x_0, D]$ if and only if $c >$ ∂θ $\mathrm{d}c$ R_f-1 $f(R_0(x))$ D for all $(c, x) \in [\underline{c}, \overline{c}] \times [x_0, D]$. Under Assumption [2](#page-23-1) in the paper, this inequality is satisfied $> \frac{\mathbb{E}\left[R_f - R\middle| R < 1\right]}{R}$ $\overline{\mathbf{a}}$ for all (c, x) if $\frac{c}{c}$ $F_R(1)$ dx $\frac{F_{R}(1)}{f_{R}(1)}$. Hence, when θ increases, decreases for D R_f-1 dc all c. Since x_0 does not change with θ , this implies that $x(c)$ decreases for all funds, and the decrease is stronger for funds with relatively low fixed costs of default. \Box

 \Box

Proof of Corollary [2b.](#page-68-0) Obvious from Proposition [2b.](#page-67-0)

Appendix IA.4

Data Construction

Data on fund characteristics are from iMoneyNet. These data are the most comprehensive source of information on MMFs for the period considered in the paper and are widely used for both academic research and investment decisions. KS check that the iMoneyNet database covers the universe of U.S.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 whole sample is from January 5, 1999 to August 26, 2008. Data are at the weekly, share class level. The sample contains 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 of all share classes add up to total fund size (available in the iMoneyNet data). 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 classes, which are available only to retail investors, and institutional 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. The rationale for this identification is that institutional share classes are typically much larger than retail share classes. Over the whole period 01/1999– 08/2008, I identify 219 funds as institutional and 237 funds as retail. 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 stronger flow-performance relation than retail funds.

To calculate sponsor reputation concerns as described in Section [5,](#page-26-0) 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 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 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 fund names 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.4.1](#page-97-0) 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 $Fund~Business$ is 0.82. Results are discussed in Section [5](#page-26-1) of the paper. My findings are close to those of KS, confirming that my data set is consistent with theirs.

Table [IA.4.2](#page-98-0) 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 MMF risk-taking. The left panel of Figure [IA.4.1](#page-85-0) shows the distribution of Fund Business in the population of MMFs on January 3, 2006. The distribution is widely spread on the interval $[0, 1]$, 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.4.1](#page-85-0) 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 Section [IA.1](#page-56-1) shows 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, it is important that the distribution of default costs remains relatively stable over the period of the empirical analysis.

To check that my results are not driven by the same cross-sectional heterogeneity con-

(a) Cross-section of Fund Business in $1/3/2006$.

(b) Time evolution of $Fund~Business$ distribution.

Figure IA.4.1: The sample is all U.S. institutional prime MMFs. Left panel: distribution of Fund Business as of $1/3/2006$. 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 $1/1/2002$ to $8/31/2008$.

sidered 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. Incurred Cost is the incurred expense ratio in $\%$, and *Conglomerate* is a dummy variable equal to 1 if the fund belongs to a financial conglomerate and 0 otherwise. Figure [IA.4.2](#page-86-0) 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 a 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 then. For robustness, I estimate the following regression at the weekly frequency:

$$
Fund\ Business_{i,t} = \alpha_i + \mu_t + \beta X_{i,t} + \varepsilon_{i,t}
$$
\n(IA.4.1)

where X is either Incurred Cost and Conglomerate. α_i and μ_t are fund and week fixed effects, respectively. Since Conglomerate is constant over time for most funds, I also estimate regression [\(IA.4.1\)](#page-85-1) without fund fixed effects, i.e., with only week fixed effects. Results are in Table [IA.4.3.](#page-98-1) 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%.

Figure IA.4.2: Correlation between Fund Business and Incurred Cost (left panel) and between Fund Business and Conglomerate (right panel) in the cross-section of U.S. prime institutional MMFs at a weekly frequency from January 2002 to August 2008. The solid black line is the Pearson correlation coefficient in each week. Black dashed lines are 10% confidence intervals, and the dashed red lines are 1% confidence intervals.

Appendix IA.5 Flow-performance: robustness

This appendix contains robustness checks of the analysis of the flow-performance relation in the MMF industry. Table [IA.5.1](#page-99-0) shows the results for the estimation of regression [\(B.1\)](#page-49-1) 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 on the right-hand side (RHS) of regression [\(B.1\)](#page-49-1), past Spread loses 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.5.2](#page-100-0) shows the results for the estimation of regression [\(B.1\)](#page-49-1) 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 on the RHS of the regression.

All flow-performance regressions in the paper and appendix include time fixed effects to control for industry-wide time-varying effects. However, to further control for secular "flightto-quality" episodes, I run regression [\(B.1\)](#page-49-1) normalizing fund flows by time-period. That is, fund-week inflows are normalized by that week's mean inflow, and fund-week outflows are normalized by that week's mean outflows. All other regression variables are defined as above. Results are in Table [IA.5.3](#page-101-0) for the specification with both time and fund fixed effects, and in Table [IA.5.4](#page-102-0) for the specification with only time fixed effects. In both cases, the results are very similar to those in the paper, both qualitatively and quantitatively. I also run the flow-performance regression normalizing fund flows by weekly median flows; results are in Tables [IA.5.5](#page-103-0) and [IA.5.6](#page-104-0) and very similar.

As a further robustness check, I run regression [\(B.1\)](#page-49-1) using trimming conditions based on the interquartile range. Results are similar and omitted for brevity. This empirical evidence confirms that performance rank explains money flows to MMFs better than raw performance, supporting the choice of a pure tournament model.

IA.5.1 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, which proxy for the model's cost of default. 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 this is not the case over 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 $(B.1)$ 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.5.7.](#page-105-0) 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. For robustness, I also repeat the same regression exercise using the normalized flows defined in the previous section as dependent variable, to further control for secular "flight-to-quality" episodes. The results are quantitatively and qualitatively very similar (see Table [IA.5.8\)](#page-106-0). I also 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 always similar and omitted for brevity. These findings suggest that investors do not risk-adjust fund performance based on sponsor reputation concerns, supporting the assumption of an exogenous flow-performance relation in my MMF model.

Appendix IA.6 MMF risk-taking: robustness

This section contains robustness checks of the empirical results on MMF risk-taking that aim to test my model's predictions.

IA.6.1 *Pre* and *Post* July 2007: Robustness

Since in the model a fund's risky investment is determined by the rank of its default cost in the fund population, the rank of $Fund$ Business is a natural explanatory variable in regression (6) . However, for robustness, I also run regression (6) using raw Fund Business as main explanatory variable. Results are in Table [IA.6.1;](#page-107-0) standard errors are HACSC robust to account for correlations both within and across funds. Results are similar to those of Table [2](#page-44-0) in the paper, confirming the model's predictions: funds with lower Fund Business always take on more risk and do so more when either the risk premium increases or the risk-free rate decreases.

Contrary to KS, I find that funds with lower default costs take more risk also in the Pre period. To check the robustness of my results, I run the same regression specification as KS:

$$
Risk_{i,t+1} = \alpha + \mu_t + \beta_1 \text{Reputation Concerns}_{i,2006}
$$

$$
+ \beta_2 \text{Post}_t * \text{Reputation Concerns}_{i,2006} + \gamma \cdot X_{i,2006} + \varepsilon_{i,t+1} \tag{IA.6.1}
$$

where Reputation Concerns is a generic name for either Fund Business or Conglomerate. Post and X are defined as in equation (6) . Both sponsor's reputation concern and the controls are measured as of January 3, 2006 to mitigate possible endogeneity issues. μ_t are week fixed effects to account for macroeconomic conditions. To measure MMF risk-taking, I use Spread, Holdings Risk, and Maturity Risk as KS, but also Holdings Risk^{dyn} and $Safe$ Holdings. All these risk-taking proxies are defined in Section [5.1](#page-28-0) of the paper.

To be consistent with KS (see Table IV therein), Table [IA.6.2](#page-108-0) shows the results when both Fund Business and Conglomerate are included on the RHS of [\(IA.6.1\)](#page-89-0). 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 [\(IA.6.1\)](#page-89-0) 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 β_1 and β_2 are positive and statistically significant at the 1% level, in agreement with the model and empirical results of Section [5.2.](#page-31-0)

In regression [\(IA.6.1\)](#page-89-0), the sponsor's reputation concern is instrumented with its value as of January 3, 2006. While eliminating possible endogenous correlations between the sponsor's reputation concern and the unobserved regression error, this choice 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 this reason, regression [\(6\)](#page-32-0) in Section [5.2](#page-31-0) extends the analysis of KS by using the lagged value of sponsor's reputation concern as the main explanatory variable.

IA.6.2 Risk-taking in the time series

This section presents robustness checks of the results in Table [3,](#page-45-0) which test the 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.6.1](#page-91-0) 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 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.

To have a quantitative robustness check of the results in Table [3,](#page-45-0) I estimate regression [\(7\)](#page-33-0) using the 3-month T-bill rate as a proxy for the risk-free rate (Table [IA.6.3\)](#page-109-0), and lagging all fund-specific time-varying controls by two lags (Table [IA.6.4\)](#page-110-0). Both robustness checks give results that are qualitatively and quantitatively similar to those in the paper. 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 3-month T-bill rate pushes all MMFs to tilt their portfolios toward safer asset classes. However, MMFs compensate this shift to safer asset classes by lengthening the maturity of their portfolios, as observed also in Table [3.](#page-45-0)

As a further robustness check, I estimate regression [\(7\)](#page-33-0) changing the identification of high- and low-default-cost funds in several ways. First, I identify as funds with high default costs those whose sponsor's reputation concern (Fund Business) is above the industry $40th$ percentile in every month. That is, relatively to the specification in the paper, I am changing the cutoff between high-c and low-c funds from the median to the $40th$ percentile. In this way, each group contains roughly the same number of funds: 25 funds with high default

Figure IA.6.1: Industry average risk-taking over time. 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.

costs and 21 funds with low default costs. As in the paper, this identification of high- c and low-c funds does not change over time by construction. For the specification that uses Spread Index as proxy for the risk premium and the 1-month T-bill rate as proxy for the risk-free rate, results are in Table [IA.6.5](#page-111-0) and very similar to those in Table [3](#page-45-0) of the paper. The only interesting difference is that the effect of the risk premium on funds with low default costs seems to be stronger and is always statistically significant, while that on funds with high default costs seems to be weaker and is statistically significant only when risk-taking is measured as $Safe$ Holdings. This is not surprising since I am using a lower, more stringent cutoff to identify low-c funds. For the specification that uses Gilchrist-Zakrajsek's excess bond premium as proxy for the model's risk premium, results are in Table [IA.6.6](#page-112-0) and very similar to those in Table [4](#page-46-0) of the paper.

Second, I use a time-varying identification of high-c and low-c funds. That is, for each month t, I identify as funds with high default costs those whose $Fund Business$ in month $t-1$ is above the 60th (or 70th) percentile of the cross-section distribution, and as funds with low default costs those whose Fund Business in month $t-1$ is below the 40th (or $30th$) percentile. Under this specification, the dummies High FB and Low FB on the RHS of regression [\(7\)](#page-33-0) vary over time and are lagged by one month to mitigate endogeneity issues. When the cutoffs are the $40th$ and $60th$ percentiles, results are in Table [IA.6.7;](#page-113-0) when the cutoffs are the 30th and 70th percentiles, results are in Table [IA.6.8.](#page-114-0) Again, in both cases, they are qualitatively similar to those in Table [3,](#page-45-0) confirming the model's predictions. The only notable difference is that for the 30^{th} –70th percentile cutoff, the effect of the risk premium tends to be less statistically and economically significant for both high-c and low-c funds. This is probably because that identification, although using more extreme percentiles than the one in the paper, only uses last month's distribution of Fund Business to identify high-c and low-c funds in the current month. On the other hand, the identification in the paper and that in Table [IA.6.5](#page-111-0) of this appendix use the distribution of Fund Business over the whole period of analysis and are therefore more robust.

IA.6.2.1 *Pre* and *Post* period separately

I also run regression [\(7\)](#page-33-0) separately on the P re period $(01/2006-07/2007)$ and P ost period (08/2007–08/2008). Results are in Tables [IA.6.9](#page-115-0) and [IA.6.10,](#page-116-0) respectively. The risk premium is proxied by *Spread Index*, and the risk-free rate is proxied by the 1-month T-bill rate. All other variables, including the dummies for funds with high default costs $(High FB)$ and low default costs $(Low FB)$, are defined as in the paper. Overall results are similar to those for the whole 01/2002–08/2008 period, but there are some important differences.

In the P re period, the effect of S *pread Index* on low-c funds is stronger, while that on high-c funds is weaker and statistically significant only when risk-taking is proxied by Holdings Risk^{dyn}. This is probably because Spread Index, i.e., the average yield on the debt of the financial firms borrowing from MMFs, started to rise a few months before July 2007, while the market perception of the riskiness of those firms changed drastically only in the second half of July 2007, when Bear Stearns disclosed that two of its subprime hedge funds had lost nearly all of their value. The early increase in spreads led MMFs with low default costs to reach for yield and buy more risky debt already in the Pre period, while MMFs with high default costs started to cut their risky exposures only in the *Post* period, after the surge in risk became fully apparent. This interpretation is consistent with Figure [1,](#page-5-0) which shows that low-c funds start to increase their net risky investment in the first half of 2007, while high-c funds decrease their risky investment only from August 2007.

As for the effect of the risk-free rate in the Pre period, it is consistent with the model's predictions for both low-c and high-c funds; moreover, contrary to the empirical results for the whole period, it is consistent also when risk-taking is measured in terms of portfolio maturity. However, for low-c funds, the effect of the risk-free rate is never statistically significant, and its magnitude is smaller than over the whole period. This is probably because the risk-free rate does not vary much over the P re period (except for a steady but slight increase in the first five months), which greatly weakens the identification.

In the Post period, when risk-taking is proxied by $Holdings$ Risk^{dyn}, the effect of Spread Index on low-c funds seems to be weaker than for the whole period, and that on high-c funds becomes statistically insignificant. As for the risk-free rate, its effect on high-c funds is consistent with the model's predictions for all risk-taking proxies (except portfolio maturity, exactly as for the whole period). However, when risk-taking is measured in terms of Safe Holdings, its effect of low-c funds seems to be weaker than for the whole period, and when risk-taking is proxied by either Holdings Risk or Holdings Risk^{dyn}, its effect of low-c funds becomes statistically insignificant. These results probably occur because the sample is much smaller (only $T = 13$ points in the time series), and the risk premium and risk-free rate are strongly negatively correlated, so that the effects of independent changes in both variables are less precisely estimated.

I also repeat the same regression exercise using the excess bond premium for financial firms from Gilchrist and Zakrajsek (2012) as proxy for the model's risk premium. Results are qualitatively similar to those in the paper for the whole 2002–2008 period but face the same problems discussed above about estimating regression (7) separately on the Pre and Post period (i.e., smaller samples, little variation in risk-free rates during the Pre period, slight asynchronicity between surge in yields and realization of risk across Pre and $Post$ period, and co-movement of risk premia and risk-free rates during the *Post* period).

IA.6.3 Cross-sectional risk-taking differential

I perform several robustness checks of the results in Table [5,](#page-47-0) which test the model's predictions on the different effects of risk premia and risk-free rates on the cross-sectional risk-taking differential. In my first robustness check, I estimate regression (8) using Fund Business rather than its rank as the main explanatory variable. Results are in Table [IA.6.11](#page-117-0) and are qualitatively and quantitatively similar to those of Table [5,](#page-47-0) 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 (8) using the GZ Premium as a proxy for the risk premium (Table [IA.6.12\)](#page-118-0), using the 3-month T-bill rate as a proxy for the risk-free rate (Table [IA.6.13\)](#page-119-0), and lagging all fund-specific RHS variables by two lags (Table [IA.6.14\)](#page-120-0). Again, the results are qualitatively and quantitatively close to those of Table [5,](#page-47-0) confirming 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 portfolio composition, 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 [5,](#page-47-0) 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– Zakrajsek excess bond premium, the magnitude of the effect of the risk-free rate diminishes.

Appendix IA.7 Microfoundation of the tournament

This appendix presents a random utility model of fund investors that rationalizes the rankbased payoff function of the MMF tournament. The standard theoretical justification for the empirically observed positive relation between fund flows and past performance is that investors assume that fund managers have idiosyncratic, unobservable skills, which investors try to infer from historical data. Higher past performance is perceived as a signal of higher ability and generates money inflows.

Suppose 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:

investor
$$
c
$$
 invests in

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

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 the 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, more formal 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 the agent's 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 (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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Table IA.4.1: Summary statistics for all U.S. institutional prime MMFs as of 1/3/2006. Fund Business 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 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 financial 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.

$sd(Fund Business)/mean(Fund Business)$ (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		4.5 0.6^-		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.4.2: Top panel: coefficient of 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 crosssection (i.e., within month). The sample is all U.S. institutional prime MMFs active from $1/1/2002$ to $8/31/2008$. Data are monthly. The rank is already a relative measure and therefore does not need to be normalized. 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 $99/\sqrt{12} \approx 28.6$.

 $***p<0.01,$ $**p<0.05,$ $*p<0.1$

Table IA.4.3: Fund Business vs. Incurred Cost and Conglomerate. The sample is all U.S. institutional prime MMFs from $1/1/2002$ to $8/31/2008$. Data are weekly. Fund Business is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. Incurred Cost is the incurred expense ratio in percentage points. Conglomerate is a dummy equal to 1 if the fund 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.

Table IA.5.1: 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, i.e., 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 interest. 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 in percentage points, its rank in percentiles normalized to $[0, 1]$, log of fund size in millions of dollars, fund expense ratio in basis points, fund age in years, volatility of fund flows based on past 12-week fund flows, and log of fund family size in billions of dollars. 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.

Table IA.5.2: 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 interest and trimmed at the 0.5%. Independent variables are: the weekly annualized fund spread from $t-1$ to t in percentage points, its percentile rank normalized to [0, 1], log of fund size in millions of dollars, fund expense ratio in basis points, fund age in years, volatility of fund flows based on past 12-week fund flows, and log of fund family size in billions of dollars. 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.

Table IA.5.3: Flow-performance relation. The sample is all U.S. institutional prime MMFs from $1/1/2002$ to $8/31/2008$. The dependent variable is *Normalized Fund Flow*, i.e., the percentage change in total net assets from week t to week $t + 1$, adjusted for earned interest, trimmed at the 0.5%, and normalized by that week's industry-average inflow if positive and by that week's industry-average outflow if negative. Independent variables are: the weekly annualized fund spread from $t-1$ to t in percentage points, its rank in percentiles normalized to [0, 1], log of fund size in millions of dollars, fund expense ratio in basis points, fund age in years, volatility of fund flows based on past 12-week fund flows, and log of fund family size in billions of dollars. 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.

Table IA.5.4: Flow-performance relation. The sample is all U.S. institutional prime MMFs from $1/1/2002$ to $8/31/2008$. The dependent variable is *Normalized Fund Flow*, i.e., the percentage change in total net assets from week t to week $t + 1$, adjusted for earned interest, trimmed at the 0.5%, and normalized by that week's industry-average inflow if positive and by that week's industry-average outflow if negative. Independent variables are: the weekly annualized fund spread from $t - 1$ to t in percentage points, its percentile rank normalized to [0, 1], log of fund size in millions of dollars, fund expense ratio in basis points, fund age in years, volatility of fund flows based on past 12-week fund flows, and log of fund family size in billions of dollars. 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.

Table IA.5.5: Flow-performance relation. The sample is all U.S. institutional prime MMFs from $1/1/2002$ to $8/31/2008$. The dependent variable is *Median-Normalized Fund Flow*, i.e., the percentage change in total net assets from week t to week $t + 1$, adjusted for earned interest, trimmed at the 0.5%, and normalized by that week's industry-median inflow if positive and by that week's industry-median outflow if negative. Independent variables are: the weekly annualized fund spread from $t-1$ to t in percentage points, its rank in percentiles normalized to [0, 1], log of fund size in millions of dollars, fund expense ratio in basis points, fund age in years, volatility of fund flows based on past 12-week fund flows, and log of fund family size in billions of dollars. 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.

Table IA.5.6: Flow-performance relation. The sample is all U.S. institutional prime MMFs from $1/1/2002$ to $8/31/2008$. The dependent variable is *Median-Normalized Fund Flow*, i.e., the percentage change in total net assets from week t to week $t + 1$, adjusted for earned interest, trimmed at the 0.5%, and normalized by that week's industry-median inflow if positive and by that week's industry-median outflow if negative. Independent variables are: the weekly annualized fund spread from $t - 1$ to t in percentage points, its percentile rank normalized to [0, 1], log of fund size in millions of dollars, fund expense ratio in basis points, fund age in years, volatility of fund flows based on past 12-week fund flows, and log of fund family size in billions of dollars. 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.

 $***p<0.01,$ $**p<0.05,$ $*p<0.1$

Table IA.5.7: 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 interest and trimmed at the 0.5%. Independent variables are: the rank of weekly annualized fund spread from $t-1$ to t , log of fund size in millions of dollars, fund expense ratio in basis points, fund age in years, volatility of fund flows based on past 12-week flows, and log of fund family size in billions of dollars. 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 a dummy equal to 1 if the fund 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.

Table IA.5.8: Flow-performance relation. The sample is all U.S. institutional prime MMFs from $1/1/2002$ to $8/31/2008$. The dependent variable is *Normalized Fund Flow*, i.e., the percentage change in total net assets from week t to week $t + 1$, adjusted for earned interest, trimmed at the 0.5%, and normalized by that week's industry-average inflow if positive and by that week's industry-average outflow if negative. Independent variables are: the rank of weekly annualized fund spread from $t - 1$ to t, log of fund size in millions of dollars, fund expense ratio in basis points, fund age in years, volatility of fund flows based on past 12-week flows, and log of fund family size in billions of dollars. 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 a dummy equal to 1 if the fund 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.

 $*^*p < 0.01$, $*^*p < 0.05$, $*p < 0.1$ *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ Table IA.6.1: Cross-sectional risk-taking differential in the Pre and Post period. The sample is all U.S. institutional prime of safe assets in a fund's portfolio (Safe Holdings) in columns (9)–(10). For a detailed discussion of Holdings Risk^{dyn}, see Section 5.1 and Appendix C. Fund Business is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. Post is a dummy equal to 1 from $8/1/2007$ to $8/31/2008$, and 0 otherwise. The other MMFs continuously active from $1/1/2006$ to $8/31/2008$ $(n = 122)$. Data are weekly $(T = 139)$. The dependent variables are: in days in columns (5)–(6); the weekly annualized fund spread (Spread) in basis points in columns (7)–(8); and the percentage independent variables (Controls) are: fund size, expense ratio, fund age, and fund family size. All regressions include week and 1% , 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics are roughly Table IA.6.1: Cross-sectional risk-taking differential in the Pre and $Post$ period. The sample is all U.S. institutional prime the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., U.S. treasuries, GSE debt, and repos) in a fund's portfolio (H oldings Risk) in columns (1)-(2); the percentage of each week's riskiest asset GSE debt, and repos) in a fund's portfolio (Holdings Risk) in columns (1)–(2); the percentage of each week's riskiest asset 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 [5.1](#page-28-0) and Appendix [C.](#page-51-0) F und Business is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. Post is a dummy equal to 1 from $8/1/2007$ to $8/31/2008$, and 0 otherwise. The other independent variables (Controls) are: fund size, 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 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 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., U.S. treasuries, class net of safe assets in a fund's portfolio ($Holdings$ $Risk^{dyn}$) in columns (3)–(4); average portfolio maturity (Maturity Risk) class net of safe assets in a fund's portfolio (H oldings Risk^{dyn}) in columns (3)–(4); average portfolio maturity (Maturity Risk) 2.97, 2.20 1.82, respectively. $2.97, 2.20$ 1.82, respectively

in column (3); the weekly annualized fund spread (Spread) in basis points in column (4); and the percentage of safe assets in a week and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 12-week lag. ***, *, Table IA.6.2: Cross-sectional risk-taking differential in the Pre and Post period. The sample is all U.S. institutional prime 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 week and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 12-week lag. ***, **, Fund Business is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund are: fund size, expense ratio, fund age, and fund family size. All RHS variables are as of 1/3/2006. All regressions include represent $1\%, 5\%,$ and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics are Table IA.6.2: Cross-sectional risk-taking differential in the P_{re} and Post period. The sample is all U.S. institutional prime the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., U.S. 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 fund's portfolio (Safe Holdings) in column (5). For a detailed discussion of Holdings Risk^{dyn}, see Section 5.1 and Appendix C. fund's portfolio (Safe Holdings) in column (5). For a detailed discussion of Holdings Riskdyn, see Section [5.1](#page-28-0) and Appendix [C.](#page-51-0) F und Business is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. Post is a dummy equal to 1 from $8/1/2007$ to $8/31/2008$, and 0 otherwise. The other independent variables (Controls) are: fund size, expense ratio, fund age, and fund family size. All RHS variables are as of 1/3/2006. All regressions include represent $1\%, 5\%,$ and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics are $T = 139$). 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., U.S. treasuries, assets. Post is a dummy equal to 1 from $8/1/2007$ to $8/31/2008$, and 0 otherwise. The other independent variables (Controls) \vdash $n = 122$). Data are weekly (7) nMMFs continuously active from $1/1/2006$ to $8/31/2008$ (*n* roughly 2.97 , 2.20 1.82, respectively roughly 2.97, 2.20 1.82, respectively.

Table IA.6.3: 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., U.S. 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 [5.1](#page-28-0) and Appendix [C.](#page-51-0) The risk premium rp is the index of spreads available to MMFs defined by equation [\(5\)](#page-26-0) in percentage points. The risk-free rate rf_t is the return on 3-month T-bills. *High* (*Low*) FB_i is a dummy equal to 1 if fund is Fund Business is always above (below) the cross-sectional median throughout the 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 size, 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.

Table IA.6.4: 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., U.S. 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 [5.1](#page-28-0) and Appendix [C.](#page-51-0) The risk premium rp is the index of spreads available to MMFs defined by equation [\(5\)](#page-26-0) in percentage points. The risk-free rate rf_t is the 1-month T-bill rate in percentage points. High (Low) FB_i is a dummy equal to 1 if fund is Fund Business is always above (below) the cross-sectional median throughout the 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 size, 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.

Table IA.6.5: 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., U.S. 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 [5.1](#page-28-0) and Appendix [C.](#page-51-0) The risk premium rp is the index of spreads available to MMFs defined by equation [\(5\)](#page-26-0) in percentage points. The risk-free rate rf_t is the 1-month T-bill rate in percentage points. High (Low) FB_i is a dummy equal to 1 if fund is Fund Business is always above (below) the cross-sectional $40th$ percentile throughout the 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 size, 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.

Table IA.6.6: 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., U.S. 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 [5.1](#page-28-0) and Appendix [C.](#page-51-0) The risk premium rp is the excess bond premium for financial firms from Gilchrist and Zakrajsek (2012) in percentage points. The risk-free rate rf_t is the 1-month T-bill rate in percentage points. *High* (Low) FB_i is a dummy equal to 1 if fund i's Fund Business is always above (below) the cross-sectional $40th$ percentile throughout the 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 size, 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.

Table IA.6.7: 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., U.S. 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 [5.1](#page-28-0) and Appendix [C.](#page-51-0) The risk premium rp is the index of spreads available to MMFs defined by equation [\(5\)](#page-26-0) in percentage points. The risk-free rate rf_t is the 1-month T-bill rate in percentage points. High (Low) $FB_{i,t}$ is a dummy 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 size, 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.

Table IA.6.8: 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., U.S. 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 [5.1](#page-28-0) and Appendix [C.](#page-51-0) The risk premium rp is the index of spreads available to MMFs defined by equation [\(5\)](#page-26-0) in percentage points. The risk-free rate rf_t is the 1-month T-bill rate in percentage points. High (Low) $FB_{i,t}$ is a dummy equal to 1 if fund i's Fund Business is above (below) the 70th $(30th)$ 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 size, 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.

Table IA.6.9: 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 $8/31/2008$ $(n = 85)$. The regression is run over the Pre period (01/2006–07/2007), and data are monthly $(T = 19)$. 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., U.S. 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 [5.1](#page-28-0) and Appendix [C.](#page-51-0) The risk premium rp is the index of spreads available to MMFs defined by equation [\(5\)](#page-26-0) in percentage points. The risk-free rate rf_t is the 1-month T-bill rate in percentage points. *High* (*Low*) FB_i is a dummy equal to 1 if fund i's Fund Business is always above (below) the cross-sectional median throughout the 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 size, 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 4.62, 3.29, and 2.66. For the Wald statistics they are roughly 20.61, 9.90, and 6.39.

Table IA.6.10: 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 $8/31/2008$ $(n = 85)$. The regression is run over the *Post* period (08/2007–08/2008), and data are monthly ($T = 13$). 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., U.S. 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 [5.1](#page-28-0) and Appendix [C.](#page-51-0) The risk premium rp is the index of spreads available to MMFs defined by equation [\(5\)](#page-26-0) in percentage points. The risk-free rate rf_t is the 1-month T-bill rate in percentage points. *High* (*Low*) FB_i is a dummy equal to 1 if fund i's Fund Business is always above (below) the cross-sectional median throughout the 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 size, 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 $5.25, 3.94$, and 3.28 . For the Wald statistics they are roughly 23.09, 12.24, and 8.30.

column (3); the monthly annualized fund spread (Spread) in basis points in column (4); and the percentage of safe assets in a Table IA.6.11: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime GSE debt, and repos) in a fund's portfolio (H oldings 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 monthly 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 5.1 and Appendix C. Fund Business is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. The risk premium rp is the index of spreads available to MMFs defined by equation (5) in percentage points. The riskfree rate rf_t is the 1-month T-bill rate in percentage points. Controls are: fund size, expense ratio, fund age, fund family size, and their interactions with rp and rf . All regressions include month and fund fixed effects. Standard errors are HACSC robust Table IA.6.11: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., U.S. treasuries, GSE debt, and repos) in a fund's portfolio (H oldings 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 fund's portfolio (Safe Holdings) in column (5). For a detailed discussion of Holdings Risk^{dyn}, see Section [5.1](#page-28-0) and Appendix [C.](#page-51-0) F und Business is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. The risk premium rp is the index of spreads available to MMFs defined by equation ([5\)](#page-26-0) in percentage points. The risk-
 $\frac{1}{\sqrt{2}}$ free rate $r f_t$ is the 1-month T-bill rate in percentage points. Controls are: fund size, expense ratio, fund age, fund family size, and their interactions with rp and rf . All regressions include month and fund fixed effects. Standard errors are HACSC robust $T = 80$). 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., U.S. treasuries, from Driscoll and Kraay (1998) with 8-month lag. ***, ** represent 1% , 5% , and 10% statistical significance, respectively 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. The corresponding critical values from fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85. \vdash $n = 85$). Data are monthly (7 nMMFs continuously active from $1/1/2002$ to $8/31/2008$ (*n*

∗∗∗p < 0.01, ∗∗p < 0.05, $*p < 0.01$, $*p < 0.05$, $*p < 0.1$

column (3); the monthly annualized fund spread (Spread) in basis points in column (4); and the percentage of safe assets in a Table IA.6.12: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime CSE debt, and repos) in a fund's portfolio (H oldings $Risk$) 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 monthly annualized fund spread (Spread) in basis points in column (4) ; and the percentage of safe assets in a FB Rank is the rank of Fund Business, which is the share of mutual fund assets other than institutional prime MMFs in the fund's portfolio (Safe Holdings) in column (5). For a detailed discussion of Holdings Risk^{dyn}, see Section 5.1 and Appendix C. sponsor's total mutual fund assets. FB Rank is expressed in percentiles normalized to $[0, 1]$. The risk premium rp is the excess T-bill rate in percentage points. Controls are: fund size, expense ratio, fund age, fund family size, and their interactions with Table IA.6.12: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., U.S. treasuries, GSE debt, and repos) in a fund's portfolio (H oldings 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 fund's portfolio (Safe Holdings) in column (5). For a detailed discussion of Holdings Riskdyn, see Section [5.1](#page-28-0) and Appendix [C.](#page-51-0) F B Rank is the rank of F und Business, which is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. F B Rank is expressed in percentiles normalized to $[0, 1]$. The risk premium rp is the excess bond premium for financial firms from Gilchrist and Zakrajsek (2012) in percentage points. The risk-free rate rf_t is the 1-month bond premium for financial firms from Gilchrist and Zakrajsek (2012) in percentage points. The risk-free rate $r f_t$ is the 1-month T-bill rate in percentage points. Controls are: fund size, expense ratio, fund age, fund family size, and their interactions with r p and rf . All regressions include month and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay 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 (1998) with 8-month lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical $T = 80$. 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., U.S. treasuries, $\overline{}$ $n = 85$). Data are monthly (7 values from fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85. values from fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85. \mathcal{C} MMFs continuously active from $1/1/2002$ to $8/31/2008$ (*n*

column (3); the monthly annualized fund spread (Spread) in basis points in column (4); and the percentage of safe assets in a month and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with 8-month lag. ***, *, *, * Table IA.6.13: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime CSE debt, and repos) in a fund's portfolio (H oldings $Risk$) 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 monthly annualized fund spread (Spread) in basis points in column (4) ; and the percentage of safe assets in 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 rp is the index of Controls are: fund size, expense ratio, fund age, fund family size, and their interactions with 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 percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., U.S. treasuries, fund's portfolio (Safe Holdings) in column (5). For a detailed discussion of Holdings Risk^{dyn}, see Section 5.1 and Appendix C. sponsor's total mutual fund assets. F B Rank is expressed in percentiles normalized to $[0, 1]$. The risk premium rp is the index of spreads available to MMFs defined by equation (5) in percentage points. The risk-free rate r_{ft} is the return on 3-month T-bills. Table IA.6.13: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime GSE debt, and repos) in a fund's portfolio (H oldings 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 fund's portfolio (Safe Holdings) in column (5). For a detailed discussion of Holdings Riskdyn, see Section [5.1](#page-28-0) and Appendix [C.](#page-51-0) F B Rank is the rank of F und Business, which is the share of mutual fund assets other than institutional prime MMFs in the Controls are: fund size, expense ratio, fund age, fund family size, and their interactions with rp and rf. All regressions include represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from fixed-b asymptotics for $T = 80$. 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., U.S. treasuries, spreads available to MMFs defined by equation [\(5\)](#page-26-0) in percentage points. The risk-free rate $r f_t$ is the return on 3-month T-bills. $\overline{}$ $n = 85$). Data are monthly (7 \mathcal{C} MMFs continuously active from $1/1/2002$ to $8/31/2008$ (*n* the *t*-statistics are roughly 3.03, 2.24, and 1.85. the t-statistics are roughly 3.03, 2.24 , and 1.85.

column (3); the monthly annualized fund spread (Spread) in basis points in column (4); and the percentage of safe assets in a Table IA.6.14: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime CSE debt, and repos) in a fund's portfolio (H oldings $Risk$) in column (1); the percentage of each month's riskiest asset class column (3); the monthly annualized fund spread (Spread) in basis points in column (4) ; and the percentage of safe assets in a FB Rank is the rank of Fund Business, which is the share of mutual fund assets other than institutional prime MMFs in the the percentage of bank obligations (i.e., the riskiest asset class over the whole period) net of safe assets (i.e., U.S. treasuries, net of safe assets in a fund's portfolio (Holdings Risk^{dyn}) in column (2); average portfolio maturity (Maturity Risk) in days in fund's portfolio (Safe Holdings) in column (5). For a detailed discussion of Holdings Risk^{dyn}, see Section 5.1 and Appendix C. sponsor's total mutual fund assets. FB Rank is expressed in percentiles normalized to $[0,1]$. The risk premium rp is the index All regressions include month and fund fixed effects. Standard errors are HACSC robust from Driscoll and Kraay (1998) with Table IA.6.14: Cross-sectional risk-taking differential: risk premium vs. risk-free rate. The sample is all U.S. institutional prime GSE debt, and repos) in a fund's portfolio (H oldings 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 fund's portfolio (Safe Holdings) in column (5). For a detailed discussion of Holdings Riskdyn, see Section [5.1](#page-28-0) and Appendix [C.](#page-51-0) F B Rank is the rank of F und Business, which is the share of mutual fund assets other than institutional prime MMFs in the sponsor's total mutual fund assets. F B Rank is expressed in percentiles normalized to $[0,1]$. The risk premium rp is the index f_1 and f_2 and f_3 is the index of $[0,1]$. The risk premium rp is the index f_2 an of spreads available to MMFs defined by equation (5) in percentage points. The risk-free rate rf_t is the 1-month T-bill rate in of spreads available to MMFs defined by equation [\(5\)](#page-26-0) in percentage points. The risk-free rate $r f_t$ is the 1-month T-bill rate in percentage points. Controls are: fund size, expense ratio, fund age, fund family size, and their interactions with rp and rf . percentage points. *Controls* are: fund size, expense ratio, fund age, fund family size, and their interactions with rp and r*f*.
All regressions include month and fund fixed effects. Standard errors are HACSC robust from 8-month lag. ***, * $*$ represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from 8-month lag. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively. The corresponding critical values from $T = 80$. 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., U.S. treasuries, $\overline{}$ $n = 85$). Data are monthly (7 fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85. fixed-b asymptotics for the t-statistics are roughly 3.03, 2.24, and 1.85 \mathcal{C} MMFs continuously active from $1/1/2002$ to $8/31/2008$ (*n*