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Asset managers, market liquidity and bank regulation*

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Abstract

We challenge the argument that bank regulation amplifies the adverse effect of asset managers' fire sales. Evidence from investments by US money market funds over the past decade is consistent with asset managers herding for reputational reasons. In the presence of such herding, we derive that the asset management sector may take on too much liquidity risk from a social perspective. Importantly, asset managers' investment decisions today are affected by the spread that banks will charge for absorbing fire sales tomorrow. When regulation constrains banks' balance-sheet space, the resulting higher spread reins in asset managers' excessive risk-taking, thus raising social welfare.

JEL Classification: G21, G23, G28, D62

Keywords: Investment funds, Herding, Bank regulation, Leverage ratio, Social welfare

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1 Introduction

As the asset management sector has grown over the past decades, so has its impact on financial market liquidity (Committee on the Global Financial System, 2014; Financial Stability Board, 2019, 2020). The recent market turmoil stemming from the Covid-19 pandemic testifies to this (Schnabel, 2020). A recurrent argument is that asset managers exacerbate market stress because strong liquidity mismatches at investment funds are coupled with reduced balance sheet capacity of dealer banks (Bessembinder et al., 2018; Cimon and Garriott, 2019; Cai et al., 2019; Saar et al., 2020; Fender and Lewrick, 2015) for both regulatory and internal risk-management reasons (Committee on the Global Financial System, 2014, 2017).

We challenge the notion that bank regulation necessarily contributes to asset managers' destabilising behaviour, arguing instead that it could correct for distortions in the asset management sector. Granted, when accommodating investor redemptions, asset managers count on dealers – mostly large banks – to make markets. When such service is not readily forthcoming, redemption runs generate outsize price swings and fire-sale costs. But to the extent that asset managers are inherently prone to load on fire-sale risk (Coval and Stafford, 2007; Carney, 2018), they would generate such outcomes with or without regulatory constraints on dealers' balance sheets. In fact, by raising the cost of balance-sheet use, bank regulation may perform a beneficial disciplining function in the asset-management sector, reining in the excessive risk-taking there.

We develop our argument on the basis of a theoretical model in which asset managers interact with dealers, à la Shleifer and Vishny (1997, 2011). There are two types of dealers in this model: bank and non-bank. While the two types face the same risk-return trade-offs, only bank dealers are subject to a regulatory capital requirement. The non-bank dealers thus also proxy for highly capitalised banks, for which the regulatory constraint never binds. In turn, asset managers make investment decisions in anticipation of possible redemption shocks that force fire sales. They differ from each other in terms of the probability of such shocks. The stronger are dealers' willingness and capacity to absorb fire sales, the lower is the spread they charge asset managers. This spread is our proxy for the impairment of market liquidity.

In the baseline version of the model, the private equilibrium attains the social optimum. Individual asset managers do not internalise their impact on the spread, which reduces the welfare of their sector. But the mirror image of this externality is an exact transfer to the dealer sector, with a zero net effect on social welfare. In this context, a constraint on bank dealers is thus harmful, as it takes the private equilibrium away from the social optimum.

We depart from the baseline with one distortion: *herding* by asset managers. Concretely, we assume that a fraction of the asset managers disregard their probabilities of redemption shocks and mimic the average action in the sector.[1] In considering herding that does not follow informational motives, we are inspired by the arguments of Buffa et al. (2014); Edwards et al. (2020) that the multi-layer delegation in investment funds' governance structure creates incentives for asset managers to align their behaviour with that of their peers. The literature refers to such behaviour as "reputational" herding (Scharfstein and Stein, 1990; Wermers, 1999; Graham, 1999).

Herding is a distortion in the model because it decouples risk-taking from the probabilities of redemption shocks. When the asset fundamentals – that is, the risk-adjusted expected return – are weak, too many of the herding asset managers take on more risk than what their redemption-shock probabilities call for. Thus, the private equilibrium generates excessive risk-taking from a social perspective.

In this context, regulation can improve social welfare by increasing the cost of dealers' market-making services. In the light of the ongoing policy debate (Committee on the Global Financial System, 2017), we study a leverage-ratio regulatory constraint, which caps the amount of fire-sale volume that bank dealers can absorb. Since now non-bank dealers – equivalently, unconstrained bank dealers – need to assume more risk, they charge a higher spread. In other words, regulation impairs market liquidity, which is costly to asset managers. That said, the anticipation of the higher costs incentivises asset managers to reduce the excess in their risk-taking. There are binding levels of the regulatory constraint at which the latter, indirect, effect dominates and social welfare is thus higher than that in the absence of regulation. Furthermore, the optimal regulation is more constraining when a larger fraction of asset managers herd. In sum, the beneficial disciplining effect of regulation on risk-taking stems from a *reduction* of market liquidity.

In searching for evidence in support of our specific departure from the baseline model, we test first for the existence and then for the type of herding in the asset management sector. To this end, we employ the herding measure developed in Sias (2004), which allows us to measure the extent to which investors imitate each other over time by herding around the instruments issued by specific entities.[2] We construct this measure on the basis of the month-end portfolio holding data that US money market funds (MMFs) submit to the Securities and Exchange Commission under the N-MFP form, and that Crane data collect. We consider all fund types together, as well as prime and non-prime funds separately. If we find that herding does exist, we test whether the underlying motives could be other than reputational. For this, we use Refinitiv's issuer- and sector-level data

[1]We thus abstract from herding that stems from agents following common signals or inferring other investors' private information (Banerjee (1992), Bikhchandani et al. (1992a), Froot et al. (1992) and Hirshleifer et al. (1994) and the subsequent related literature).

[2]Switching to the measure by Lakonishok et al. (1992) does not make a material difference (Appendix E).

on stock returns, CDS spreads, ratings, market capitalisation and average outstanding maturity of instruments. Our datasets run from February 2011 to June 2020.

The empirical findings are consistent with reputational herding in the asset management sector, that is, with asset managers imitating peers for non-informational reasons. For one, we find evidence that – both at the fund and the fund-family level – herding does exist and is particularly pronounced among prime funds. These funds are more likely to be driven by reputational motives because they are inherently more prone to redemption runs than non-prime funds, which invest mainly in government securities. We obtain further evidence for the relevance of such motives, as we reject a hypothesis that the observed herding stems instead from self-imitation over time – whereby investors that invest in the instruments of a specific issuer are likely to continue doing so. Last but not least, we find that herding is not driven by signals about the underlying fundamentals – stemming either from public information (i.e. common signals) or from the behaviour of informationally superior investors (i.e. information cascades).

We make both empirical and conceptual contributions to the literature on investment funds. Cai et al. (2019) provide evidence on herding by institutional investors in the US corporate bond market from 1998 to 2014, whereas Sias (2004) also finds herding on the basis of data obtained from the filings of US institutional investment managers from 1983 to 1997. Neither concludes, however, that the underlying motives are reputation-related. Focusing on the US MMF sector over the latest decade, we establish herding as well but then check systematically for and rule out informational motives, which points to reputational herding. Incorporating such herding in our theoretical model delivers a novel policy implication that spans the investment-fund and banking sectors. When asset managers act in anticipation of the spread that dealers will charge to absorb fire sales in the future, bank regulation improves social welfare by disciplining asset managers' risk-taking.

Roadmap. Section 2 presents the baseline model, which specifies the interaction between asset managers and dealers. We depart from the baseline in Section 3, where we introduce reputational herding in the asset management sector and show that such behaviour creates scope for bank regulation to improve social welfare. Section 4 presents empirical evidence on the type of herding we model. Section 5 concludes. Extensions and proofs are in appendices.

2 Baseline model

2.1 Model setup

The financial system evolves over three periods – $t = 0, 1, 2$ – features two assets – one risk-free and one risky – and three categories of agents – asset managers, bank dealers and non-bank dealers. Within each type, the agents form a continuum. Asset managers invest in the assets at $t = 0$, secondary-market trading between asset managers and dealers takes place at $t = 1$, and all uncertainty is resolved at $t = 2$.

2.1.1 Assets

The risk-free asset is worth 1 at any t. Thus, in the background, the risk-free interest rate is zero.

The price of the risky asset evolves over time as follows: $\left\{1, R_1, \tilde{R}_2\right\}$. The price that asset managers pay for this asset at $t = 1$ is 1. If they need to sell the asset at $t = 1$, they obtain the market-clearing price R_1 from dealers. The agents holding the asset at $t = 2$ obtain the stochastic $\tilde{R}_2$, which has a mean $R_2 > 1$ and variance σ^2.

2.1.2 Asset managers

The asset managers are of unit mass, are risk neutral and enter $t = 0$ with an endowment of one unit of the risk-free asset. We denote them by i. When deciding whether to buy the risky asset, each one is aware of her probability of early liquidation – that is, of a redemption shock at $t = 1$ – which is drawn independently across asset managers and uniformly from the unit line: $\varepsilon_i \sim U[0, 1]$. Denoting by $a_i \in [0, 1]$ asset manager i's investment in the risky asset, her expected utility is:

$$\begin{aligned} U_i &= a_i (1 - \varepsilon_i) R_2 + a_i \varepsilon_i R_1 + (1 - a_i) \\ &= 1 + \underbrace{a_i (R_2 - 1)}_{\text{gain from investing}} - \underbrace{a_i \varepsilon_i s}_{\text{loss from liquidation}} \end{aligned} \tag{1}$$

where $s = R_2 - R_1$ is the market-clearing risk premium at $t = 1$, henceforth "the spread," which is our proxy for market liquidity. This means that asset managers are either fully invested in the risky asset or not at all:

$$
\begin{aligned}
a_i &= 1 \text{ if } R_2 - 1 < \varepsilon_i s \qquad (2)\\
a_i &= 0 \text{ otherwise,}
\end{aligned}
$$

We are interested in the case in which early liquidation leaves asset managers worse off than investing in the risk-free asset, i.e. $R_1 < 1$. This implies an interior threshold probability, $\hat{\varepsilon} \equiv (R_2 - 1)/s \in [0, 1]$, with asset managers investing in the risky asset if and only if $\varepsilon_i < \hat{\varepsilon}$. Thus, the aggregate investment in the risky asset (q) and the corresponding liquidation volume (y_a) are equal, respectively, to:

$$q = \int_0^{\hat{\varepsilon}} d\varepsilon_i = \hat{\varepsilon} \qquad (3)$$

$$y_a = \int_0^{\hat{\varepsilon}} \varepsilon_i d\varepsilon_i = \frac{\hat{\varepsilon}^2}{2} \qquad (4)$$

2.1.3 Dealers

There are β bank and $(1 - \beta)$ non-bank dealers – denoted by b and n, respectively – with each dealer $j \in \{b, n\}$ endowed with equity capital that is worth k. Dealer j acts at $t = 1$. Being competitive, he decides on what amount of the risky asset, y_j, to purchase from asset managers, taking the market-clearing spread s as given. He finances the purchase with equity and debt, where the latter is equal to $y_j R_1 - k$ and is borrowed for one period at the risk-free rate. Dealers make markets with these purchases, bridging the gap between the time when asset managers need to liquidate their risky asset holdings ($t = 1$) and the time when the risky asset's fundamental value materialises ($t = 2$).

Each dealer j is risk averse. His utility, net of the additive constant k, is:

$$
\begin{aligned}
U_j &= E\left(\tilde{R}_2 - R_1\right) y_j - \frac{\rho}{2} Var(\tilde{R}_2 - R_1) y_j^2\\
&= s y_j - \frac{\rho\sigma^2}{2} y_j^2 \equiv s y_j - \frac{c}{2} y_j^2 \qquad (5)
\end{aligned}
$$

where $c \equiv \rho\sigma^2$ stands for the (effective) riskiness of the asset. Given that it refers to dealers in particular, we can interpret c as capturing "inventory risk". Without constraints, all dealers have the same utility-maximising purchase schedule:

$$y_j = \frac{s}{c} \text{ for } j = b, n. \qquad (6)$$

Alternatively, if bank dealers are subject to a regulatory leverage-ratio constraint, λ:

$$y_b \le \frac{1}{\lambda}k \equiv \kappa, \text{ where } \lambda \in (0,1) \tag{7}$$

In either case, market clearing implies

$$y_a = \beta y_b + (1-\beta)\, y_n \tag{8}$$

We close this section by noting that non-bank dealers proxy for *any* unconstrained dealers. The analysis would not change if we assumed that a fraction $(1-\beta)$ of the dealers were banks, facing the leverage-ratio constraint in (7) but with a capital endowment larger than 1. By (4) and (8), the constraint would never bind for these highly capitalised banks.

2.1.4 Information sets and timeline.

Figure 1 summarises the timeline and the information sets. There is uncertainty at $t = 0$, as regards *individual* asset managers' obligation to liquidate at $t = 1$, and at $t \in \{0, 1\}$, as regards the realisation of the risky return.

Figure 1: The baseline model in a nutshell

$t = 0$

- Each AM i knows
  – Own probability of liquidation at $t = 1$: ε_i;
  – Distribution of ε_i in the AM sector;
  – Parameters $\{R_2, c, \beta, \kappa\}$
- Investments reflect full knowledge of the aggregate endogenous variables, which materialise at $t = 1$: q, y_a, y_b, y_n, s.
- Since each AM i decides on a_i per (2), overall investment volume is q per (3).

$t = 1$

- Liquidating AMs obtain R_1, which they invest in the risk-free asset.
- The aggregate liquidation volume y_a is set per (4).
- Bank and non-bank dealers decide on buy volumes, y_b and y_n, per (6) and (7).
- The equilibrium is defined by the spread s that clears the risky-asset market, per (8).

$t = 2$

- The risky-asset return $\tilde{R}_2$ is realized.
- The profit/loss of each agent is final.

2.2 Equilibrium without regulatory constraint

Without a regulatory constraint, the bank and non-bank dealers are identical and set y_j as in (6).

2.2.1 Market outcomes

By asset managers' and dealers' decision rules (2) and (6) and the market-clearing condition (8), the threshold probability $\hat{\varepsilon}$ (i.e. the marginal asset manager) and the spread s, are given by

$$\hat{\varepsilon} s = R_2 - 1 \tag{9}$$

$$s = c\frac{\hat{\varepsilon}^2}{2} \tag{10}$$

Solving in terms of the exogenous "fundamentals", R_2 and c, we obtain:

$$\hat{\varepsilon} = \left(\frac{2(R_2 - 1)}{c}\right)^{\frac{1}{3}} \tag{11}$$

$$s = \left(\frac{c}{2}\right)^{\frac{1}{3}} (R_2 - 1)^{\frac{2}{3}} \tag{12}$$

Thus, by raising the liquidation volume through a higher $\hat{\varepsilon}$, a higher expected return R_2 raises the spread s. In turn, the riskiness, c, affects s through two channels: the direct compensation channel raises s and dominates the indirect investment volume channel, which lowers s. We summarise the above in the following proposition:

Proposition 1. ***The equilibrium without regulatory constraint (baseline)*** *is defined by the threshold liquidation probability, $\hat{\varepsilon}$, in (11), or equivalently, the market-clearing spread, s, in (12). Asset managers invest in the risky asset if and only if their liquidation probability is lower than $\hat{\varepsilon}$.*

2.2.2 Welfare

We first consider the utilities in the asset management and dealer sectors separately and then combine them to derive social welfare.

By (1)-(4), the overall utility in the asset management sector is:

$$\begin{aligned} U_a &= 1 + q(R_2 - 1) - y_a s \\ &= 1 + \hat{\varepsilon}(R_2 - 1) - c\frac{\hat{\varepsilon}^4}{4} \end{aligned} \tag{13}$$

which increases in the excess expected return from investing in the risky asset (second term) and decreases in the fire-sale cost (third term). The second line in expression (13) implies also that individual asset managers' overinvestment lowers the sector's aggregate utility. In particular, the threshold liquidation probability that maximises U_a is $(R_2 - 1)/2s$, which is lower than the privately optimal $\hat{\varepsilon}$ in (9). The overinvestment stems from the atomistic asset managers not internalising the fact that the aggregate investment volume raises the spread s per (10).

By (5) and (6), the utility in the dealer sector is

$$U_b + U_n = \frac{y_a s}{2}, \tag{14}$$

which reveals that asset managers' liquidation costs generate benefits for the dealers.

In fact, at the level of social welfare, the transfer from asset managers to dealers offsets *exactly* the negative externality in the asset management sector. Concretely, social welfare is equal to:

$$\begin{aligned} W = U_a + U_b + U_n &= 1 + \hat{\varepsilon}(R_2 - 1) - \frac{1}{2} y_a s, \\ &= 1 + \hat{\varepsilon}(R_2 - 1) - \frac{c}{8}\hat{\varepsilon}^4. \end{aligned} \tag{15}$$

This expression reveals that a benevolent dictator would set the same threshold liquidation probability as the privately chosen one: the value of $\hat{\varepsilon}$ that maximises W is the one in (11).

2.3 Equilibrium and welfare with regulatory constraint

The regulatory constraint affects the equilibrium only if it forces bank dealers to buy less than the privately optimal amount of liquidated assets at the prevailing spread. This happens whenever:

$$\kappa < \frac{1}{2}\left(\frac{2(R_2 - 1)}{c}\right)^{\frac{2}{3}}, \tag{16}$$

where, by equations (4), (8) and (11), the right-hand side is equal to dealer's purchase amount at the unconstrained equilibrium. Thus, the requirement is binding for sufficiently weak fundamentals of the risky asset: low excess expected return, $R_2 - 1$, and/or high riskiness, c.

A binding regulatory constraint is sure to lower social welfare in the baseline model. This follows from the fact that social welfare in equation (15) is strictly concave and is maximised in the unconstrained equilibrium. We derive this result in Appendix A.

3 Departure from the baseline: herding

We now study a modification of the baseline model in which asset managers overinvest in the risky asset. This creates an environment where a regulatory constraint can improve social welfare. The ultimate question then is whether the improvement can be achieved by a leverage-ratio constraint in the bank-dealer sector, i.e. *not* the sector engaging in excessive risk-taking.

Our specific departure from the baseline model stems from herding behavior in the asset management sector. Large institutional investors typically have a complex governance structure with multiple layers of delegation, which generates information frictions and principal-agent problems. In this environment, asset managers build and maintain reputation by performing well in peer comparisons. To this end, they would seek to match – i.e. herd around – the aggregate action, rather than act in line with asset fundamentals (Buffa et al., 2014; Edwards et al., 2020).[3] It is this type of herding that we allow for in our model.

3.1 Herding: the setup

Let there be two types of asset managers. A fraction $(1-\omega) \in (0,1)$ of the asset managers are of the first type and are identical to those in the baseline model above. The remaining fraction, ω, mimic the average risky-asset investment in the sector. We refer to the latter asset managers as "herding" and the other ones as "non-herding".

The rest of the setup is as in the baseline model. The actual liquidation probability is distributed uniformly on the unit interval within *each* asset manager type. Thus, there is herding only in investment, not in liquidation. Since all parameter values – including ω – and probability distributions are common knowledge, so is the aggregate volume of the risky-asset investment. Finally, dealers remain the same as presented in Section 2.1.3 and the timeline is as in Section 2.1.4.[4]

Denoting the non-herding and herding asset managers by *nh* and *h*, respectively, the investment strategies at $t = 0$ are as follows:

$$a_i^{nh} = 1 \text{ if } \varepsilon_i \leq \hat{\varepsilon}, \qquad a_i^{nh} = 0 \text{ if } \varepsilon_i > \hat{\varepsilon}, \qquad a_i^h = \hat{\varepsilon} \quad \forall \varepsilon_i \tag{17}$$

and imply that the liquidation volume at $t = 1$ is:

$$y_a = (1-\omega)\frac{\hat{\varepsilon}^2}{2} + \omega\frac{\hat{\varepsilon}}{2}. \tag{18}$$

[3] See also Lakonishok et al. (1992), Wermers (1999), for analyses of different herding motives.

[4] In principle, dealers could take proactive steps to take advantage of asset managers' herding. Since herding raises the fire-sale volume (see Section 3.2), they could expand their capacity to absorb this volume by raising more capital. However, more capital would make a qualitative difference only if it helps avoid a binding regulatory constraint on market making, which would violate a key stylised fact discussed in the introduction. Alternatively, dealers could overhaul their business model – that is, change the preference-related component of c. There is no evidence, however, of material changes to the attractiveness or performance of dealer banks' business model in the post-great financial crisis period, when the importance of asset managers evolved substantially (Roengpitya et al., 2017).

Since herding is a feature of the asset management sector only, it does not affect the problem of the bank and non-bank dealers. Until we introduce a bank-specific constraint (Section 3.3), the implications of the baseline model thus apply: the buy volume of a bank and a non-bank dealer is equal to $y_b = y_n = y_a$ and the market clearing spread is $s = y_a c$.

3.2 Herding: a distortion

We now derive how herding affects the private equilibrium (characterised by the threshold liquidation probability $\hat{\varepsilon}^H$) and the equilibrium under the control of a social planner (characterised by the corresponding $\hat{\varepsilon}^*$). The underlying proofs are in Appendix B.[5]

To pin down $\hat{\varepsilon}^H$, we refer to equation (9), the herding-driven liquidation volume y_a in (18), and the attendant spread s:

$$\underbrace{\hat{\varepsilon}^H}_{=\text{ threshold probability}} \underbrace{\left((1-\omega)\frac{\hat{\varepsilon}^{H2}}{2} + \omega\frac{\hat{\varepsilon}^H}{2}\right)c}_{=s} \;=\; R_2 - 1, \tag{19}$$

Proposition 2. ***The equilibrium without regulatory constraint under herding*** *is defined by the threshold probability $\hat{\varepsilon}^H$ or, equivalently, the market-clearing spread s in (19). Herding reduces the privately optimal investment volume but increases the corresponding liquidation volume:*

$$\frac{\partial\hat{\varepsilon}^H}{\partial\omega} \;<\; 0, \qquad \frac{\partial y_a(\hat{\varepsilon}^H;\omega)}{\partial\omega} > 0. \tag{20}$$

The intuition is as follows. For a given threshold liquidation probability $\hat{\varepsilon}^H$, more herding (i.e. a higher ω) raises the liquidation volume, by (18), and the attendant spread. Since a higher spread at $t = 1$ is a higher cost for asset managers, it disincentivises investment in the risky asset at $t = 0$, thus lowering $\hat{\varepsilon}^H$. However, the liquidation volume, y_a, still increases with ω because (a growing fraction of) herding asset managers do not optimise their investment decision.

Herding is a distortion because it reduces welfare. To see why this is the case in the private equilibrium, we refer to the first line in the welfare expression (15) and the inequalities in (20). By reducing the investment volume, $q = \hat{\varepsilon}^H$, herding reduces the social benefits, $\hat{\varepsilon}(R_2 - 1)$. By raising the liquidation volume, y_a, and the spread, s, it raises the social costs, $y_a s/2$.

[5] We omit superscripts from other endogenous variables that are functions of $\hat{\varepsilon}^H$ or $\hat{\varepsilon}^*$ – i.e. y_a, s and W – whenever the meaning is obvious from the context.

Herding is similarly a distortion when a social planner determines the equilibrium by picking the threshold liquidation probability of non-herding asset managers that maximises social welfare. In this equilibrium, the social planner internalises the impact of $\hat{\varepsilon}^*$ on the liquidation volume, y_a, thus replacing (19) with the following condition:

$$\underbrace{\left((1-\omega)\hat{\varepsilon}^* + \frac{\omega}{2}\right)}_{=dy_a/d\hat{\varepsilon}} \underbrace{\left((1-\omega)\frac{\hat{\varepsilon}^{*2}}{2} + \omega\frac{\hat{\varepsilon}^*}{2}\right)c}_{=s} \;=\; R_2 - 1. \tag{21}$$

Welfare again decreases with herding because a higher ω increases the weight of herding asset managers, who do not invest efficiently: those who actually have low (high) liquidation probabilities under (over) invest. The same mechanism affects the private equilibrium as well. We thus close this subsection by recording the following proposition.

Proposition 3. *Welfare decreases with herding in both the private equilibrium and the "social planner" equilibrium:*

$$\frac{\partial W(\hat{\varepsilon}^H;\omega)}{\partial\omega} \;<\; 0, \quad \frac{\partial W(\hat{\varepsilon}^*;\omega)}{\partial\omega} < 0. \tag{22}$$

3.3 Herding: the impact of a regulatory constraint

A regulatory constraint on banks would reduce the capacity of these dealers to absorb asset managers' liquidation volume at $t = 1$. In anticipation of this, the asset managers would reduce at $t = 0$ the volume of their aggregate investment in the risky asset. Given this, regulation can be beneficial only if, in its absence, asset managers take on an excessive amount of risk, i.e. if $\hat{\varepsilon}^H > \hat{\varepsilon}^*$.

For the relative magnitudes of private and socially optimal risk-taking, we refer to (19) and (21). These expressions indicate that there is, in general, a wedge between the two equilibria: $\hat{\varepsilon}^H \neq \hat{\varepsilon}^*$. This wedge stems from the fact that the threshold liquidation probability, i.e. $\hat{\varepsilon}$ – which enters the private first-order condition (19) together with the spread s – differs from the rate at which the marginal asset manager raises the liquidation volume, i.e. $\partial y_a/\partial\hat{\varepsilon} = (1-\omega)\hat{\varepsilon} + \omega/2$, which enters the first-order condition for the social optimum (21).

There is excessive risk-taking in the private equilibrium at sufficiently weak underlying fundamentals, i.e. if the risk-adjusted return $(R_2 - 1)/c$ is below a threshold. And the level of this threshold increases in the fraction of herding asset managers. Concretely, equations (19) and (21) lead to the following lemma.

Lemma 1. $\hat{\varepsilon}^H > \hat{\varepsilon}^*$ *if and only if*

$$\frac{R_2 - 1}{c} < \frac{1}{16}(1 + \omega). \tag{23}$$

In the rest of this subsection, we assume that condition (23) is satisfied.

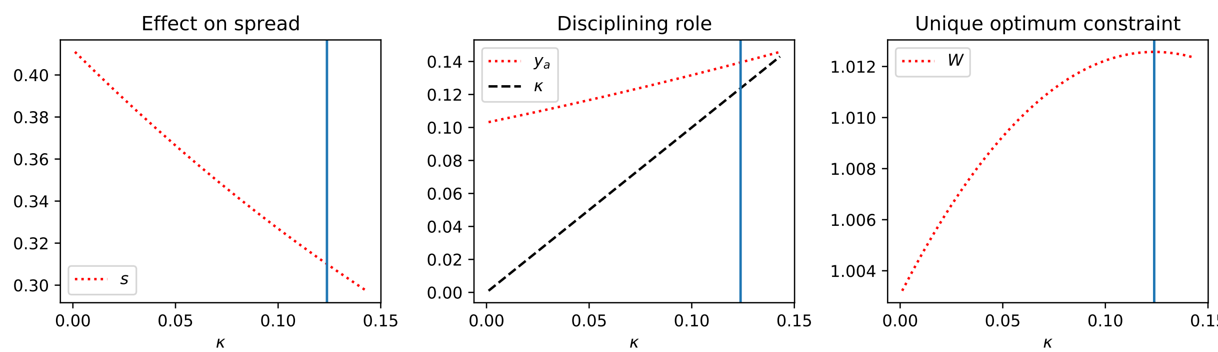
We prove that a binding regulatory constraint on bank dealers improves total welfare when herding induces asset managers to take on an excessive amount of risk (Appendix B):

Proposition 4. ***Regulation improves welfare.*** *If $\omega > 0$ and (23) holds, then the level of bank dealers' regulatory constraint that maximises social welfare is unique and binding: $\kappa^* \in (0, y_a)$.*

The socially optimal constraint balances two counteracting forces. On the one hand, it reduces the balance sheet capacity of bank dealers, which raises the equilibrium spread, s, thus amplifying the distortion from herding. On the other hand, a higher s represents a higher fire-sale cost and thus dissuades risk-taking. This disciplining effect results in a lower fire-sale volume, y_a. Figure 2 illustrates these effects (left-hand and centre panels) and that the beneficial disciplining effect dominates at binding levels of the constraint: W is maximised at $\kappa < y_a$ (right-hand panel).

Figure 2: Effects of tighter regulation, i.e. smaller κ

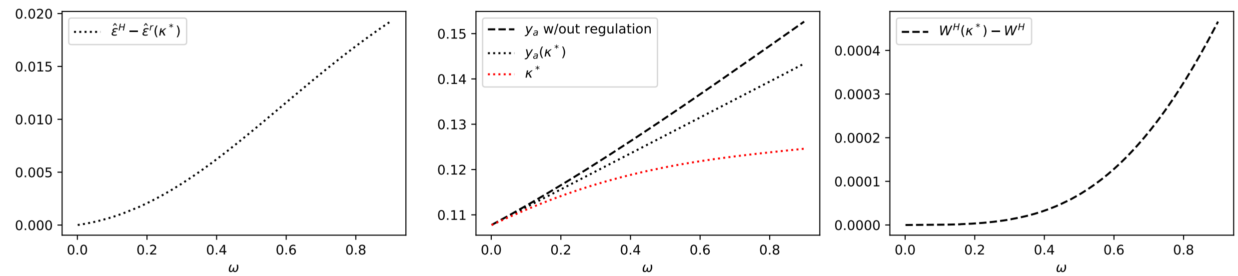
The vertical line is at the socially optimal κ^*. Parameter values: $R_2 = 1.1, c = 2, \beta = 0.5, \omega = 0.8$.



Numerical simulations reveal that the impact of regulation is stronger when herding is stronger (see Figure 3, where $\hat{\varepsilon}^r$ stands for the volume of risk-taking under a regulatory constraint). For one, the optimal κ (κ^*) reduces risk-taking by more when ω is higher: $\hat{\varepsilon}^H - \hat{\varepsilon}^r$ increases in ω (left-hand panel). This translates into a greater reduction in fire-sale volume when herding is stronger (centre panel, difference between the two black lines). Ultimately, the positive impact of optimal regulation on social welfare increases in the extent of herding (right-hand panel).

Figure 3: The regulatory impact changes with the extent of herding, ω

Underlying parameter values: $R_2 = 1.1, c = 2, \beta = 0.5$.



4 Empirical evidence on herding

We measure herding by US MMFs and assess the extent to which this behaviour reflects *not* informational but reputational motives. In the light of our theoretical model, such herding motives would point to a distortion that bank regulation can help address. We look for an indication of the underlying motives from differences in the extent of herding across different funds: prime vs. non-prime.[6] Funds of the former type have greater exposure to run risk, which brings reputation to the fore.[7] We also verify whether herding happens only among funds in the same family, where centralised decision-making could be an important driver. Another indication of the motives would stem from the role of *ex-ante* information about the issuer of instruments that prime funds invest in: while such information should play no role for reputational herding, it would drive "investigative herding", whereby several asset managers respond similarly to a common signal (Graham, 1999). Finally, we also look for *ex-post* improvements in the performance or riskiness of popular issuers, which would be consistent with asset managers herding around a peer for its superior information ("information cascades", Bikhchandani et al. (1992b)) as opposed to for reputational reasons.

The rest of this section runs as follows. First, we describe our data sources and sampling approach. Then, we use these data to measure herding. Finally, we develop a battery of tests for whether the measured herding reflects other than reputational motives and report results. Related additional tables are in Appendix D and robustness exercises are in Appendix E.

[6] Sias (2004) and Cai et al. (2019) also study herding by investor type and the former uses the findings to infer the underlying motives.

[7] Appendix C reverts to the theoretical model to prove that the impact of herding on the volume of investment in the risky asset is stronger for funds that face a higher likelihood of fire sales, e.g. prime relative to non-prime funds.

4.1 Data

Our key data source are the regulatory filings that US-based MMFs submit on a monthly basis to the Securities and Exchange Commission (SEC N-MFP forms) and Crane Data collects. From these filings we obtain detailed information on the month-end portfolio holdings of MMFs, which include *inter alia*: the type of instruments MMFs invest in (e.g. repos, commercial paper, certificates of deposits), the identity of the issuer of those instruments, the transacted volumes, the prices that MMFs obtain for providing funding, the outstanding maturity of reported positions. We work with data from February 2011 to June 2020.

We complement the above with a dataset from Refinitiv which includes information on issuers' sector (based on the North American Industry Classification System, NAICS), credit ratings, stock returns, market capitalisation, and CDS spreads. There is also information on the average maturity of outstanding instruments at the issuer level as well as on the stock returns and CDS spreads at the level of each issuer's sector.

The information we use in the analysis is at the level of fund-issuer pairs. We thus aggregate all positions between a fund f and issuer i for each month in the sample. Then, we follow the literature and define a "trade" as a change in a fund's holdings from one month to the next. That is, we say that "fund f bought (sold) instruments issued by issuer i in month t" if the volume of f's holdings of i increased (decreased) between $t-1$ and t. We construct three main samples: one covering prime funds only, the second only for non-prime funds, and the third combining these two fund types. We exclude public issuers (mostly the US Treasury), as these represent the safest of assets and therefore do not correspond to the risk-taking behaviour that is at the centre of the theoretical model.[8] Following the literature, we also narrow each sample in month t by excluding all issuers that are traded by fewer than five funds that month. Tables 4 and 5 in Appendix D report respectively variable definitions and data sources, and present summary statistics for the three samples.

4.2 Herding measure

For our empirical analysis, we define herding as the act of investors following themselves or each other into and out of the same investments over a time period. This definition – which combines both time and cross-sectional dimensions – corresponds exactly to the herding measure in Sias (2004), which we adopt for our exercise.[9] The appeal of this measure is twofold. First, it lends

[8] Including the US Treasury as an issuer does not affect the results in the subsections that follow.

[9] In Appendix E, we also introduce the alternative herding measure of Lakonishok et al. (1992) and use it in a robustness check. This alternative abstracts from the time dimension and incorporates a specific notion of what

itself naturally to an assessment of the drivers of any identified herding. Second, it allows for a wide range of *distinct potential* drivers: in addition to the reputational motives that would be consistent with the model in Section 3, these include self-imitation through time, common signals about the issuer's fundamentals, or imitation of other (known to be better-informed) investors.

Concretely, the measure is constructed in the following steps. First, we calculate the number of funds buying and selling issuer i in period t, n_{it}^{buy} and n_{it}^{sell}, respectively. Second, we calculate the share of buyers among all the funds that trade issuer i in period t:

$$p_{it} = \frac{n_{it}^{buy}}{n_{it}^{buy} + n_{it}^{sell}} \tag{24}$$

Third, focusing on all the issuers in the corresponding month, we standardise this share by subtracting the cross-sectional mean and the attendant standard deviation:[10]

$$q_{it} = \frac{p_{it} - \bar{p}_t}{\sigma(p_{it})} \tag{25}$$

The demeaning implies that we abstract from any market-wide trends, eg persistent generalised issuance of debt for funding balance-sheet growth.

Following Sias (2004), we say that there is herding if the trading pattern across issuers tends to be stable from one month to the next. That is, if those issuers that experience greater than average buy or sell pressure in month $t-1$ experience similar pressure in month t. Concretely, this means that β_t in the following specification is persistently positive over time:[11]

$$q_{it} = \beta_t q_{it-1} + \epsilon_{it} \tag{26}$$

where ϵ_{it} is an error term. Given the standardisation of q_{it}, $\beta_t \in (0, 1)$ is a correlation coefficient.

A positive β_t could reflect individual funds' persistent investment in the same issuers (self-imitation) or funds herding around an issuer after others have invested in it (imitating others). To differentiate the two motives, Sias (2004) decompose β_t as follows:

$$\beta_t = \underbrace{\delta_t \sum_{i=1}^{I_t} \left[\sum_{f=1}^{F_{it}} \frac{(D_{fit} - \bar{p}_t)(D_{fit-1} - \bar{p}_{t-1})}{F_{it} F_{it-1}} \right]}_{\beta_{1t}\text{: self-imitation}} + \underbrace{\delta_t \sum_{i=1}^{I_t} \left[\sum_{f=1}^{F_{it}} \sum_{m=1, m \neq f}^{F_{it-1}} \frac{(D_{fit} - \bar{p}_t)(D_{mit-1} - \bar{p}_{t-1})}{F_{it} F_{it-1}} \right]}_{\beta_{2t}\text{: imitating others}} \tag{27}$$

constitutes an "abnormal" buy/sell volume for a given issuer. Switching to it does not make a material difference.

[10] Throughout this section, we use the "bar" notation to denote an average.

[11] We expand on this specification in Section 4.3.

where: I_t is the number of issuers whose instruments were traded in month t, $\delta_t \equiv \frac{1}{(I_t-1)\sigma(p_{it})\sigma(p_{it-1})}$, D_{fit} is a dummy equal to one (zero) if fund f is a buyer (seller) of issuer i in month t and F_{it} denotes the total number of funds trading issuer i in month t.[12]

The two terms on the right-hand side of equation (27) have distinct interpretations. The first one, β_{1t}, will be positive if funds tend to buy (sell) securities issued by the same issuers from which they bought (sold) a month earlier. Symmetrically, $\beta_{1t} < 0$ indicates that individual funds tend to reverse – from one month to the next – their buying/selling of instruments from given issuers. In turn, $\beta_{2t} > 0$ if buy (sell) herding stems from funds imitating others' previous trades. By contrast, $\beta_{2t} < 0$ if funds tend to sell (buy) those issuers that others bought (sold) the previous month.

4.3 Testing for herding and the underlying motives

With the herding measure under our belts, we investigate whether the data are consistent with the behaviour that we attribute to some of the asset managers in our theoretical model: aligning actions with that of peers for non-informational reasons. Thus, if we establish that herding exists, we need to study the underlying motives. For the latter, we consider the herding measure from as many angles as our data allow for, testing in particular whether asset managers align their investment decisions around information about issuers' fundamentals. Rejecting informational motives would allow us to conclude that our data are consistent with the assumption in Section 3 of reputation-driven herding.

Concretely, we perform tests that fall into two general categories. The first comprises tests of the existence of herding in the MMF sector. Provided that we establish existence, we check if herding is stronger at funds that are *a priori* more likely to be driven by reputational motives. Then, we move to the second category, which comprises direct tests for three potential underlying drivers: (i) self-imitation, (ii) herding in response to a common signal on the fundamentals of issuers, and (iii) imitation of an informationally superior investor.

Extant studies that use the same herding measure but rely on different datasets covering different investor types find evidence of herding by institutional investors (Sias, 2004; Wermers, 1999; Cai et al., 2019). Our first hypothesis (Hypothesis 1) is that this is not the case for the MMF sector.

Hypothesis 1 (No herding). *MMFs do not exhibit herding behavior in their investment decisions: the average value of β_t ($\bar{\beta}$) is equal to zero.*

As argued above, herding would be stronger for prime funds if the main underlying drivers are

[12] While β_t does not contain information about individual funds – since p_{it} and q_{it} do not – β_{1t} and β_{2t} do contain such information – as revealed by the inner sums in equation (27).

reputational motives. Thus, Hypothesis 2 posits that reputational motives are not important.

Hypothesis 2 (Herding by fund type). *Herding is stronger at non-prime funds.*

Conditional on the existence of herding ($\bar{\beta} > 0$), the next step is to shed light on whether the underlying motives could be reputational. As a first attempt in this direction, we look at the importance of the self-imitation element in equation (27): if it explains the entire herding measure, then we can rule out the reputational motive that we are after. Thus we test the following:

Hypothesis 3 (Herding type). *Self-imitation is the only component of herding: ($\bar{\beta}_1 > 0$) and ($\bar{\beta}_2 = 0$).*

Table 1 summarises the results for Hypotheses 1, 2 and 3. The first column captures the average estimate of β_t ($\bar{\beta}$) obtained from estimating equation (26) for all months in the sample. The second and third columns show respectively the time average of the two components of the decomposition of $\bar{\beta}$, namely $\bar{\beta}_1$ (self-imitation) and $\bar{\beta}_2$ (imitating others).[13] The rows correspond to different (sub)samples: all funds, prime funds, and non-prime funds.

Table 1: Herding – Time persistence and imitation

	$\bar{\beta}$	$\bar{\beta}_1$	$\bar{\beta}_2$	avR^2
All	0.121***	-0.008**	0.129***	0.033
Prime	0.127***	-0.009**	0.136***	0.034
Non-Prime	-0.140***	-0.059***	-0.082***	0.091
Diff Prime-NonPrime	0.267***	0.050***	0.217***	

Notes: The first column presents the average estimate of β_t ($\bar{\beta}$) across all time periods, obtained from the cross-sectional estimation of equation (26) for every month in the sample. The second and third columns respectively show the time average of the two components of β_t, capturing *self-imitation* ($\bar{\beta}_1$) and *imitating others* ($\bar{\beta}_2$), as per equation (27). The last column presents the average R^2 (avR^2) obtained from estimating equation (26) for every month in the sample. The sample contains all maturities and is restricted to issuer-months with at least 5 funds trading. Standard errors are adjusted for serial correlation and heteroscedasticity. *** and ** denote statistical significance at the 1% and 5% significance levels respectively.

The results reject Hypotheses 1, 2 and 3. First, the positive and significant value of $\bar{\beta}$ in the first row/first column indicates that MMFs do herd.[14] In turn, the second and third entries in the first

[13] Table 6 in Appendix D presents information on the number of positive and negative estimates of β_t, how many of them are statistically significantly different from zero. It also reports the number of positive and negative estimates of β_{1t} and β_{2t}.

[14] Quantitatively, our results are close to those in Sias (2004). The latter in turn are somewhat smaller than those in Cai et al. (2019), which stand in the neighborhood of 0.3.

column indicate that only prime funds herd, whereas issuers that experience strong *buying*/selling by non-prime funds tend to experience strong *selling*/buying by the same funds the following month. Third, the second and third columns reveal that imitating others ($\bar{\beta}_2$) accounts for the lion's share of herding. The contribution of $\bar{\beta}_1$ is even negative, although very small for prime funds.

Individual MMFs belong to fund families, i.e. investment companies that manage a group of funds. Fund families could influence investment patterns across constituent funds. We thus test whether the herding we find in the data could stem from centralised decision-making – following others from the *same* family. To this end, we redo the analysis in Table 1 by aggregating all funds belonging to a fund family into a single entity. The results – presented in Table 7 in Appendix D – confirm the initial message: herding exists, is present only for prime funds, where it does not reflect self-imitation.[15]

Since the findings so far are consistent with herding only by prime funds, we concentrate on them for the remaining tests. Concretely, Hypothesis 4 rules out reputational herding by positing that prime funds only appear to imitate other prime funds because they follow common signals (i.e. public information) about the issuers.

Hypothesis 4 (Herding and fundamentals: ex-ante information). *Public information about issuers drives prime funds' trading decisions.*

To test this hypothesis, we generalise the regression specification in equation (26). Alongside the auto-regressive term, the generalisation includes lags of the following issuer characteristics as explanatory variables: market capitalisation, stock returns, CDS spreads,[16] credit rating, and the average maturity of outstanding instruments bought by funds. We also include time fixed effects to absorb variation that is common to all funds and issuers, such as the stance of monetary policy or broader macroeconomic conditions. Finally, in some specifications we also include issuer sector fixed effects.

Our results – reported in Table 2 – reject Hypothesis 4. Concretely, the auto-regressive coefficient remains close to its initial value (of roughly 0.13 in Table 1) and statistically significant when we: add only time fixed effects to equation (26) (column 1); add also issuer-sector fixed effects (column 2); replace the latter with CDS spreads of the issuer and the sector of the issuer (column 3). The findings are similar when we: expand the latter specification by including the stock returns of issuers, their S&P rating, market capitalisation, and the average maturity of outstanding instruments (column 4); add issuer-sector fixed effects (column 5). These findings are thus consistent

[15] The estimates of β are lower in Table 7 than in Table 1. This is unsurprising: the scope of herding is smaller if there are fewer actors to imitate – in our full sample we have 509 funds versus 79 fund families.

[16] We consider the stock returns and CDS spreads both at the issuer level and at the level of the issuer sector.

with herding being driven by factors other than *ex-ante* public information about issuers.

Finally, we investigate whether funds could be herding around a peer that is known to have superior *private* information about the issuers. If this is the case, those issuers that experience buy (sell) herding would perform better (worse) subsequently. In our data, we proxy issuers' performance by stock returns, CDS spreads and/or the liquidity of the instruments they issue. We measure liquidity as the *minimum* between (i) the sum of buy volumes across all funds and (ii) the corresponding sum of sell volumes. All in all, this reasoning leads us to test the following hypothesis, which Sias (2004) failed to reject:

Hypothesis 5 (Herding and fundamentals: ex-post information). *Issuers' ex-post performance helps explain herding.*

For the test, we follow Sias (2004) and compute the cross-sectional correlation between q_{it} and different leads and lags of issuers' stock returns, CDS spreads and our measure of issuer-level liquidity.

The test results – reported in Table 3 – lead us to reject Hypothesis 5. For one, we find no relationship between stronger buying of an issuer's instruments and this issuer's stock returns. In addition, buying tends to be associated with *higher* CDS spreads, suggesting that herding cannot be valuable to MMFs for informational reasons. Similar is the message from the results on the liquidity measure, which indicate that issuers experiencing stronger buying also tend to have *less* liquid instruments.[17]

In sum, all our results are consistent with herding for non-fundamental reasons. That is, herding of the type that we modeled in Section 3 and that features in Buffa et al. (2014).

Table 3: Herding and issuer performance

	$k = t-1$	$k = t$	$k = t+1$	$k = t+3$	$k = t+6$	$k = t+9$	$k = t+12$
Corr($q_{it}, returns_{ik}$)	0.001	0.009	0.001	-0.013	0.004	0.023	-0.001
Corr(q_{it}, CDS_{ik})	0.048***	0.051***	0.045***	0.043***	0.034**	0.033**	0.029*
Corr(q_{it}, liq_{ik})	-0.025	-0.040**	-0.052**	-0.035*	0.056***	-0.036*	-0.045**

Notes: The table reports the average cross-sectional correlation between the q_{it} and leads and lags of issuer i's stock returns, CDS spreads and a measure of liquidity. For variable definitions and sources see Table 4. The sample used contains all maturities and is restricted to issuer-months with at least 5 funds trading. ***, ** and * respectively denote statistical significance at the 0.01, 0.05 and 0.1 levels.

[17] In a context of sticky information (Mankiw and Reis, 2002), herding could materialise in a gradual updating of portfolios. Note that because of how our herding measure is constructed (see Equation 25 and Equation 27), gradual updating would be picked up by the *self-imitation* component, which turns out to be very small.

Table 2: Herding by prime funds and issuer fundamentals

	(1)	(2)	(3)	(4)	(5)
	q_{it}	q_{it}	q_{it}	q_{it}	q_{it}
q_{it-1}	0.141***	0.109***	0.169***	0.132***	0.117***
	(0.020)	(0.022)	(0.038)	(0.038)	(0.040)
$CDSissuer_{it-1}$			0.025	0.002	-0.033
			(0.062)	(0.066)	(0.071)
$CDSissuer_{it-2}$			0.075	0.040	0.045
			(0.104)	(0.109)	(0.112)
$CDSissuer_{it-3}$			0.039	0.025	0.007
			(0.098)	(0.104)	(0.110)
$CDSsector_{it-1}$			-36.797*	-89.296	-94.284
			(22.007)	(67.088)	(61.280)
$CDSsector_{it-2}$			27.278	-91.138***	-88.833***
			(23.246)	(30.325)	(30.429)
$CDSsector_{it-3}$			20.030	-28.126	-22.556
			(13.672)	(41.033)	(42.512)
$IssuerReturns_{it-1}$				-1.092***	-1.002**
				(0.368)	(0.383)
$IssuerReturns_{it-2}$				-1.170***	-1.093***
				(0.386)	(0.408)
$IssuerReturns_{it-3}$				-0.305	-0.053
				(0.358)	(0.353)
$RatingSP_{it-1}$				0.915	4.248
				(8.905)	(9.100)
$RatingSP_{it-2}$				8.848	10.316
				(10.588)	(11.550)
$RatingSP_{it-3}$				-14.253**	-17.927***
				(6.527)	(6.338)
$MarketCap_{it-1}$				0.450*	0.485
				(0.253)	(0.326)
$MarketCap_{it-2}$				0.186	0.153
				(0.283)	(0.337)
$MarketCap_{it-3}$				-0.544	-0.558
				(0.333)	(0.426)
$Maturity_{it-1}$				-263.537***	-288.585***
				(73.391)	(70.014)
Observations	10453	8325	3741	3061	2796
R^2	0.023	0.044	0.064	0.091	0.103
TimeFE	Yes	Yes	Yes	Yes	Yes
IssuerSectorFE	No	Yes	No	No	Yes
Issuers	278	222	93	64	58

Notes: The dependent variable q_{it} denotes the standardised fraction of institutional investors buying issuer i in period t, as defined in equation (25). For ease of visibility of coefficients, q_{it} is multiplied by 100 (this does not affect the coefficient on q_{it-1}). Ratings are transformed into numerical scale, with higher numbers indicating worse rating. For variable definitions and sources see Table 4. The sample used contains all maturities and is restricted to issuer-months with at least 5 funds trading. Standard errors are clustered at the issuer level. *, ** and *** denote statistical significance at the 10, 5 and 1 percent level respectively.

5 Conclusion

While commentary on bank regulation tends to praise the post-crisis resilience of the banking sector, it often stresses that constraints on banks' balance-sheet space adversely affect market liquidity and, thus, the functioning of other sectors in the financial system. Some see the latter effects as a necessary price to pay for supporting financial stability (Borio et al., 2020). We argue instead that, by reducing market liquidity, regulation in the banking sector can actually improve the functioning of other financial sectors. In a theoretical model, we derive conditions under which a leverage-ratio constraint on banks exerts a beneficial disciplining effect on the risk-taking in an asset-management sector that depends on bank-based market-making. And we show that a key condition – herding in this sector – is empirically relevant.

Since excessive risk-taking is an inherent feature of the pro-cyclicality of the financial system, it could be useful to extend the analysis in this paper to an environment featuring boom-bust transitions. We would expect such an extension to underscore that the disciplining role of a leverage-ratio constraint evolves with the financial cycle, coming to the fore during booms, exactly when risk-taking is the highest. This would result in banks' leverage-ratio constraint generating countercyclical effects in the asset management sector: dampening excesses in booms and disruptions in busts. We leave the analysis of this conjecture to future research.

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Appendix

A Regulatory constraint in the baseline model

In this appendix, we assume that inequality (16) holds. This implies that the regulatory constraint (7) would be binding for bank dealers, i.e. $y_b = \kappa$, if the spread, s, is at least as high as in the unconstrained equilibrium, per (12). Below, we study the constrained equilibrium in the presence of (16) (flagged with a superscript r). For the variables that are functions of $\hat{\varepsilon}^r$ (e.g., y_a and s), the superscript is omitted whenever the meaning is obvious from the context.

In this constrained equilibrium, s is higher than in the unconstrained equilibrium. This implies that (16) is a necessary and sufficient condition for a binding regulatory constraint.

When $y_b = \kappa$, the equilibrium conditions are:

$$\hat{\varepsilon}^r s = R_2 - 1 \tag{A1}$$

$$s = \frac{c}{1-\beta}\left(\frac{(\hat{\varepsilon}^r)^2}{2} - \beta\kappa\right), \tag{A2}$$

which imply that the following pins down the threshold liquidation probability:

$$\frac{\hat{\varepsilon}^r}{1-\beta}\left(\frac{(\hat{\varepsilon}^r)^2}{2} - \beta\kappa\right) = \frac{R_2 - 1}{c}, \tag{A3}$$

Referring back to (16), we then obtain

$$\hat{\varepsilon}^r < \hat{\varepsilon},$$

Thus, by (4) and (A3), stricter regulation (i.e. lower κ) lowers the investment in the risky asset and the attendant liquidation volume. In parallel, the combination of (A2) and (A3) implies that a higher κ raises the spread, s, as foreshadowed at the beginning of the appendix.

We then turn to welfare analysis. First, we note that the overall utility in the asset management sector is given by (13). The utility in the dealer sector takes a different form:

$$U_b + U_n = \frac{y_a s}{2} + \frac{\beta\kappa}{2}(s - c\kappa). \tag{A4}$$

Thus, total welfare is

$$W^r = 1 + \hat{\varepsilon}^r(R_2 - 1) - \frac{y_a s}{2} + \frac{\beta\kappa}{2}(s - c\kappa). \tag{A5}$$

Taking the derivative with respect to κ delivers:

$$
\begin{aligned}
\frac{\partial W^r}{\partial \kappa} &= (R_2-1)\frac{\partial \hat{\varepsilon}^r}{\partial \kappa} - \frac{1}{2}\frac{\partial\left[\frac{y_a c}{1-\beta}(y_a-\beta\kappa)\right]}{\partial \kappa} + \frac{\beta}{2}(s-c\kappa) + \frac{\beta\kappa}{2}\left(\frac{\partial\left[\frac{c}{1-\beta}(y_a-\beta\kappa)\right]}{\partial \kappa} - c\right), \\
&= \underbrace{\left(R_2 - 1 - \frac{\hat{\varepsilon}^r c}{1-\beta}(y_a-\beta\kappa)\right)}_{=R_2-1-\hat{\varepsilon}^r s=0 \text{ by (4) and (A3)}}\frac{\partial \hat{\varepsilon}^r}{\partial \kappa} + \frac{1}{2}\underbrace{\frac{\beta c}{1-\beta}(y_a-\beta\kappa)}_{=\beta s \text{ by (4) and (A2)}} + \frac{\beta s}{2} - \beta\kappa c, \\
&= \frac{\beta c}{1-\beta}(y_a-\kappa) = \beta c(y_n-\kappa) = \beta(s-c\kappa) \geq 0.
\end{aligned}
$$

where the inequality follows from the earlier result that the binding constraint raises the spread s. Thus, social welfare increases in κ and the optimal regulatory constraint is nonbinding: $\kappa = y_a$, which is equivalent to $s = ck$. In other words, a strictly binding constraint reduces unambiguously social welfare in the baseline model.

B Herding in the asset management sector: proofs

In this appendix, we prove results in the presence of herding.

No regulatory constraint

First, we note that total differentiation of equation (19) yields

$$
d\varepsilon^H/d\omega = -\varepsilon^H\left(1-\varepsilon^H\right)/\left(3\varepsilon^H(1-\omega)+2\omega\right) < 0
$$

because $\varepsilon \in (0,1)$ and $\omega \in (0,1)$. This substantiates the first inequality in (20).

Second, using $d\varepsilon^H/d\omega$ and (18), we obtain

$$
dy_a/d\omega = \varepsilon^H\left(1-\varepsilon^H\right)\left(\varepsilon^H(1-\omega)+\omega\right)/\left(6\varepsilon^H(1-\omega)+4\omega\right) > 0.
$$

This is the second inequality in (20).

Third, for social welfare, we refer to the first line in expression (15). Given that $d\varepsilon^H/d\omega < 0$, $dy_a/d\omega > 0$ and $s = cy_a$, it follows that $\partial W^H/\partial\omega < 0$, which is the first inequality in (22).

Turning to the equilibrium in the presence of a social planner, we record the following. Now, the impact of herding on investment volume is:

$$
d\varepsilon^*/d\omega = -\varepsilon^*\left(3\varepsilon^* + 2\omega - 4\varepsilon^{*2} - 6\varepsilon\omega + 4\varepsilon^{*2}\omega\right)/\left(6\varepsilon^{*2}(1-\omega)^2 + 6\varepsilon^*\omega(1-\omega) + \omega^2\right),
$$

which can be of either sign, depending on the level of ε^*. By (21), the level of ε^* depends on the fundamentals $(R_2 - 1)/c$, as well as on ω.

Next, the impact of herding on liquidation volume is

$$\frac{dy_a}{d\omega} = \frac{\varepsilon\left(2\varepsilon^3 (1-\omega)^2 + 4\varepsilon^2\omega(1-\omega) + \varepsilon\omega(2\omega-1) - \omega^2(1-\varepsilon)\right)}{\left(12\varepsilon^2(1-\omega)^2 + 12\varepsilon\omega(1-\omega) + 2\omega^2\right)}.$$

This is unambiguously positive at $\omega = 0$ and equal to $\varepsilon(2\varepsilon - 1)/2$ at $\omega = 1$. Since the numerator in the expression for $dy_a/d\omega$ is a decreasing function of ω and the denominator is unambiguously positive, referring to equation (21) we obtain that: (i) $(R_2 - 1)/c > 1/8 \Leftrightarrow y_a$ always increases in ω; (ii) $(R_2 - 1)/c \in (1/16, 1/8) \Leftrightarrow y_a$ initially increases in ω, then decreases but always stays above $y_a|_{\omega=0}$; (iii) $(R_2 - 1)/c < 1/16 \Leftrightarrow y_a$ initially increases in ω, then decreases and ultimately drops below $y_a|_{\omega=0}$.

Turning to the implications of ω on social welfare when the planner fixes ε^*, we refer back to the first line in (15) and use (18) to rewrite it as follows:

$$\begin{aligned} W^* &= 1 + \hat{\varepsilon}^*(R_2 - 1) - \frac{1}{2}y_a s \\ &= 1 + \left(\hat{\varepsilon}^* - \frac{1}{2}\frac{(1-\omega)\frac{\hat{\varepsilon}^{*2}}{2} + \omega\frac{\hat{\varepsilon}^*}{2}}{(1-\omega)\hat{\varepsilon}^* + \frac{\omega}{2}}\right)(R_2 - 1) \\ &= 1 + \frac{3}{4}\hat{\varepsilon}^*(R_2 - 1) - \frac{\omega}{4}\frac{1}{2\hat{\varepsilon}^*(1-\omega) + \omega}(R_2 - 1). \end{aligned}$$

Together with the above expression for $d\varepsilon^*/d\omega$, we then obtain that $dW^*/d\omega =$ $-\varepsilon(1-\varepsilon)/(2\varepsilon(1-\omega)+\omega) < 0$, which substantiates the second inequality in (22).

Regulatory constraint on banks

The proof below uses condition (23) and establishes that there is a unique binding capital requirement that maximises social welfare: κ^* is smaller than y_a. To simplify notation, we continue using the superscript of r (instead of Hr) when studying the constrained equilibrium in the case of herding. We also omit the superscripts for the intermediary variables that are functions of $\hat{\varepsilon}^r$.

Proof. First, per (A5), total welfare is $W^r = 1 + \hat{\varepsilon}^r(R_2 - 1) - \frac{y_a s}{2} + \frac{\beta\kappa}{2}(s - c\kappa)$, where $s = (y_a - \beta\kappa)c/(1-\beta)$ and y_a is as in (18). Hence, total welfare can be rewritten as:

$$W^r = 1 + \hat{\varepsilon}^r(R_2 - 1) - \frac{\left((1-\omega)\frac{\hat{\varepsilon}^{r2}}{2} + \omega\frac{\hat{\varepsilon}^r}{2}\right)\left((1-\omega)\frac{\hat{\varepsilon}^{r2}}{2} + \omega\frac{\hat{\varepsilon}^r}{2} - \beta\kappa\right)c}{2(1-\beta)}$$
$$+ \frac{\beta\kappa}{2}\left(\frac{\left((1-\omega)\frac{\hat{\varepsilon}^{r2}}{2} + \omega\frac{\hat{\varepsilon}^r}{2} - \beta\kappa\right)c}{(1-\beta)} - c\kappa\right). \tag{A6}$$

Then the first-order condition with respect to κ is:

$$\frac{\partial W^r}{\partial\kappa} = (R_2-1)\frac{\partial\hat{\varepsilon}^r}{\partial\kappa} - \frac{1}{2}\frac{\partial\left[\frac{y_a c}{1-\beta}(y_a - \beta\kappa)\right]}{\partial\kappa} + \frac{\beta}{2}(s - c\kappa) + \frac{\beta\kappa}{2}\left(\frac{\partial\left[\frac{c}{1-\beta}(y_a - \beta\kappa)\right]}{\partial\kappa} - c\right),$$
$$= \frac{\beta c}{1-\beta}(y_a - \kappa) - \omega s\left(\frac{1}{2} - \hat{\varepsilon}^r\right)\frac{\partial\hat{\varepsilon}^r}{\partial\kappa}, \tag{A7}$$

where, per the equilibrium condition $s\hat{\varepsilon}^r = R_2 - 1$, we have:

$$\frac{\partial\hat{\varepsilon}^r}{\partial\kappa} = \frac{\beta\hat{\varepsilon}^r}{\frac{3}{2}(1-\omega)(\hat{\varepsilon}^r)^2 + \omega\hat{\varepsilon}^r - \beta\kappa} > 0. \tag{A8}$$

An optimal κ satisfies $s\hat{\varepsilon}^r = R_2 - 1$ and (A7). We rewrite these two conditions as follows:

$$\kappa = \left(\frac{1}{\varepsilon^r} - \left(\frac{1}{2} - \varepsilon^r\right)\frac{2\omega}{2(1-\omega)\varepsilon^{r2} + \omega\varepsilon^r + \frac{2\theta}{\varepsilon^r}(1-\beta)}\right)\theta$$
$$\kappa = \left(\frac{1-\omega}{2}\varepsilon^{r2} + \frac{\omega}{2}\varepsilon^r - \theta\frac{1-\beta}{\varepsilon^r}\right)\frac{1}{\beta}$$

where we replace $\frac{R_2-1}{c}$ with $\theta \in (0, (1+\omega)/16)$.

From (A7), we know that, in order to maximise social welfare, $\kappa < y_a$.

Existence. The following four expressions show that – over ε^r's support $(0, 1/2)$ – the first functions starts above the second and finishes below it. Thus, the two cross, implying existence.

$$\lim_{\varepsilon^r \to 0} \left(\frac{1}{\varepsilon^r} - \left(\frac{1}{2} - \varepsilon^r \right) \frac{2\omega}{2(1-\omega)\varepsilon^{r2} + \omega\varepsilon^r + \frac{2\theta}{\varepsilon^r}(1-\beta)} \right) \theta = \infty, \tag{A9}$$

$$\lim_{\varepsilon^r \to 1/2} \left(\frac{1}{\varepsilon^r} - \left(\frac{1}{2} - \varepsilon^r \right) \frac{2\omega}{2(1-\omega)\varepsilon^{r2} + \omega\varepsilon^r + \frac{2\theta}{\varepsilon^r}(1-\beta)} \right) \theta = 2\theta, \tag{A10}$$

$$\lim_{\varepsilon^r \to 0} \left(\frac{1-\omega}{2}\varepsilon^2 + \frac{\omega}{2}\varepsilon^r - \theta\frac{1-\beta}{\varepsilon^r} \right) \frac{1}{\beta} = -\infty, \tag{A11}$$

$$\lim_{\varepsilon^r \to 1/2} \left(\frac{1-\omega}{2}\varepsilon^{r2} + \frac{\omega}{2}\varepsilon^r - \theta\frac{1-\beta}{\varepsilon^r} \right) \frac{1}{\beta} = \left(\frac{1}{8}\omega + \frac{1}{8} - 2\theta(1-\beta) \right) \frac{1}{\beta} > 2\theta \tag{A12}$$

where the last inequality stems from condition (23).

Uniqueness follows from the fact that the first κ function is downward sloping, whereas the second is upward sloping:

$$\frac{d\left(\frac{1}{\varepsilon^r} - \left(\frac{1}{2} - \varepsilon^r \right) \frac{2\omega}{2(1-\omega)\varepsilon^{r2} + \omega\varepsilon^r + \frac{2\theta}{\varepsilon^r}(1-\beta)} \right)}{d\varepsilon} = -\frac{2}{\varepsilon^{r2}} \frac{\theta(1-\beta)\left(2\theta(1-\beta) + 4\varepsilon^{r3}(1-\omega) + \varepsilon^{r2}\omega(3-4\varepsilon^r)\right) + 2\varepsilon^{r6}(1-\omega)}{(2\theta + 2\varepsilon^{r3} - 2\theta\beta + \varepsilon^{r2}\omega - 2\varepsilon^{r3}\omega)^2}$$
$$< 0, \tag{A13}$$

$$\frac{d\left(\frac{1-\omega}{2}\varepsilon^{r2} + \frac{\omega}{2}\varepsilon^r - \theta\frac{1-\beta}{\varepsilon^r} \right)}{d\varepsilon} = \frac{1}{2\varepsilon^{r2}} \left(2\theta(1-\beta) + 2\varepsilon^{r3}(1-\omega) + \varepsilon^{r2}\omega \right) > 0. \tag{A14}$$

□

C Fire-sale intensity and herding

In this appendix, we show that the results obtained in the main text carry through when we allow for different levels of fire-sale intensity. In addition, we show that the herding-induced overinvestment in the risky asset strengthens if this intensity increases.

Suppose that liquidation risk, ε_i, is distributed uniformly across asset managers on $[0, \gamma]$, where a higher γ stands for greater fire-sale intensity. Then $\varepsilon_i = \gamma i$, where $i \in [0, 1]$.

The a-type asset managers' problem remains the same, implying a marginal manager $\hat{i}$ with $\hat{\varepsilon} = \gamma\hat{i}$. Thus, the average investment for the a-type asset mangers is $\hat{i}$, which means that each m-type manager will invest $\hat{i}$:

$$a_i^a = 1 \text{ if } i \leq \hat{i}, \qquad a_i^a = 0 \text{ if } i > \hat{i}, \qquad a_i^m = \hat{i} \forall i. \tag{A15}$$

In turn, the liquidation volume at $t = 1$ is $y_a = (1-\omega)\gamma\hat{i}^2/2 + \omega\gamma\hat{i}/2$.

As the dealer sector remains unchanged from the baseline model, the market clearing spread is $s = y_a c$ and the buy volume of a bank and a non-bank dealer is $y_j = y_a$ for $j = b, u$.

The marginal asset manager is then pinned down by the following equilibrum condition:

$$\gamma\hat{i}^H\left(\underbrace{\left((1-\omega)\gamma\frac{\hat{i}^{H2}}{2} + \omega\gamma\frac{\hat{i}^H}{2}\right)c}_{s}\right) = R_2 - 1, \tag{A16}$$

in which γ and $\hat{i}$ do not enter only as a product.

Interaction of fire-sale intensity with herding. We now show that a higher γ leads to a larger impact of herding on investment in the risky asset. With herding, the investment is $q^H = \hat{\varepsilon}^H = \gamma\hat{i}^H$, with $\hat{i}^H$ defined in (A16). Without herding, the investment in the risky asset is $q = \hat{\varepsilon} = \gamma\hat{i}$, where $\hat{i}$ also satisfies (A16) but with $\omega = 0$. Thus,

$$\begin{aligned}
\frac{\partial(q^H - q)}{\partial\gamma} &= \hat{i}^H + \gamma\frac{\partial\hat{i}^H}{\partial\gamma} - \hat{i} - \gamma\frac{\partial\hat{i}}{\partial\gamma}; \\
&= \hat{i}^H + \hat{i}^H\underbrace{\frac{2(1-\omega)\hat{i}^H + 2\omega}{3(1-\omega)\hat{i}^H + 2\omega}}_{>\frac{2}{3}} - \hat{i} - \frac{2\hat{i}}{3}; \\
&> \frac{5}{3}(\hat{i}^H - \hat{i}) > 0.
\end{aligned} \tag{A17}$$

Accordingly, if a group of asset managers faces a higher liquidation risk, their herding incentives will lead to a higher (over)investment compared to the benchmark case without herding.

Socially optimal equilibrium. Given total welfare $W = 1 + \hat{i}(R_2 - 1) - \frac{y_a s}{2}$, the first order condition with respect to $\hat{i}$ is:

$$\underbrace{\gamma\left((1-\omega)\hat{i}^* + \frac{\omega}{2}\right)}_{dy_a/d\hat{i}}\underbrace{\left((1-\omega)\gamma\frac{\hat{i}^{*2}}{2} + \omega\gamma\frac{\hat{i}^*}{2}\right)c}_{s} = R_2 - 1. \tag{A18}$$

These imply that a stronger herding incentive (ω) leads to a lower investment volume both in the private equilibrium and in the socially optimal equilibrium:

$$\frac{\partial \hat{i}^H}{\partial \omega} < 0, \quad \frac{\partial \hat{i}^*}{\partial \omega} < 0. \tag{A19}$$

We rewrite social welfare in the private and socially optimal equilibrium as follows

$$W^H = 1 + \frac{3}{4}\hat{i}^H(R_2 - 1) - \frac{\omega}{4}(1 - \hat{i}^H)(R_2 - 1), \tag{A20}$$

$$W^* = 1 + \frac{3}{4}\hat{i}^*(R_2 - 1) - \frac{\omega}{4}\frac{1}{2\hat{i}^*(1-\omega)+\omega}(R_2 - 1), \tag{A21}$$

which allows us to see that each decreases in ω: both $\hat{i}^H$ and $\hat{i}^*$ decrease in ω, and both $\frac{\omega}{4}(1 - \hat{i}^H)$ and $\frac{\omega}{4}\frac{1}{2\hat{i}^*(1-\omega)+\omega}$ increase in ω.

The effect of the regulatory constraint. When the regulatory constraint is binding, the spread is $s = (y_a - \beta\kappa)c/(1-\beta)$ and total welfare is $W^r = 1 + \hat{i}^r(R_2 - 1) - \frac{y_a s}{2} + \frac{\beta\kappa}{2}(s - c\kappa)$. The first-order condition with respect to κ is

$$\frac{\partial W^r}{\partial \kappa} = \frac{\beta c}{1-\beta}(y_a - \kappa) - \gamma\omega s\left(\frac{1}{2} - \hat{i}^r\right)\frac{\partial \hat{i}^r}{\partial \kappa} \tag{A22}$$

where $\frac{\partial \hat{i}^r}{\partial \kappa} = \frac{\beta \hat{i}^r}{\frac{3}{2}(1-\omega)\gamma(\hat{i}^r)^2 + \omega\gamma\hat{i}^r - \beta\kappa} > 0$, which implies that: (i) the investment volume ($\hat{i}^r$) is smaller than that in the private equilibrium ($\hat{i}^H$); and (ii) the optimal κ^* is smaller than y_a.

With the optimal regulatory constraint, κ and $\hat{i}^r$ are pinned down by

$$\frac{c}{1-\beta}\left(\frac{1-\omega}{2}\gamma\hat{i}^{r2} + \frac{\omega}{2}\gamma\hat{i}^r - \kappa\right) = \left(\frac{1}{2} - \hat{i}^r\right)\frac{\omega(R_2 - 1)}{\frac{3}{2}(1-\omega)\gamma(\hat{i}^r)^2 + \omega\gamma\hat{i}^r - \beta\kappa}, \tag{A23}$$

$$\frac{c\gamma\hat{i}^r}{1-\beta}\left(\frac{1-\omega}{2}\gamma\hat{i}^{r2} + \frac{\omega}{2}\gamma\hat{i}^r - \beta\kappa\right) = R_2 - 1. \tag{A24}$$

Finally, following Appendix B, we establish existence and uniqueness of the optimal κ.

D Additional tables from empirical analysis

Table 4: Variable definitions and sources

Variable	Definition	Source
n_{it}^{buy}	Number of funds buying issuer i in period t	Crane Data
n_{it}^{sell}	Number of funds selling issuer i in period t	Crane Data
N_{it}	Number of funds active on issuer i in period t (= n_{it}^{buy} + it^{sell})	Crane Data
I_t	Number of issuers whose instruments were traded in month t	Crane Data
p_{it}	Share of buyers in all the funds that trade issuer in period t (see (24))	Crane Data
$\bar{p}_t$	Cross-sectional average of p_{it}	Crane Data
q_{it}	Standardised p_{it} (see (25))	Crane Data
liq_{it}	Minimum of the aggregate (across all fund types) buy and sell volumes for that issuer, where the aggregates are calculated by considering only MMFs that are net buyers, respectively sellers, for the issuer	Crane Data
$CDS\,issuer_{it}$	CDS spread net of the Z-spread for a fixed-rate cash bond of the same issuer (in basis points)	Refinitiv
$CDS\,sector_{it}$	CDS spread of the sector of issuer net of the Z-spread of the sector (in basis points)	Refinitiv
$IssuerReturn_{it}$	Monthly appreciation in the closing price for the issuer, plus any dividends paid, divided by the previous month price of the stock. Expressed in percentage points, e.g. a value of 1 means a 1% total return.	Refinitiv
$RatingSP_{it}$	Issuer Long-Term Rating assigned by S&P. Transformed into numerical scale, with higher numbers indicating worse rating	Refinitiv
$MarketCap_{it}$	Market capitalisation of issuer expressed (in billion USD)	Refinitiv
$Maturity_{it}$	Outstanding maturity in years: Maturity = (Maturity Date - Observation Date)/365.25. Left-censored at 0, i.e. if Observation date ¿ Maturity Date (which would give a negative difference), Maturity = 0.	Refinitiv

Table 5: Summary statistics

	Obs	Mean	SD	Min	Max
All funds					
n_{it}^{buy}	12,087	18.6	17.5	0	111
n_{it}^{sell}	12,087	14.4	15.8	0	120
N_{it}	12,087	33.0	31.4	5	151
I_t	12,087	112.0	12.8	74	144
p_{it}	12,087	0.6	0.2	0.0	1.0
$\bar{p}_t$	12,087	0.6	0.0	0.5	0.8
q_{it}	12,087	0.0	1.0	-4.4	2.9
Non-Prime funds					
n_{it}^{buy}	3,569	14.3	11.0	0	72
n_{it}^{sell}	3,569	13.2	10.2	0	74
N_{it}	3,569	27.5	18.6	5	92
I_t	3,569	33.7	6.7	24	44
p_{it}	3,569	0.5	0.2	0.0	1.0
$\bar{p}_t$	3,569	0.5	0.1	0.4	0.7
q_{it}	3,569	0.0	1.0	-3.3	3.3
Prime funds					
n_{it}^{buy}	11,530	14.9	12.6	0	81
n_{it}^{sell}	11,530	10.8	10.8	0	69
N_{it}	11,530	25.8	21.6	5	104
I_t	11,530	107.6	15.1	68	140
p_{it}	11,530	0.6	0.2	0.0	1.0
$\bar{p}_t$	11,530	0.6	0.0	0.4	0.8
q_{it}	11,530	0.0	1.0	-4.2	2.9
Additional controls					
$CDS\,issuer_{it}$	5,508	-10.0	47.1	-361.5	175.6
$CDS\,sector_{it}$	4,287	0.0	0.1	-2.9	1.1
$IssuerReturn_{it}$	9,431	0.7	13.7	-41.1	614.6
$RatingSP_{it}$	6,170	4.3	2.2	0.0	12.0
$MarketCap_{it}$	8,788	86.1	108.3	0.0	1359.0
$Maturity_{it}$	11,470	0.1	0.8	0.0	18.2
liq_{it}	2,295	2.0	5.2	0.0	85.5

Notes: The samples used contain all maturities and are restricted to issuer-months with at least 5 funds trading. For variable definitions and sources see Table 4. Controls refer only to those used in the regressions for the sample of prime funds.

Table 6: Herding – Summary of β_t across periods

	All	Prime	Non-prime
$\#\beta_t > 0\ (< 0)$	91 (20)	95 (16)	35 (76)
of which: significant	40 (1)	42 (1)	6 (30)
$\#\beta_{1t} > 0\ (< 0)$	43 (68)	42 (69)	19 (92)
$\#\beta_{2t} > 0\ (< 0)$	95 (16)	101 (10)	40 (71)

Notes: This table presents more details on the numbers of β_t, β_{1t} and β_{2t} underlying the results in Table 1. β_{1t} and β_{2t} refer to the decomposition in equation (27). Rows show the number of positive (respectively negative) estimates obtained by running equation (26) for every month in the sample (111 regressions). For β_t we are also able to calculate how many are statistically significantly different from zero (at the 10% level). Columns denote different samples based on fund type: all funds, prime funds, and non-prime funds. The sample used contains all maturities and is restricted to issuer-months with at least 5 funds trading. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

Table 7: Herding at fund family level– Time persistence and imitation

	$\bar{\beta}$	$\bar{\beta}_1$	$\bar{\beta}_2$	avR^2
All	0.040***	-0.024***	0.064***	0.017
Prime	0.051***	-0.025***	0.076***	0.016
Non-Prime	-0.185***	-0.073***	-0.112***	0.104
Diff Prime-NonPrime	0.236***	0.048***	0.188***	

Notes: The first column presents the average estimate of β_t ($\bar{\beta}$) across all time periods, obtained from cross-sectional estimates of equation (26) for every month in the sample. The second and third columns respectively show the time average of the two components of β_t, capturing *self-imitation* ($\bar{\beta}_1$) and *imitating others* ($\bar{\beta}_2$), as per equation (27). The last column presents the average R^2 (avR^2) obtained from estimating equation (26) for every month in the sample. The sample contains all maturities and is restricted to issuer-months with at least 3 fund families trading. Standard errors are adjusted for serial correlation and heteroscedasticity. *** and ** denote statistical significance at the 1% and 5% significance levels respectively.

E Robustness with alternative herding measure

An early measure of herding by institutional investors was proposed by Lakonishok et al. (1992) – henceforth LSV. It quantifies the extent to which issuers are bought/sold *disproportionately* relative to the market-wide buy/sell intensity in a given period. In our context, it quantifies issuer-specific buy/sell herding.

The measure builds on equation (24) and is constructed for each issuer i in period t as follows:

$$LSV_{it} = |p_{it} - E[p_{it}]| - E|p_{it} - E[p_{it}]| \tag{A25}$$

where the $E[p_{it}]$ captures the expected level of buy intensity, estimated through the market-wide intensity of buying ($\tilde{p}_t$), which varies only over time:

$$\tilde{p}_t = \frac{\sum_i^{I_t} n_{it}^{buy}}{\sum_i^{I_t} n_{it}^{buy} + \sum_i^{I_t} n_{it}^{sell}} \tag{A26}$$

and the total number of issuers traded in period t is denoted by I_t.

Some remarks on equation (A25) are in order. The first component on the right-hand side captures the difference between the actual trading on issuer i in period t and the expected (that is, average) trading on all issuers for the same period. The second component is an adjustment factor introduced to ensure that that the expected value of LSV_{it} is zero under the null hypothesis of no herding (Lakonishok et al., 1992).[18] Accordingly, a positive/negative value of LSV_{it} indicates buy/sell herding on issuer i in period t.

Since the measure LSV_{it} does not have a time dimension, we can use it for testing only Hypotheses 1, 2, 4 and 5 from the main text. We report the results of the tests in Tables 8 - 10. With the exception of prime and non-prime funds exhibiting a similar degree of herding (Table 8), all other results are fully consistent with the ones we report in the main text on the basis of the Sias (2004) herding measure.

[18] Under the null hypothesis of no herding, all investors make independent decisions and no issuer should have a higher probability of being sold or bought. Accordingly, n_{it}^{buy} follows a binomial distributions with parameters $(n, p) = (n_{it}^{buy} + n_{it}^{sell}, E[p_{it}])$, and the adjustment factor is computed based on this. See Lakonishok et al. (1992) and Sias (2004).

Table 8: Herding measure (LSV_{it}) by fund type

	All funds		Prime		Non-prime	
	(1)	(2)	(3)	(4)	(5)	(6)
≥ 2 traders, all mat	0.111***	(19,157)	0.111***	(18,649)	0.093***	(4,599)
≥ 5 traders, all mat	0.070***	(12,087)	0.067***	(11,530)	0.066***	(3,569)
≥ 10 traders, all mat	0.061***	(8,781)	0.058***	(8,233)	0.056***	(2,906)
≥ 2 traders, mat > 1 week	0.117***	(16,645)	0.115***	(16,318)	0.141***	(1,879)
≥ 5 traders, mat > 1 week	0.070***	(10,728)	0.068***	(10,500)	0.087***	(1,161)
≥ 10 traders, mat > 1 week	0.060***	(7,492)	0.058***	(7,303)	0.057***	(791)

Notes: Average of the herding measure from Lakonishok et al. (1992) across all issuer-months. Rows indicate different subsamples, depending on the minimum number of active traders of any given issuer on any given period and the maturity of the positions funds have vis-à-vis these issuers. For each fund type, the first column represents the average herding measure and the second column represents the number of observations underlying that number. ***, ** and * respectively denote statistical significance at the 0.01, 0.05 and 0.1 levels.

Table 9: Herding by prime funds and issuer fundamentals - Robustness with LSV_{it} measure

	(1) LSV_{it}	(2) LSV_{it}	(3) LSV_{it}	(4) LSV_{it}	(5) LSV_{it}
LSV_{it-1}	0.115***	0.109***	0.090***	0.081***	0.082***
	(0.014)	(0.015)	(0.019)	(0.020)	(0.021)
CDSissuer_{it-1}			0.009	0.015**	0.013*
			(0.008)	(0.007)	(0.007)
CDSissuer_{it-2}			0.010	0.005	0.001
			(0.009)	(0.010)	(0.010)
CDSissuer_{it-3}			-0.008	-0.013	-0.015
			(0.008)	(0.009)	(0.010)
CDSsector_{it-1}			-6.524*	-20.985**	-21.722***
			(3.485)	(9.342)	(8.031)
CDSsector_{it-2}			0.342	-5.915	-4.766
			(2.456)	(5.484)	(5.616)
CDSsector_{it-3}			6.006***	7.435	7.308
			(1.910)	(6.020)	(6.162)
$\text{IssuerReturns}_{it-1}$				-0.042	-0.035
				(0.051)	(0.053)
$\text{IssuerReturns}_{it-2}$				0.022	0.048
				(0.046)	(0.047)
$\text{IssuerReturns}_{it-3}$				-0.002	0.006
				(0.051)	(0.051)
RatingSP_{it-1}				-2.121**	-1.843*
				(0.965)	(1.061)
RatingSP_{it-2}				1.090	0.788
				(1.830)	(2.033)
RatingSP_{it-3}				0.818	1.069
				(1.360)	(1.530)
MarketCap_{it-1}				0.005	-0.011
				(0.044)	(0.057)
MarketCap_{it-2}				-0.058	-0.045
				(0.056)	(0.068)
MarketCap_{it-3}				0.056	0.052
				(0.036)	(0.042)
Maturity_{it-1}				-2.312	3.692
				(6.235)	(6.644)
Observations	10453	8325	3741	3061	2796
R^2	0.028	0.035	0.046	0.052	0.070
TimeFE	Yes	Yes	Yes	Yes	Yes
IssuerSectorFE	No	Yes	No	No	Yes
Issuers	278	222	93	64	58

Notes: The dependent variable LSV_{it} denotes the herding measure of Lakonishok et al. (1992), for issuer i in period t. For comparability with the main regression table we also include the lag of LSV_{it} as a regressor. Ratings are transformed into numerical scale, with higher numbers indicating worse rating. For variable definitions and sources see Table 4. Standard errors are clustered at the issuer level. *, ** and *** denote statistical significance at the 10, 5 and 1 percent level respectively.

Table 10: Herding and issuer performance - Robustness with LSV_{it} measure

	$k = t-1$	$k = t$	$k = t+1$	$k = t+3$	$k = t+6$	$k = t+9$	$k = t+12$
Corr(LSV_{it}, $returns_{ik}$)	-0.005	0.005	-0.011	0.006	-0.002	-0.004	-0.010
Corr(LSV_{it}, CDS_{ik})	0.057***	0.049***	0.049***	0.050***	0.053***	0.042***	0.037**
Corr(LSV_{it}, liq_{ik})	-0.011	-0.008	-0.007	-0.001	-0.032	-0.031	-0.035

Notes: The table reports the average cross-sectional correlation between the herding measure LSV_{it} (Lakonishok et al., 1992) and leads and lags of issuer i's stock returns, CDS spreads and a measure of liquidity. For variable definitions and sources see Table 4. The sample used contains all maturities and is restricted to issuer-months with at least 5 funds trading. ***, ** and * respectively denote statistical significance at the 0.01, 0.05 and 0.1 levels.

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