Journal of Economics and Finance (2021) 45:544–571
https://doi.org/10.1007/s12197-021-09539-7

Is fund performance driven by flows into connected funds? spillover effects in the mutual fund industry

Bing Zhu[1] · René-Ojas Woltering[2]

Accepted: 5 January 2021 / Published online: 22 February 2021

Abstract
Mutual funds are connected with each other through overlapping portfolio holdings. We document that the performance of individual mutual funds is affected by spillover effects from fund flows to connected mutual funds. Spillover-effects are particularly pronounced during crisis periods, when a one standard deviation increase in flows to the tercile of funds with the highest overlapping portfolio holdings is associated with a monthly excess returns of 1.50%. Small cap stock funds are more heavily impacted, suggesting that the spillover effect is related to underlying asset liquidity. Moreover, we shed light on the dark side of diversification, as highly diversified funds are more exposed to the spillover risk factor.

Keywords Fund Flows · Price Pressure · Spillover Effects

JEL Classification G11 · G14 · G24

1 Introduction

The relationship between fund flows and financial performance is one of the most intensely researched topics in the mutual fund literature. Warther (1995), Edelen and Warner (2001), Goetzmann and Massa (2003), and Ben-Rephael et al. (2011) provide clear evidence that fund flows into equity mutual funds can exert price pressure on aggregate stock market returns. More recently, Coval and Stafford (2007),

✉ Bing Zhu
b.zhu@tum.de

René-Ojas Woltering
Rene-Ojas.WOLTERING@ehl.ch

1 Department of Civil, Geo and Environmental Engineering, Technical University of Munich, Arcisstraße 21, 80333, Münich, Germany

2 Ecole hôtelière de Lausanne, HES-SO University of Applied Sciences and Arts Western Switzerland, Lausanne, Switzerland

Frazzini and Lamont (2008), and Lou (2012) document how individual stock returns can be affected by fund flows into equity mutual funds. In addition, mutual fund flows themselves have been suggested as a potential source for the well-documented underperformance of mutual funds relative to their benchmarks as extreme inflows or outflows force mutual funds to engage in costly transactions (Grinblatt and Titman 1989; Wermers 2000). Edelen (1999) and Rakowski (2010) provide direct evidence for the hypothesis that fund flow-induced transaction costs are a cause of the underperformance of mutual funds.

While the effects of fund flows on the performance of individual stocks and on the funds themselves are well-documented, thus far little is known about the flow-return dynamics among mutual funds. We aim to fill this gap in the literature, by analysing how fund returns are affected by flows into *other* mutual funds.

In this paper, we test whether the performance of individual mutual funds is subject to spillover risk caused by fund flows into connected mutual funds. We measure the degree of connectedness between two mutual funds by their share of overlapping portfolio holdings. The interconnectedness among entities from investing in common assets is considered an important channel for the propagation of systemic risk (see (Elliott et al. 2014a; Lin and Guo 2019) and many others). However, the majority of the literature uses the network analysis method and emphasizes the position of an entity inside the network (see for example (Eisenberg and Noe 2001; Gai and Kapadia 2010; May and Arinaminpathy 2010; Lin and Guo 2019)). Only few studies focus on network externalities. Antón and Polk (2014) provide evidence of excessive co-movement in individual stock returns caused by the shared ownership of active mutual funds. Blocher (2016) studies the impact of overlapping portfolio holdings on the co-movement in the returns of mutual funds. Different from previous literature, this paper studies the characteristics that can affect a firms' vulnerability to network externalities. Building on the price pressure effects documented in the mutual fund literature, we hypothesize that flows into connected funds can affect individual mutual fund performance. Moreover, we examine whether there is a predictive relationship, by testing the spillover hypothesis not only based on actual flows, but also using expected fund flows, which are predicted from past fund returns and flows. Our empirical study is based on a global sample of 3,010 US-focused equity mutual funds over the January 2005 to December 2014 period.

Building up on the works of Lou (2012) and Blocher (2016), we confirm that flows into connected mutual funds impact the abnormal performance of individual mutual funds in a predictable way. We find that a one standard deviation increase in monthly expected flows to connected funds is associated with an annualized excess return of 0.22%. When splitting the sample of connected funds into three equal groups, we find that a one standard deviation increase in flows to the most connected funds is associated with an annualized spillover effect of 1.13%.

We make several contributions to the literature. First, we contribute to the literature on liquidity-based price pressure in the mutual fund industry. When mutual funds experience strong outflows, they are reliant on the liquidity provided by other market participants and may be forced to sell assets at 'fire-sale' prices (Coval and Stafford 2007). Our results provide evidence that spillover effects are significantly more pronounced during periods of constrained market liquidity.[1] During crisis periods, a one standard deviation increase in expected flows to the tertile of funds with the highest overlap is associated with a monthly excess return of 1.50%.

Second, we document that the spillover effect is more pronounced for small cap stock mutual funds relative to large cap mutual funds. During periods with strong outflows, the spillover effect to small cap stock funds is 1.07% per month, while only 0.02% for large cap stock funds. Several papers have challenged the suitability of the open-end fund structure as an investment vehicle. Stein (2005) argues that the risk of sudden withdrawals in case of short-term underperformance makes open-end funds managers unlikely to bet on profitable long term opportunities, where convergence to fundamental values is unlikely to be either smooth or rapid (see also Shleifer and Vishny (1997)). Cherkes et al. (2009) emphasize the suitability of closed-end funds to hold illiquid securities, because they are not subject to large-scale creation or redemption of shares, which can lead to potentially large transaction costs, as is the case with open-end funds. Chen et al. (2010) document that funds investing in less liquid stocks exhibit a stronger sensitivity of outflows to poor past performance than funds with liquid assets. The authors argue an investor's tendency to withdraw increases when there is a concern for the damaging effect of other investors' redemptions, due to higher trading costs. Our findings contribute to this strand of the mutual fund literature by showing that the spillover risk-factor is predominantly a concern for small cap stock funds. In contrast, the open-end mutual fund structure is more suitable for large cap stock funds, as suggested by their robustness with respect to the spillover risk factor.

The third contribution we make is related to a recent strand of the financial literature that focuses on the dark side of diversification. While the diversification is generally perceived positively due to well-documented reduction for the risk of individual financial entities, Slijkerman et al. (2013) argue that it can lead to increased systemic risk. Allen et al. (2010) show that diversification results in more overlap and more similarities among the portfolios of financial entities, thereby increasing the probability of coinciding failures with other similar institutions. However, thus far only very little empirical evidence is provided to support this argument. Most of the analyses are from theoretical or analytical perspective (see for example (Allen and Gale 2000; Upper and Worms 2004; Acemoglu et al. 2015; Elliott et al. 2014b, October)). In this paper, we empirically test whether similarity in portfolio positions results in increased spillover effects. For this purpose, we group funds into highly and less diversified funds. During periods with strong outflows, the spillover effect to the 25 percentile of most diversified funds rises to 2.6% per month, while the effect is only 0.1% for the 25 percentile of least diversified funds. These results confirm that funds with more diversified assets are most seriously affected by the spillover effect. This finding provides empirical evidence that diversification can increase the transfer of risks between financial institutions. The reduction of the risks at the individual

[1] The academic literature on spillover effects is broad. While we focus on fund-flow induced spillover effects in the mutual fund industry, other strands of the literature examine for example spillovers of return volatilities among international equity markets (e.g. Budd (2018) and Jain and Sehgal (2019)).

portfolio level does hence come at the cost of increased risk sharing between entities with similar portfolio positions.

The remainder of this paper is organized as follows. Section 2 introduces the dataset and descriptive statistics. Section 3 introduces the methodology. The empirical results are provided in Section 4. Section 5 contains the conclusion.

2 Data and descriptive statistics

2.1 Mutual fund data

Our empirical study is based on the global universe of open-end equity mutual funds with an investment focus on US stocks, including non-surviving funds. While many mutual fund studies focus on US-domiciled funds only, we also include international funds, because they are also likely to contribute to any spillover effects as long as the funds share a common investment focus. Our main data source is Morningstar Direct, a survivorship bias-free institutional research database, which provides one of the most comprehensive coverage of open-end mutual funds across the globe.

A necessary criterion for the inclusion in our sample is the availability of data on the funds' portfolio holdings. According to SEC rules, all US-domiciled funds have been required to report their holdings on a quarterly basis since February 2004. For non-US-domiciled funds no uniform regulation exists, so we include all international funds for which quarterly holding data are available in Morningstar.

Since the names of portfolio holdings are often ambiguous, we use a more conservative approach by identifying overlapping positions based on ISINs. A disadvantage of this method is that ISINs are not provided in some cases. To identify the portfolio holdings of a fund reasonably well, we require the share of non-identified holdings in a given quarter to be less than 20%. Furthermore, we require the share of non-US stock holdings to be smaller than 30% to ensure that the funds in our sample are actually focused on US stocks.

Moreover, our analysis is conducted at the fund level and not at the share class level. Different share classes of the same fund hold a common portfolio and opposing flows into different share classes may offset each other at the fund level. Hence, we use the total flow to all share classes to measure any spillover effect on other funds.

Fund returns, total net assets (TNA) and other fund characteristics are also obtained from Morningstar Direct. For non-US-domiciled funds, all financial data are converted to US dollars. Overall, our sample contains 3,010 distinct US-focused equity mutual funds and 209,458 fund-month observations over the 2005-2014 period.[2] Table 1 contains some descriptive characteristics on the funds in our sample. On average, the monthly fund return is 0.78% with a standard deviation of 5.06%. The average family size is 52.8 billion USD and the average age is around 14 years. The average expense ratio is 1.18%. Moreover, the funds in our sample exhibit an

[2] In our sample, over 90% of the funds are U.S. funds. If we exclude all non-US-domiciled funds, the results are very robust. The results are available from the authors upon request.

Table 1 Descriptive statistics of fund characteristics

	Mean	Std. dev.	Min	5% Perc.	95% Perc.	Max	N
Return (%)	0.78	5.06	–34.79	–8.22	3.73	57.37	209458
Excess return (%)	0.00	1.72	–23.15	–2.66	2.67	45.37	209458
Actual flow	–1.24	37.96	–159.91	–49.82	45.15	172.28	209458
Expected flow	0.53	36.33	–139.64	–45.16	49.49	173.75	209458
Fund size (TNA)	1.69	7.74	0.00	0.01	5.98	383.00	209458
Family size	52.80	144.66	0.00	0.04	409.60	1412.01	209458
Age	172.65	144.63	7.00	31.00	449.00	1085.00	209458
Expense ratio (%)	1.18	0.52	–0.51	0.36	2.00	10.92	209458
Cash ratio (%)	3.30	6.02	–656.71	0.00	10.91	330.73	209458
Turnover ratio (%)	75.31	178.50	–397.05	5.00	205.00	31596.00	209458

This table shows the descriptive statistics of monthly data on the fund characteristics over the 2005-2014 period. Return is the monthly fund return. Excess return is the monthly fund return in excess of the average return of all other funds with an investment focus on US stocks. Actual flow is the absolute dollar net flow, measured in millions of USD, to the fund as calculated by Eq. 1. Expected flow is the predicted net inflow, as estimated by Eq. 2. Fund size is the total fund size (aggregated over all share classes) in billions of USD. Family size is the total size of all funds aggregated by fund family (also measured in billions of USD). Age is the age of the fund measured in months. Expense ratio is the annual total expense ratio as reported in the annual report. Cash is the cash holdings of the fund relative to the fund size as reported by Morningstar. The turnover ratio is the annual turnover ratio of the fund over the previous 12 months

average cash ratio of 3.3% and a turnover ratio of 75%. Overall, these statistics are consistent with the literature on US mutual funds.

2.2 Fund flows

Following prior literature, we compute fund flows using monthly total net assets (TNA) and fund returns (Ippolito 1992; Guercio and Tkac 2002). The net flow of funds to mutual fund j during month t is defined as:

$$Flow_{j,t} = TNA_{j,t} - TNA_{j,t-1}(1 + R_{j,t}), \tag{1}$$

where $TNA_{j,t}$ is the Morningstar TNA value for fund j at the end of month t, and $R_{j,t}$ is the monthly return for fund j over month t.[3]

In our empirical analysis we measure spillover effects of fund flows on returns two different ways: (1) by using actual fund flows; and (2) by using expected fund flows. Measuring the spillover effect based expected flows enables us to test whether flows into connected funds impact fund performance in a predictable way. Moreover, expected flows circumvent potential endogeneity issues. It is well-documented in the literature that fund flows are strongly related to past performance (e.g., Sirri and Tufano, 1998). Given our monthly data set, it cannot be excluded that fund flows

[3] Consistent with Coval and Stafford (2007) we require changes in TNA are not too extreme in order to generate a reliable data set: $-0.50 < \Delta TNA_{j,t}/TNA_{j,t-1} < 2.0$.

towards the end of the month react to returns at the beginning of the month. This could potentially lead to a biased estimation of spillover intensity if the explanatory variable (fund flows) is correlated with the error term. On the other hand, fund flows may cause spillover effects irrespective of their source or use of origin, so we choose to report the results based on actual flows, too.

We follow Coval and Stafford (2007) and estimate expected flows from fund returns and flows over the previous 12 months as the explanatory variables:

$$Flow(\%)_{j,t} = a_i + \sum_{k=1}^{12} b_i Flow(\%)_{j,t-k} + \sum_{k=1}^{12} c_i R_{j,t-k} + e_{i,t}. \tag{2}$$

where $Flow(\%)_{j,t}$ is the percentage net flow to fund j relative to the funds' TNA at the end of the previous period.

The fitted values of $\widehat{Flow(\%)}_{j,t}$ from Eq. 2 on average explain 41.4% of the variation in flows,[4] suggesting that fund flows can be predicted reasonably well using past flows and returns. We then calculate expected flows ($\widehat{Flow}_{j,t}$) by multiplying ($\widehat{Flow(\%)}_{j,t}$) with $TNA_{j,t-1}$. As shown in Table 1, the average monthly actual fund flow is -1.24 million USD, with a standard deviation of 37.96 million USD. The negative outflow is consistent with the general trend of falling assets under management within the active mutual fund industry in recent years. Moreover, many funds have suffered substantial outflows during the global financial crisis. Expected flows, exhibit a slightly positive average of 0.53 million USD and a standard deviation of 36.33 million USD, which is in line with the volatility of actual fund flows. The average fund size is 1.69 billion USD with a standard deviation of 7.74 billion USD.

2.3 Measuring connectedness from overlapping portfolio holdings

A necessary condition for any spillover effect from the flows to one fund on the returns of another fund is some connection between the two funds. We measure the degree of connectedness between two funds by their overlapping portfolio positions. If two funds hold the same stock, we define the size of their overlapping portfolio position as the smaller one of both positions, measured by the size of the position relative to the size of the total portfolio. If one fund owns a stock, while another fund has a short position in the same stock, we calculate their overlapping portfolio position as the difference between both positions.

In formal terms, s, the overlapping portfolio position between two funds regarding each stock l, is defined as the minimum holding of stock l by the two funds, or, as the difference between the position if one fund holds stock l, while the other fund is short stock l:

$$s_{l,i,j,t} = \begin{cases} \min(|h^l_{i,t}|, |h^l_{j,t}|) & \text{if } h^l_{i,t} \times h^l_{j,t} \geq 0 \\ -(|h^l_{i,t}| + |h^l_{j,t}|) & \text{if } h^l_{i,t} \times h^l_{j,t} < 0 \end{cases} \tag{3}$$

[4] Detailed results are available from the authors upon request.

where $h^l_{i,t}$ is the percentage ratio of fund i's position in stock l in period t. For example, if Fund 1 holds 20% of Stock A, and Fund 2 holds 10% of Stock A, then the overlapping portfolio position between the two funds regarding stock A is 10%, and if Fund 1 holds 5% of Stock B, while Fund 2 has a short position of -2% in Stock B, their overlapping position regarding Stock B is -7%.

We then calculate S, the total share of overlapping portfolio positions between two funds by summing up their overlapping positions over all stocks:

$$S_{i,j,t} = \sum_{l=1}^{L_t} s_{l,i,j,t}, \tag{4}$$

where L_t is total number of stocks in period t. With the given example, the total share of overlapping portfolio positions between Fund 1 and Fund 2 is $10\% + (-7\%) = 3\%$, assuming there are no other overlapping positions except for Stock A and Stock B.

Almost all mutual funds in our sample file their reports at the end of a quarter. For the rare exceptions, we calculate overlapping positions assuming that portfolio compositions remain constant until the new report is released. For example, if one fund reports by the end of December and another fund by the end of January, we measure an updated overlapping ratio by the end of January, which remains constant during February and March until the first fund reports new holdings by the end of March.

Table 2 provides descriptive statistics on the number of portfolio positions by fund and on the number of connected and unconnected funds over our sample period. Two funds are referred to be connected if they share at least one common portfolio position in a given period. On average, each fund in our sample has 176 portfolio positions.

Table 2 Portfolio positions and connections between funds

	Portfolio positions by fund					Connections between funds		
	Mean	Std. dev.	Min	Max	N (stocks)	Connected	Unconnected	N (funds)
2005	157	254	1	2582	6890	509	923	1432
2006	164	274	1	2894	8428	749	1148	1897
2007	168	283	1	2759	9313	870	1220	2090
2008	176	304	1	2861	9208	1010	1310	2320
2009	183	329	1	2999	8684	1046	1389	2435
2010	180	298	1	2764	8432	1034	1489	2523
2011	179	308	1	2602	8929	1042	1522	2564
2012	181	319	1	2652	8747	1060	1544	2604
2013	185	327	1	2837	8485	1046	1565	2611
2014	190	342	1	2999	9166	1102	1594	2696
Total	176	304	1	2999	30034	947	1370	2317

This table shows descriptive statistics of yearly average numbers of portfolio positions by fund, the total number of distinct portfolio positions, the number of connections between funds, and the total number of funds. Two funds are connected if they share at least one common portfolio position in a given period

Given that all funds hold about 9,000 distinct positions in an average year, it is not surprising that many funds are not connected at all. For example, there is no reason why a fund which focuses on large cap stocks would share any positions with a small cap stock fund. On the other hand, there is a considerable degree of variation in the number of positions per fund, ranging from 1 to 2,999, which increases the chances of overlapping positions. The average number of connected funds is 947, and the average ratio of connected funds relative to all funds in our sample is 40.9%.

Table 3 shows the distribution of overlapping portfolio holdings for the sample of connected funds. The average portfolio overlap between two connected funds is 9.73% with a standard deviation of 10.94%. The intensity of any spillover effect of flows from one fund on the returns of another fund is most likely related to the degree of overlapping portfolio holdings. For the purpose of our empirical analysis, we rank all connected funds by their overlapping ratio and split them into three equal groups. The average overlapping ratio for the tertile of connected funds with the lowest overlap is 1.08%, 5.98% for the middle tertile, and 21.7% for the upper tertile.

3 Modelling spillover effects in the mutual fund industry

To estimate potential spillover effects, we examine how the excess returns of mutual funds are affected by flows to other mutual funds. The excess return $\widetilde{R}$ of fund i in period t is defined as the difference between the fund return and fund size-weighted

Table 3 Distribution of overlapping portfolio holdings between connected funds

	Standard		Percentiles					Average overlap by tertile		
	Mean	Deviation	Min	33%	Median	66%	Max	1	2	3
2005	10.27	11.47	–25.12	2.72	6.11	11.52	101.72	1.13	6.36	22.91
2006	9.09	10.53	–51.66	2.38	5.04	9.71	100.05	1.01	5.30	20.57
2007	9.35	10.79	–77.37	2.45	5.26	10.05	107.18	0.99	5.51	21.07
2008	9.61	11.10	–82.79	2.58	5.43	10.18	123.91	1.01	5.67	21.63
2009	10.42	11.55	–106.87	2.91	6.15	11.51	120.83	1.15	6.42	23.17
2010	10.01	10.95	–115.81	2.83	6.05	11.30	121.30	1.14	6.31	22.09
2011	9.63	10.71	–101.07	2.73	5.80	10.70	103.11	1.11	6.03	21.29
2012	9.97	11.01	–87.12	2.78	6.02	11.17	129.46	1.11	6.27	22.04
2013	9.60	10.70	–62.76	2.79	5.86	10.55	154.67	1.10	6.05	21.12
2014	9.39	10.64	–85.32	2.70	5.68	10.29	156.63	1.06	5.88	20.71
Total	9.73	10.94	–115.81	2.69	5.74	10.70	156.63	1.08	5.98	21.66

This table shows the distribution of yearly average numbers of overlapping portfolio positions for the subsample of connected funds. If two funds hold the same stock, an overlapping portfolio position is defined as the minimum holding of that stock by the two funds. For example, if fund A holds 10% of stock I, and fund B holds 20% of stock I, then the overlapping portfolio position between fund A and B regarding stock I is 10%. The total ratio of overlapping portfolio positions between two funds is then defined as the sum over all overlapping portfolio positions between the two funds average return of all US-focused equity funds in our sample: $\widetilde{R}_{i,t} = R_{i,t} - \bar{R}_t$. In our sample, the average excess return is close to zero, and the standard deviation is 1.72% (Table 1).

There are two reasons why we opt for the simple excess return rather than alternative performance measures such as raw fund returns or three or four-factor model alphas. (1) By using excess returns, we remove the return component of the general stock market. The literature documents that fund flows and contemporaneous returns are highly correlated (see for example (Warther 1995), or (Ben-Rephael et al. 2011)). Thus, it would not be clear whether positive fund returns are due to spillover effects from flows to connected mutual funds, or due to high returns in the stock market in general. (2) Three or four-factor alphas aim to capture risk exposure of the fund to small cap, value, or momentum stocks, but these risk factors might themselves be driven by above-average flows to their respective subgroups. For example, Lou (2012) finds evidence that flow-driven return effects can at least partially account for mutual fund performance persistence and stock price momentum. Hence, risk-adjusted returns are not ideally suited to isolate any fund flow-driven spillover effects.[5]

Our base model to estimate spillover effects of fund flows on the performance of other mutual funds is represented by the following equation:

$$\widetilde{R}_{i,t} = \rho \sum_{j=1, j\neq i}^{N_t} w_{i,j,t} Flow_{j,t} + \beta Control_{i,t} + u_i + \varepsilon_{i,t} \tag{5}$$

where ρ is the coefficient for the spillover effect of flows to connected funds on fund returns. Flows to connected funds are measured by the term $\sum_{j=1, j\neq i}^{N_t} w_{i,j,t} Flow_{j,t}$, where $Flow$ is either the actual or expected flow to fund j in period t, as described in the previous section.[6]

The list of control variables ($Control_{i,t}$) is consistent with the literature on fund performance and includes fund flows, lagged fund returns, fund size, the size of the fund family, fund age, the expense ratio, the fund's cash ratio, and the turnover ratio. u_i stands for the firm fixed effects, which captures time-invariant firm characteristics, such as the country.

A special emphasis needs to be placed on how flows to connected funds are weighted. The strength of the total spillover effect from the flows of all connected funds is likely to be related to the number of connections and the degree of connectedness between each pair of funds. Thus, perhaps the most intuitive approach is to

[5] Our results remain qualitatively robust if we employ these alternative performance measures. The results are available from the authors upon request.

[6] Using the weight matrix to quantify the impact of interconnections between entities or markets has been used in previous literature. For instance, Asgharian et al. (2013) study the impact of cross-border bilateral trade on the co-movement of the stock market across countries. They construct the weight matrix based on geographic distance, bilateral trade, bilateral FDI, and etc. In order to measure the interdependence of stock returns, Fernandez (2011) construct the weight matrix using the difference in firms' characteristics, including market capitalization, market-to-book, and other financial ratios.

weight the total flows to all connected funds by the respective total share of overlapping portfolio positions between each pair of funds, as $\sum_{j=1, j\neq i}^{N} S_{i,j,t} Flow_{j,t}$, where $S_{i,j,t}$ is the total share of overlapping portfolio positions between fund i and fund j in period t. This weighted sum of all fund flows to connected funds can then be interpreted as the total fund flow relevant to fund i. A disadvantage of this approach is, however, that it is no longer feasible to differentiate whether the spillover effect is due to a high number of connected funds, a high degree of overlapping portfolio holdings, or due to strong flows to only a few connected funds.

Bell and Bockstael (2000) suggest to row-standardize the weight matrix in order to allow for the appealing interpretation that the sum of the effects of neighbors in different bands can vary over bands. In our setting, we are interested in whether the same dollar amount of fund flows causes a stronger spillover effect for funds with a higher degree of overlapping portfolio holdings. Thus, we row-standardize the weight matrix $w_{i,j,t}$, by transforming the total share of overlapping portfolio holdings between each pair of funds, so that the total weights sum up to one for each fund:

$$w_{i,j,t} = \frac{S_{i,j,t}}{\sum_{j=1, i\neq j}^{N_t} S_{i,j,t}}. \tag{6}$$

This approach implicitly assumes that the spillover effect from the total flows to all connected funds remains constant, irrespective of the number of the connections of a fund or the share of overlapping portfolio holdings.

In order to test whether the spillover effect of funds flows is related to the degree of connectedness, we split the sample of connected funds into three groups:

$$\begin{aligned}\widetilde{R}_{i,t} = {} & \rho_1 \sum_{j=1, j\neq i}^{N_t} w_{i,j,t}^{Q1} Flow_{j,t} + \rho_2 \sum_{j=1, j\neq i}^{N_t} w_{i,j,t}^{Q2} Flow_{j,t} + \rho_3 \sum_{j=1, j\neq i}^{N_t} w_{i,j,t}^{Q3} Flow_{j,t} \\ & + \beta Control_{i,t} + u_i + \varepsilon_{i,t}\end{aligned} \tag{7}$$

where $Q1$ ($Q3$) denotes the tertile of funds with the lowest (highest) total share of overlapping portfolio holdings $S_{i,j,t}$.

4 Empirical results

4.1 Baseline results for spillover effects from fund flows to connected funds

Table 4 contains the fixed-effects panel regression results on the spillover effects of fund flows from connected funds for US-focused equity mutual funds over the January 2005 to December 2014 period. Four different specifications are estimated. In models (i) and (ii), we estimate spillover effects based on expected flows to test whether spillover effects impact fund performance in a predictable way. The results based on actual fund flows are presented in models (iii) and (iv). Model (i) is our baseline model, where we test whether there is positive spillover effect from the total

Table 4 Spillover effects of fund flows to other funds on fund performance

	Expected flows		Actual flows	
	(i)	(ii)	(iii)	(iv)
Flow_connected	0.0031***	–	0.0074***	–
	(0.0009)		(0.0006)	-
Flow_Q3	–	0.0053***	–	0.0123***
	–	(0.0007)	–	(0.0006)
Flow_Q2	–	0.0002	–	–0.0016***
	–	(0.0009)	–	(0.0007)
Flow_Q1	–	–0.0053***	–	–0.0076***
	–	(0.0008)	–	(0.0007)
Control variables				
Expected Flow_own	–0.0003**	–0.0003***	0.0004***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Excess Return_t-1	0.0362***	0.0346***	0.0348***	0.0314***
	(0.0040)	(0.0040)	(0.0040)	(0.0040)
Age	–0.0585***	–0.0619***	–0.0585***	–0.0815***
	(0.0139)	(0.0135)	(0.0133)	(0.0134)
Expense	0.0403	0.0425	0.0409	0.0449
	(0.0447)	(0.0451)	(0.0446)	(0.0448)
Family size	0.0004***	0.0004***	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Fund size	–0.0048***	–0.0048***	–0.0050***	–0.0052***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Cash	0.0009	0.0008	0.0008	0.0007
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Turnover	–0.0004	–0.0004	–0.0003	–0.0002
	(0.0010)	(0.0010)	(0.0010)	(0.0010)

flows to all connected funds. In model (ii), we split flows to connected funds into three equal groups, to test whether the intensity of the spillover effect from flows to connected funds is related to the degree of overlapping portfolio holdings. In models (iii) and (iv), we employ the same approach as in models (i) and (ii), but we use actual instead of expected fund flows. We use the same set of control variables in all specifications. The results in model (i) show there is a positive and significant spillover effect from flows to connected funds. The estimated coefficient shows the change in the monthly excess return of fund i when each of its connected funds has an expected inflow of USD 1 million.

The regression results in model (ii) reveal that there is a particularly strong spillover effect from flows to the most similar funds. For the ease of interpretation, we convert the spillover effect to the (annualized) impact of a one standard deviation

Table 4 (continued)

	Expected flows		Actual flows	
	(i)	(ii)	(iii)	(iv)
Firm FE	Yes	Yes	Yes	Yes
Observations	209458	209319	209458	209342
R squared	0.022	0.028	0.025	0.028

This table contains the fixed effects panel regression results for the spillover effects of fund flows to other funds on fund performance for a global sample of 3010 US equity-focused over the January 2005 to December 2014 period. The dependent variable is the monthly excess return of a fund relative to the fund size-weighted average return of all funds in our sample. To test if (relative) fund returns are affected by spillover effects from fund flows to other funds, we split them into connected and unconnected funds (relative to fund i). Two funds are referred to be connected if they share at least one common portfolio position in a given period. We furthermore rank the subsample of connected funds in each month by the total share of overlapping portfolio holdings between each pair of funds and split it into three equal tertiles, whereby Flow_Q3 denotes the flows to tertile of funds with the highest total share of overlapping portfolio holdings regarding fund i. Control variables include contemporaneous flows to fund i, lagged fund returns, fund size, the size of the fund family, fund age, the expense ratio, the fund cash ratio, and the turnover ratio. Models (i) and (ii) are estimated using expected fund flows as derived from the fitted values of Eq. 2. Models (iii) and (iv) are estimated using actual fund flows. Standard errors are in parentheses. Coefficients marked with ***,** and * are significant at the 1%, 5%, and 10% level, respectively

increase in flows to any of the connected funds. On average, a one standard deviation increase in expected flows to any of each connected funds is associated with an monthly excess return of 0.018% for each fund (0.22% per annum).[7] Although 0.018% isn't very remarkable, it should be noted that on average, each fund is connected to 947 other funds. If 10% of its connected funds (78 out of 947 funds) have an increase in net flows by one standard deviation, this fund will exhibit an excess return of 1.71% per month, equalling to the average standard deviation of the excess return of the 3010 funds. On average, a one standard deviation increase in flows to the tertile of connected funds with the highest overlapping portfolio holdings is associated with an annualized impact of 1.13% on fund performance.

Interestingly, the impact of flows to funds with modest or low overlapping portfolio holdings is either insignificant or even negative. As shown in Table 3, the average overlap of portfolio holdings in the tertile of funds with the lowest overlap is only 1.08% (vs. 21.66% in the tertile of funds with the highest overlap). If fund A only has 1.08% common holdings with other funds, the flows into other funds will be invested in stocks that are most likely not held by fund A. This causes a negative impact on the excess return of fund A, because these flows overwhelmingly exert price pressure on unrelated stocks, whereas the price pressure impact on common holdings is negligible. As a result, flows to other funds tend to increase only the market return, leading to the underperformance of fund A. In contrast, when the portfolio overlap

[7] The monthly effect is calculated by dividing the coefficient (0.0031) by the average number of connected funds (947) and multiplying the ratio by the monthly standard deviation of total expected flows to all connected funds (USD 5.6 bil.).

is 21.66%, our results document that the price pressure impact on common holdings outweighs, leading to a positive spillover effect. Overall, these results suggest that the general spillover effect documented in model (i) is driven by flows to those funds with the highest degree of connection between each other.

The regression results in models (iii) and (iv), are supportive of those obtained for expected flows. In fact, the coefficients on the spillover effects are even larger for actual flows.[8] A potential explanation is that expected flows only measure a fraction of the actual price pressure caused by fund flows in a given period. However, these results must be interpreted with caution because intraperiod flows may react to returns at the beginning of the month, potentially leading to an overestimation of the spillover intensity.

The regression results for the control variables are consistent with the literature. The coefficient on flows to fund i is negative and significant, suggesting that the transaction costs triggered by fund flows are detrimental to fund performance. A one standard deviation expected inflow is related to -1.08% increase in the fund monthly returns. But the actual flows have a significant positive influence on the fund excess return, confirming the finding by Rakowski (2010). Our results show an influence of 1.1% on the excess return. Besides, we also find a positive coefficient on lagged excess returns, which signals short term performance persistence. We also find a significant negative influence of fund size on fund performance, consistent of Rakowski (2010). A one standard deviation increase in fund size reduces the excess return by 3.7%. On the other hand, our results also show that fund performance is significantly positively influenced by family size, with an impact of 5.7% per standard deviation increase in fund family size. Furthermore, as shown in Table 4, younger funds achieve significantly better performance, consisting of the finding by Otten and Bams (2002) and Webster (2002). The expense ratio, cash holdings and portfolio turnover do not significantly impact excess fund returns.

4.2 Spillover effects during asset fire sale periods

In this section we investigate whether the spillover effect is related to periods of financial turmoil. Shleifer and Vishny (1997) describe how liquidity can disappear when financial distress clusters through time at the industry level. When many similar firms must sell assets because of financial distress, the potential buyers with the highest valuation for the specialized asset are other firms in the same industry, who are likely to be in a similarly dire financial situation and therefore will be unable to supply liquidity. Instead, liquidity comes from industry outsiders, who have lower valuations for specialized assets, and thus bid lower prices. Even though the stock market is considered as one of the most liquid of markets, assets sometimes sell at fire sale prices, as documented by Coval and Stafford (2007).

In our setting, the situation described by Shleifer and Vishny (1997) is comparable with periods of financial distress, such as the recent financial crisis, when nearly all

[8] The impact on monthly excess return is further amplified by the fact that the standard deviation of actual flows to all connected funds is about twice as large as the standard deviation based on expected flows.

funds were forced to liquidate parts of their portfolios due to strong outflows. During this period, market participants other than mutual funds must have been the buyers of these stocks, and often have paid discount prices as a compensation for providing liquidity, as suggested by Coval and Stafford (2007).

We hypothesize that spillover effect flows to connected funds are particularly strong during such periods of financial distress. When market liquidity is low, because many funds need to sell their assets simultaneously, and there are only a few potential buyers for these assets, the excess returns of mutual funds may be even more sensitive to the temporary price pressure caused by outflows from connected funds.

To identify such extreme situations, we relate the total outflows from all mutual funds in our sample to the total free-float market capitalization of all stocks held by the funds in our sample:

$$P_t = \frac{\sum_{i=1}^{N_{t-1}} Flow_{i,t-1}}{\sum_{k=1}^{L_{t-1}} CAP_{k,t-1}} \tag{8}$$

where N_{t-1} is the total number of funds and L_{t-1} is the total number of stocks held by all funds. $CAP_{k,t}$ is the free float market capitalization of stock k in period t. We then create a crisis indicator variable D_t^- , which is equal to one for the 5% of periods with the highest total outflows from the mutual fund industry relative to the free float market capitalization of all stocks and zero otherwise:

$$D_t^- = \begin{cases} 1 & \text{if } P_t \text{ is within the lowest } 5\% \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

We then test whether the spillover effect is particularly strong during crisis periods by interacting flows to connected funds with the crisis indicator variable:[9]

$$\begin{aligned} \widetilde{R}_{i,t} = \rho \sum_{j=1, j\neq i}^{N} w_{i,j,t} Flow_{j,t} + \rho^- D_t^- \sum_{j=1, j\neq i}^{N} w_{i,j,t} Flow_{j,t} + \rho^- D_t^- \\ + \beta Control_{i,t} + u_i + \varepsilon_{i,t} \end{aligned} \tag{10}$$

Table 5 contains the regression results for the spillover effects of fund flows to connected funds with a focus on asset fire sale periods. The dependent and explanatory variables are the same as in Table 4. Model (i) is similar to the base model of Table 4, but adds an interaction term between flows to all connected funds and the crisis indicator variable to test whether the spillover effect is stronger during asset fire sale periods. In model (ii), we add interaction terms between flows to each tertile of connected funds and the crisis dummy. Models (iii) and (iv) mirror the approach of models (i) and (ii), but are based on actual instead of expected fund flows.

The coefficient on the interaction term between flows to all connected funds and the crisis indicator variable in model (i) of Table 5 reveals that the spillover effect from fund flows to the excess returns of connected funds is particularly strong during asset fire sale periods. On average, the marginal spillover effect of the crisis on excess

[9] Our results remain robust if we use a more conservative approach and define the indicator variable to be equal to one for the 10% of most extreme situations.

Table 5 Spillover effects during asset fire sale periods

	Expected flows		Actual flows	
	(i)	(ii)	(iii)	(iv)
Flow_connected	0.0004	–	0.0068***	–
	(0.0009)	–	(0.0006)	–
Flow_Q3	–	0.0025***	–	0.0113***
	–	(0.0007)	–	(0.0006)
Flow_Q2	–	–0.0007	–	–0.0012*
	–	(0.0009)	–	(0.0007)
Flow_Q1	–	–0.0031***	–	–0.0075***
	–	(0.0009)	–	(0.0007)
Flow_connected	0.1062***	–	0.0358***	–
	(0.0072)	–	(0.0069)	–
Flow_Q3	–	0.0822***	–	0.0425***
	–	(0.0055)	–	(0.0054)
Flow_Q2	–	0.0436***	–	–0.0112*
	–	(0.0059)	–	(0.0059)
Flow_Q1	–	–0.0438***	–	–0.0024
	–	(0.0049)	–	(0.0044)
Control variables				
Expected Flow_own	-0.0003***	-0.0003***	0.0004***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
D_negative	0.2166***	0.1583***	–0.0002	–0.0403
	(0.0272)	(0.0269)	(0.0235)	(0.0259)
Excess Return_t-1	0.0348***	0.0327***	0.0345***	0.0309***
	(0.0040)	(0.0040)	(0.0040)	(0.0040)
Age	–0.0574***	–0.0567***	–0.0573***	–0.0785***
	(0.0139)	(0.0134)	(0.0132)	(0.0133)
Expense	0.0226	0.0337	0.041	0.0469
	(0.0447)	(0.0452)	(0.0446)	(0.0447)
Family size	0.0004***	0.0004***	0.0004***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Fund size	–0.0046***	–0.0046***	–0.0050***	–0.0051***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Cash	0.0008	0.0008	0.0008	0.0007
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Turnover	–0.0004	–0.0004	–0.0003	–0.0003
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Firm FE	Yes	Yes	Yes	Yes

Table 5 (continued)

	Expected flows		Actual flows	
	(i)	(ii)	(iii)	(iv)
Observations	209458	209319	209458	209342
R squared	0.028	0.029	0.027	0.029

This table contains the fixed effects panel regression results for spillover effects from fund flows on the performance of connected mutual funds with a focus on asset fire sale periods. The dependent variable is the monthly excess return of a fund relative to the fund size-weighted average return of all funds in our sample. The explanatory variables are the same as in Table 4. To test whether spillover effects are stronger during asset fire sales, we interact flows to connected funds with the crisis dummy indicator variable described in Eqs. 7 and 9. Models (i) and (ii) are estimated using expected fund flows, while models (iii) and (iv) are estimated using actual fund flows. Standard errors are in parentheses. Coefficients marked with ***,** and * are significant at the 1%, 5%, and 10% level, respectively

returns is 0.62% per month. The model (ii) results reveal the marginal impact of the crisis is particularly strong for the tertile of funds with the highest overlap. Interestingly, the base effect is no longer significant, suggesting that the spillover effects may be entirely driven by crisis periods. Figure 1 shows the coefficients and confidence intervals for spillover effects from flows to connected mutual funds on fund performance based on expected flows for three quantiles, whereby < 33 represents the spillover effect for the tertile of connected funds with the lowest overlapping portfolio holdings. The spillover effect from a one standard deviation increase in flows increases from -0.83% per month for funds with lowest overlap to 1.50% per month for funds with highest overlap.

The results based on actual flows presented in models (iii) and (iv) are qualitatively robust, but only slightly different in size. Compared to the results of models (i) and (ii), the marginal impacts of the crisis in models (iii) and (iv) are less pronounced, while the base effects remain significant. Figure 2 shows the coefficients and confidence intervals based on actual flows.

4.3 Spillover effects of small cap stock funds vs. large cap stock funds

In the previous section we investigated the time-varying impacts of the liquidity of the general market on the spillover intensity. In this section, we examine whether the spillover intensity is related to the degree of liquidity of the underlying assets held by the funds. Small cap stocks are generally considered less liquid than large cap stocks. Since we also obtain information on whether the funds in our sample have a focus on small cap stocks or on large cap stocks, we are able to test wheter the returns of small cap stock funds are more sensitive to spillover effects compared to funds holding more liquid large cap stocks.

Table 6 contains the regression results for the spillover effects of fund flows to connected funds, differentiating between the impact of flows to connected funds on small cap stock funds vs. large cap stock funds. To test whether spillover effects are stronger for small cap stock funds, we split the sample into small cap stock funds

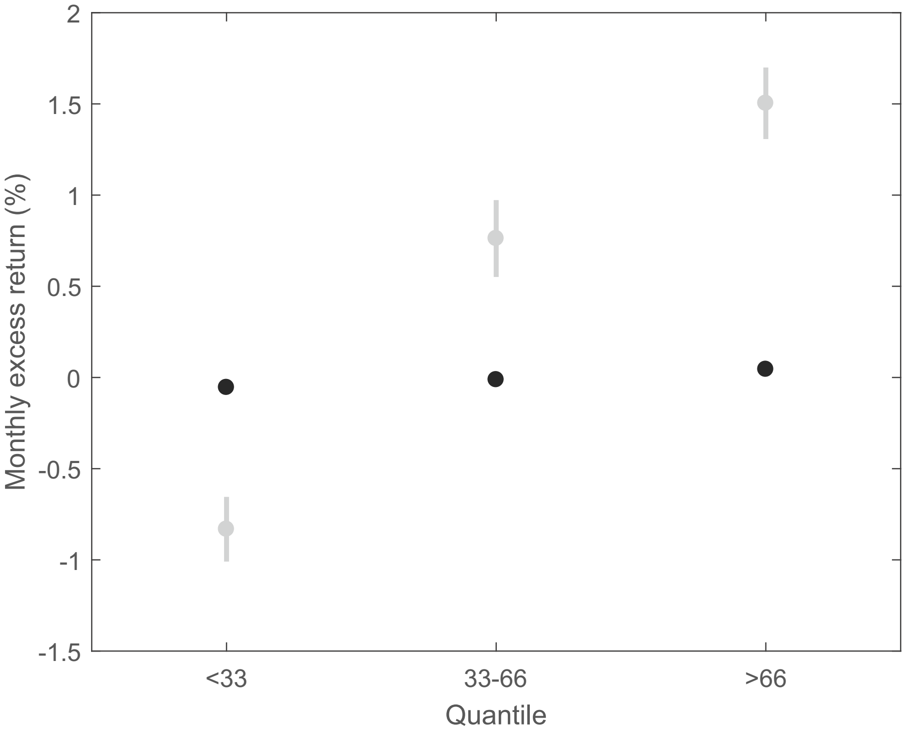

Fig. 1 The base effects are marked in black, and the marginal effects during asset fire sale periods are represented in grey

and large cap stock funds. Although we split the sample based on the category of the dependent variable, flows to connected funds are based on the whole sample, i.e. if there is a connection between a small cap stock fund and a large cap stock fund, flows to the large cap stock fund are considered within the spillover impact to the small cap stock fund. Models (i) and (ii) show the results for small cap stock funds, while models (iii) and (iv) show the results for large cap stock funds. All models are estimated using expected fund flows.[10]

The comparison of the spillover coefficients, especially the marginal impacts during periods of financial distress, reveals that the spillover effect is much more pronounced for small cap stock funds. For example, during crisis periods, the marginal impact of a one standard deviation increase in flows to all connected funds on the returns of small cap stock funds is 1.07%, but only 0.07% for large cap stock funds. Figure 3 provides a graphical illustration of the spillover effects for small cap stock

[10] The results based on actual flows are qualitatively robust.

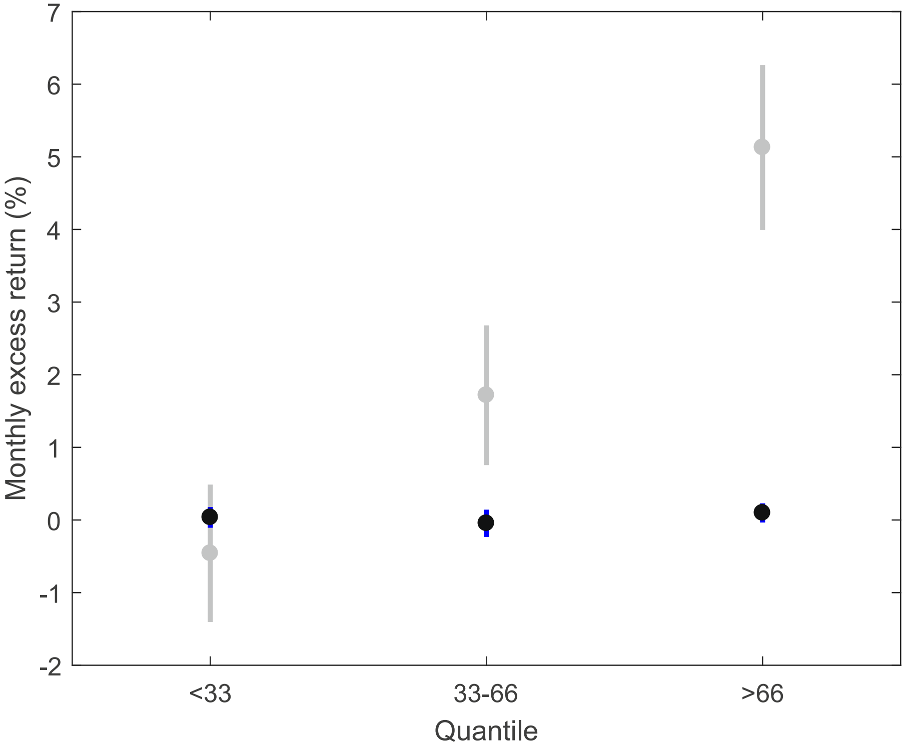

Fig. 2 The base effects are marked in black, and the marginal effects during asset fire sale periods are represented in grey

funds. During crisis periods, the spillover effect rises to 2.59% per month for the tertile of connected funds with the highest overlapping portfolio holdings. Overall, the findings in this section suggest that the spillover effect is related to the degree of underlying asset liquidity.

4.4 Spillover effects and diversification

After the financial crisis the transfer of systemic risk among financial institutions has become a matter of key interest. The extant literature on the dark side of diversification thus far predominantly focuses on theoretical contributions. Diversification increases the degree of commonality in the holdings of financial assets and may hence lead to an increased transfer of risks among financial institutions, in this case mutual funds. Our setting provides an ideal testbed to empirically test whether diversification increases risk among mutual funds via spillover effects from common portfolio holdings. To empirically test this idea, we investigate the relationship between the spillover effects and the diversification strategy of mutual funds. We measure a

Table 6 Spillover effects for small cap stock funds vs. large cap stock funds

	Small cap stock funds		Large cap stock funds	
	(i)	(ii)	(iii)	(iv)
Flow_connected	0.0027	–	0.0024***	–
	(0.0018)	–	(0.0010)	–
Flow_Q3	–	0.0029*	–	0.0002
	–	(0.0017)	–	(0.0008)
Flow_Q2	–	0.0006	–	–0.0005
	–	(0.0015)	–	(0.0010)
Flow_Q1	–	–0.0013	–	–0.0035***
	–	(0.0013)	–	(0.0011)
Flow_connected	0.1782***	–	0.0012	–
	(0.0106)	–	(0.0085)	–
Flow_Q3	–	0.1434***	–	0.0238***
	–	(0.0125)	–	(0.0065)
Flow_Q2	–	0.0252***	–	0.0180**
	–	(0.0113)	–	(0.0086)
Flow_Q1	–	–0.0201***	–	–0.0580***
	–	(0.0087)	–	(0.0064)
Control variables				
Expected Flow_own	0.0000	0.0000	–0.0003***	–0.0003***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
D_negative	0.4458***	0.3809***	–0.1366***	–0.1753***
	(0.0450)	(0.0448)	(0.0308)	(0.0325)
Excess Return_t-1	0.0295***	0.0304***	0.0347***	0.0299***
	(0.0060)	(0.0060)	(0.0046)	(0.0046)
Age	–0.1397***	–0.1340***	0.0382***	0.0337*
	(0.0216)	(0.0220)	(0.0173)	(0.0180)
Expense	0.1214	0.1230	–0.0756	–0.0532
	(0.0776)	(0.0773)	(0.0499)	(0.0499)
Family size	0.0004***	0.0004***	0.0006***	0.0006***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Fund size	–0.0380***	–0.0375***	–0.0039***	–0.0039***
	(0.0064)	(0.0064)	(0.0009)	(0.0009)
Cash	0.0022	0.0020	0.0007	0.0007
	(0.0063)	(0.0062)	(0.0008)	(0.0007)
Turnover	–0.0015	–0.0014	–0.0003	–0.0002
	(0.0025)	(0.0025)	(0.0011)	(0.0011)

Table 6 (continued)

	Small cap stock funds		Large cap stock funds	
	(i)	(ii)	(iii)	(iv)
Firm FE	Yes	Yes	Yes	Yes
Observations	87449	87449	121870	121870
R squared	0.032	0.033	0.025	0.027

This table contains the fixed effects panel regression results for spillover effects from fund flows on the performance of connected mutual funds, differentiating between the effects of small cap stock funds vs. large cap stock funds. The dependent variable is the monthly excess return of a fund relative to the fund size-weighted average return of all funds in our sample. The explanatory variables are the same as in Table 4. To test whether spillover effects are stronger for small cap stock funds, with split the sample into small cap stock funds and large cap stock funds. Models (i) and (ii) are estimated using expected fund flows, while models (iii) and (iv) are estimated using actual fund flows. Standard errors are in parentheses. Coefficients marked with ***, ** and * are significant at the 1%, 5%, and 10% level, respectively

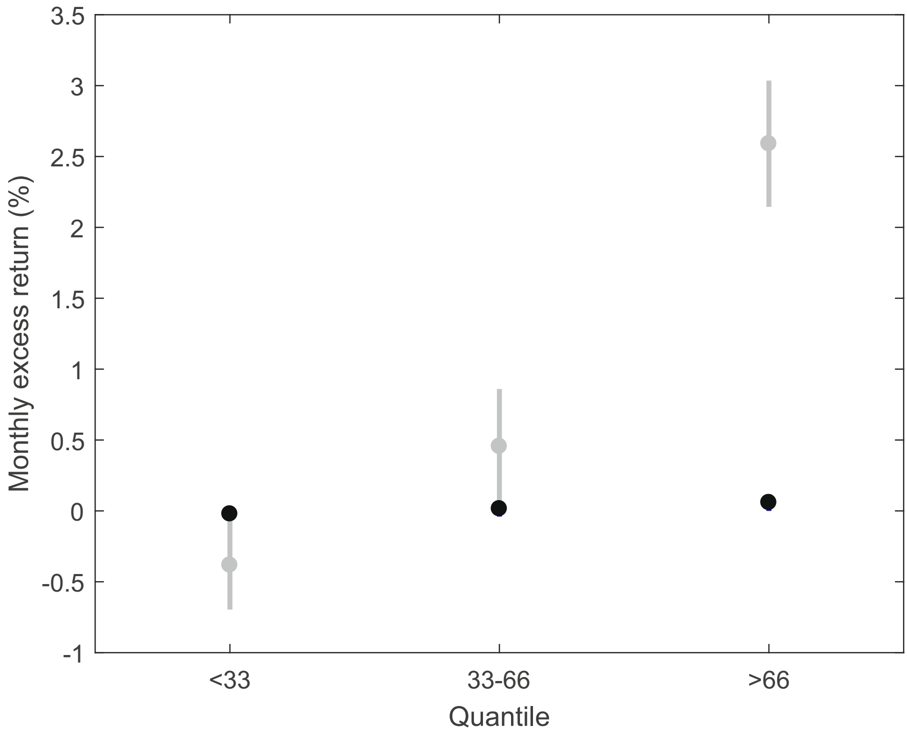

Fig. 3 The base effects are marked in black, and the marginal effects during asset fire sale periods are represented in grey

Table 7 Spillover effects for less diversified funds vs. highly diversified funds

	Less diversified funds (25% Highest HHI)		Highly diversified funds (25% Lowest HHI)		Highly diversified funds (< 50 Stocks)		Highly diversified funds (> 2000 Stocks)	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Flow_connected	–0.0092***	–	0.0063***	–	0.0003	–	0.0064*	–
	(0.0033)	-	(0.0013)	–	(0.0109)	–	(0.0038)	–
Flow_Q3	–	-0.0056**	–	0.0058***	–	0.0283***	–	0.0055
	–	(0.0029)	–	(0.0011)	–	(0.0120)	–	(0.0037)
Flow_Q2	–	-0.0044	–	0.0005	–	-0.0111	–	-0.0026
	–	(0.0028)	–	(0.0014)	–	(0.0158)	–	(0.0053)
Flow_Q1	–	-0.0016	–	-0.0011	–	-0.0231***	–	0.0020
	–	(0.0025)	–	(0.0015)	–	(0.0083)	–	(0.0040)
Crisis interaction terms								
Flow_connected	0.1058***	–	0.1780***	–	0.0960***	–	0.3744***	–
	(0.0211)	–	(0.0114)	–	(0.0420)	–	(0.0341)	–
Flow_Q3	–	0.0836***	–	0.1411***	–	0.0599	–	0.2836***
	–	(0.0170)	–	(0.0096)	–	(0.0690)	–	(0.0318)
Flow_Q2	–	-0.0061	–	0.0660***	–	0.0754	–	0.0994***
	–	(0.0207)	–	(0.0074)	–	(0.0871)	–	(0.0266)
Flow_Q1	–	-0.0060	–	-0.0588***	–	0.0460	–	-0.0279
	–	(0.0145)	–	(0.0076)	–	(0.0549)	–	(0.0264)
Control variables								

Table 7 (continued)

	Less diversified funds (25% Highest HHI)		Highly diversified funds (25% Lowest HHI)		Highly diversified funds (< 50 Stocks)		Highly diversified funds (> 2000 Stocks)	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Expected Flow_own	-0.0005	–0.0005	–0.0001	–0.0001	0.0000	–0.0014	–0.0002	–0.0002
	(0.0006)	(0.0006)	(0.0002)	(0.0002)	(0.0014)	(0.0013)	(0.0004)	(0.0004)
D_negative	0.2680***	0.2130**	0.3026***	0.2198***	0.0996	0.1039	0.2983***	0.3533***
	(0.0987)	(0.1013)	(0.0397)	(0.0381)	(0.2564)	(0.2632)	(0.1072)	(0.1181)
Excess Return_t-1	0.0799***	0.0783***	–0.0044	–0.0053	–0.0752	–0.0801	–0.0853***	–0.0846***
	(0.0136)	(0.0134)	(0.0053)	(0.0053)	(0.0568)	(0.0603)	(0.0144)	(0.0146)
Age	-0.0010**	–0.0010*	–0.0002	–0.0001	–0.0029***	–0.0039***	0.0000	0.0001
	(0.0005)	(0.0005)	(0.0002)	(0.0002)	(0.0013)	(0.0011)	(0.0007)	(0.0007)
Expense	0.0318	0.0362	0.2069***	0.2351***	–1.0728***	–1.0566***	–0.5596	–0.5448
	(0.0866)	(0.0943)	(0.0814)	(0.0810)	(0.2839)	(0.3128)	(0.3929)	(0.3879)
Family size	0.0005	0.0005	0.0003***	0.0003***	0.0005***	0.0005***	–0.0001	–0.0001
	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Fund size	-0.0567***	–0.0570***	–0.0013	–0.0013	0.1348	0.0244	0.0005	0.0005
	(0.0205)	(0.0208)	(0.0008)	(0.0008)	(0.1878)	(0.1865)	(0.0010)	(0.0010)

Table 7 (continued)

	Less diversified funds (25% Highest HHI)		Highly diversified funds (25% Lowest HHI)		Highly diversified funds (< 50 Stocks)		Highly diversified funds (> 2000 Stocks)	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Cash	0.0014	0.0015	-0.0013	-0.0015	0.1262	0.1289	-0.0443	-0.0374
	(0.0017)	(0.0018)	(0.0046)	(0.0047)	(0.0837)	(0.0880)	(0.0740)	(0.0766)
Turnover	-0.0019	-0.0019	-0.0052***	-0.0051***	0.0141	0.0181	-0.0760***	-0.0759***
	(0.0038)	(0.0037)	(0.0021)	(0.0021)	(0.0809)	(0.0791)	(0.0309)	(0.0313)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25172	25033	69500	69500	960	946	7128	7128
R squared	0.04	0.039	0.029	0.030	0.08	0.095	0.061	0.057

This table contains the fixed effects panel regression results for spillover effects from fund flows on the performance of connected mutual funds, differentiating between the effects of less diversified funds vs. highly diversified funds. The dependent variable is the monthly excess return of a fund relative to the fund size-weighted average return of all funds in our sample. The explanatory variables are the same as in Table 4. To test whether spillover effects are stronger for small cap stock funds, with split the sample into small cap stock funds and large cap stock funds. Models (i) and (ii) are estimated using expected fund flows, while models (iii) and (iv) are estimated using actual fund flows. Standard errors are in parentheses. Coefficients marked with ***, ** and * are significant at the 1%, 5%, and 10% level, respectively mutual fund's degree of portfolio diversification using the Herfindahl-Hirschman Index (HHI). The HHI of mutual fund i in period t is calculated by summing up the fund's squared portfolio postions:

$$HHI_{i,t} = \sum_{l=1}^{L_{i,t}} (h_{i,t}^{l})^2 \tag{11}$$

where $h_{i,t}^{l}$ and $L_{i,t}$ are defined as in previous section. HHI measures the level of concentration and it ranges from close to 0 to 1. When the HHI equals 1, it means that the fund holds only one stock and the concentration is highest. The lower the HHI value, the less concentrated fund's stock holding are. We split funds into two groups: Concentrated funds which are defined as the quartile of funds with highest HHI, and highly diversified funds which are defined as the quartile of funds with the lowest HHI. The regression results for the two groups of funds are reported in Table 7. Models (i) and (ii) show the results for less diversified stock funds, while models (iii)

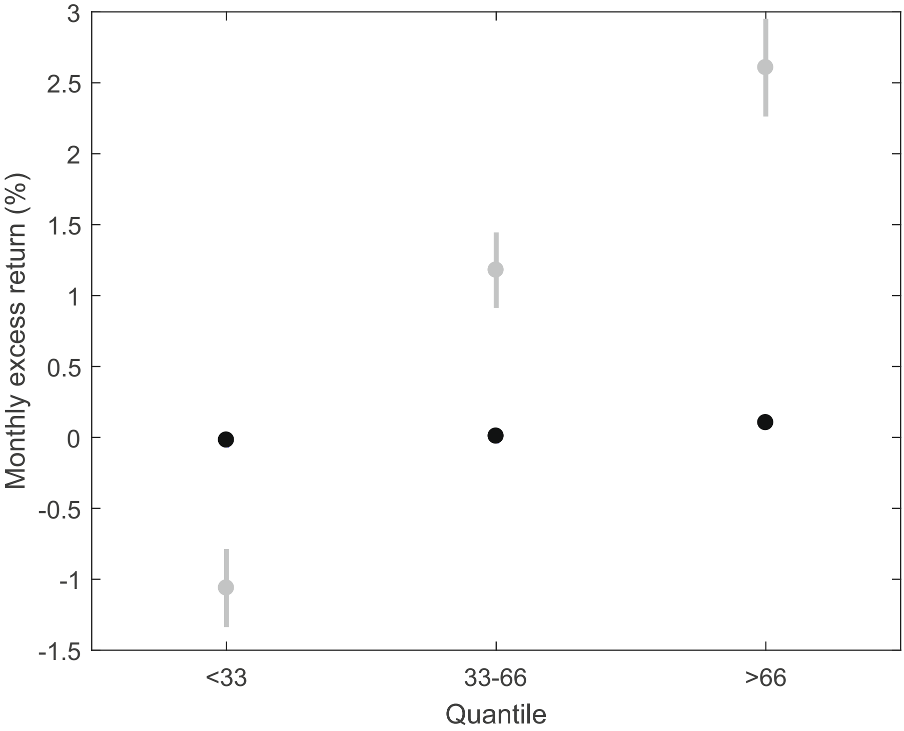

Fig. 4 The base effects are marked in black, and the marginal effects during asset fire sale periods are represented in grey

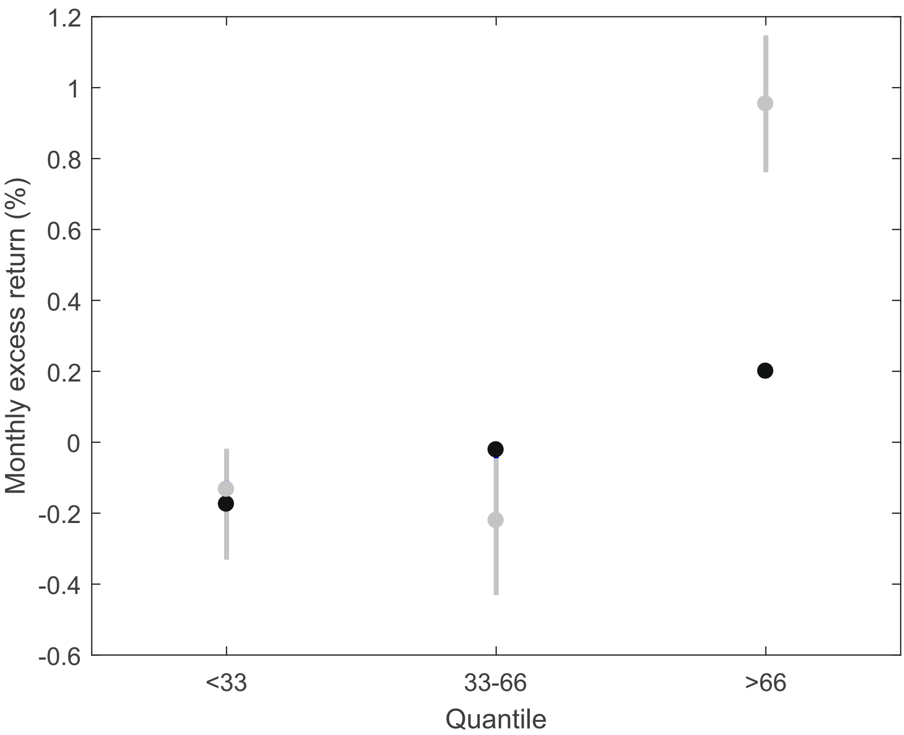

Fig. 5 The base effects are marked in black, and the marginal effects during asset fire sale periods are represented in grey

and (iv) show the results for well diversified funds. All models are estimated using expected fund flows.[11]

The coefficients for spillover effects for the two groups confirm our hypothesis that the spillover effect is more pronounced for highly diversified funds. For example, when there is a large outflow, the marginal impact of a one standard deviation increase inflows to all connected funds on the returns of highly diversified funds is 1.08%, which is around 2.5 times higher compared to concentrated funds. Figure 4 provides a graphical illustration of the spillover effects for the quartile of highly diversified funds. During crisis periods, the spillover effect rises to 2.61% per month for the tertile of connected funds with the highest overlapping portfolio holdings. It is notable that the typical level of diversification of the funds in our sample is rather high. For example, the 25 percentile of HHI is 0.014 while the 75 percentile HHI is only 0.036. To distinguish more clearly between concentrated and diversified funds,

[11] The results based on actual flows are qualitatively robust.

we also split the sample into funds holding less than 50 stocks and over 2000 stocks. Among the 3010 funds, only 14 funds invest in less than 50 stocks. Around 91 funds hold over 2000 stocks. The respective regression results are shown in models v to viii. As expected, the difference in spillover effects between these two groups is more pronounced. During crisis periods, the spillover effects for funds with over 2000 stocks amounts to 2.25%, while the funds holding less than 50 stocks obtain a spillover effect of only 0.57%. As shown in Fig. 5, the spillover effect grows to 5.13% per month for the most diversified tertile of funds within the group of highly diversified funds.

5 Conclusion

Building on the literature on flow-induced price pressure, this paper addresses a gap in the literature by providing a systematic assessment of how the relative performance of mutual funds is affected by fund flows to connected mutual funds. Using a sample of 3010 US-focused equity mutual funds, we provide strong empirical evidence for the fund flow spillover hypothesis. Moreover, our analysis provides the following three key findings: 1) the spillover effect is more pronounced noticeable during asset fire sale periods; 2) the spillover effect is particularly strong for small cap stocks funds; and 3) more diversified funds are more seriously affected by the spillover effect. Finding 1 links the spillover effect to the degree of liquidity in the market, whereas finding 2 relates the spillover effect to the degree of liquidity in the underlying assets held by the finds. Finding 3 lends empirical support to the dark side of diversification. Diversification goes hand in hand with a stronger connectivity to other funds in the industry. The resulting level of connectivity leads to an increased transfer of risks among mutual funds. Moreover, our findings on the dark side of diversification are also consistent with recent research by (Fulkerson and Riley 2019), who document higher risk-adjusted returns for less diversified mutual funds. Overall, our research demonstrates how individual mutual fund performance is affected by investor behaviour in connected mutual funds. Our results suggest that stakeholders in the open-end mutual fund industry should not only monitor industry-level fund flows, or flows to individual funds, but also consider the interrelation of individual mutual funds.

Funding Open Access funding enabled and organized by Projekt DEAL.

References

Acemoglu D, Ozdaglar A, Tahbaz-Salehi A (2015) Systemic risk and stability in financial networks. Am Econ Rev 105(2):564–608

Allen F, Babus A, Carletti E (2010) Financial connections and systemic risk

Allen F, Gale D (2000) Financial contagion. J Polit Econ 108(1):1–33

Antón M, Polk C (2014) Connected stocks. J Finance 69(3):1099–1127

Asgharian H, Hess W, Liu L (2013) A spatial analysis of international stock market linkages. J Banking Finance 37(12):4738–4754

Ben-Rephael A, Kandel S, Wohl A (2011) The price pressure of aggregate mutual fund flows. J Financ Quant Anal 46(02):585–603

Blocher J (2016) Network externalities in mutual funds. J Financ Mark 30:1–26

Budd BQ (2018) The transmission of international stock market volatilities. J Econ Financ 42(1):155–173

Chen Q, Goldstein I, Jiang W (2010) Payoff complementarities and financial fragility: Evidence from mutual fund outflows. J Financ Econ 97(2):239–262

Cherkes M, Sagi J, Stanton R (2009) A liquidity-Based theory of closed-End funds. Rev Financ Stud 22(1):257–297

Coval J, Stafford E (2007) Asset fire sales (and purchases) in equity markets. J Financ Econ 86(2):479–512

Edelen RM (1999) Investor flows and the assessed performance of open-end mutual funds. J Financ Econ 53(3):439–466

Edelen RM, Warner JB (2001) Aggregate price effects of institutional trading: A study of mutual fund flow and market returns. J Financ Econ 59(2):195–220

Eisenberg L, Noe TH (2001) Systemic risk in financial systems. Manag Sci 47(2):236–249

Elliott M, Golub B, Jackson MO (2014a) Financial networks and contagion. Am Econ Rev 104(10):3115–53

Elliott M, Golub B, Jackson MO (2014b, October) Financial networks and contagion. Am Econ Rev 104(10):3115–3153

Fernandez V (2011) Spatial linkages in international financial markets. Quant Finance 11(2):237–245

Frazzini A, Lamont OA (2008) Dumb money: Mutual fund flows and the cross-section of stock returns. J Financ Econ 88(2):299–322

Fulkerson JA, Riley TB (2019) Portfolio concentration and mutual fund performance. J Emp Finance 51:1–16

Gai P, Kapadia S (2010) Contagion in financial networks. Proc R Soc A Math Phys Eng Sci 466(2120):2401–2423

Goetzmann WN, Massa M (2003) Index funds and stock market growth. J Bus 76(1):1–28

Grinblatt M, Titman S (1989) Mutual fund performance: An analysis of quarterly portfolio holdings. J Business 393–416

Guercio DD, Tkac PA (2002) The Determinants of the Flow of Funds of Managed portfolios: Mutual Funds vs. Pension Funds. J Finan Quantit Anal 37(4):523

Ippolito RA (1992) Consumer reaction to measures of poor quality: Evidence from the mutual fund industry. J Law Econ 35:45

Jain P, Sehgal S (2019) An examination of return and volatility spillovers between mature equity markets. J Econ Financ 43(1):180–210

Lin L, Guo X-Y (2019) Identifying fragility for the stock market: Perspective from the portfolio overlaps network. J Int Financial Markets, Inst Money

Lou D (2012) A flow-Based explanation for return predictability. Rev Financ Stud 25(12):3457–3489

May RM, Arinaminpathy N (2010) Systemic risk: The dynamics of model banking systems. J R Soc Inter 7(46):823–838

Otten R, Bams D (2002) European mutual fund performance. Europ Financial Manag 8(1):75–101

Rakowski D (2010) Fund flow volatility and performance. J Financ Quant Anal 45(01):223–237

Shleifer A, Vishny RW (1997) The limits of arbitrage. J Finance 52(1):35–55

Slijkerman JF, Schoenmaker D, de Vries CG (2013) Systemic risk and diversification across european banks and insurers. J Banking Finance 37(3):773–785

Stein JC (2005) Why are most funds open-End? competition and the limits of arbitrage. Quarter J Econ 247–272

Upper C, Worms A (2004) Estimating bilateral exposures in the German interbank market: Is there a danger of contagion? Eur Econ Rev 48(4):827–849
Warther VA (1995) Aggregate mutual fund flows and security returns. J Financ Econ 39(2-3):209–235
Webster D (2002) Mutual fund performance and fund age. SSRN Electron J
Wermers R (2000) Mutual fund performance: An empirical decomposition into stock-Picking talent, style, transactions costs, and expenses. J Finance 55(4):1655–1695