Methodological details for blog post "Are Asset Managers Vulnerable to Fire Sales?"

This document describes the methodology behind analysis presented in the Liberty Street Economics blog post *Are Asset Managers Vulnerable to Fire Sales?,* published on February 18th, 2016.[1]

We discuss the different pieces of the methodology sequentially. First, how does the exogenous shock to interest rates affect individual fund performance? Second, how does a fund's performance induce investor redemptions? Third, how does the fund respond to outflows – if it sells assets, which assets and in what proportions? Fourth, what is the price impact of asset sales?

Sensitivity of fund performance to interest rate changes. The relationship between unanticipated interest rate changes and fund performance can be approximated by knowledge of the fund portfolio's average duration d. At first approximation, a parallel shift of the yield curve by Δr percentage points translates into a $\Delta r \times d$ percentage point decrease in the value of the assets in the portfolio.[2]

Sensitivity of investors' flows to fund performance. There is extensive academic literature analyzing theoretically the drivers behind the flow-performance relationship and well-established identification strategies to derive quantitative estimates of such relationships.[3] Following this literature, we estimate a fund-specific flow-performance sensitivity b. The methodology for calculating flow sensitivity is outlined in the Methodology section below.

Funds' response to investors' redemptions. We assume that funds respond to investor outflows with partial liquidation of the assets in their portfolio. Asset sales are not the only strategy a fund can adopt in response to outflows. For instance, a fund could first just reduce its cash buffer, activate existing credit lines with banking institutions, access existing cross-fund borrowing arrangements, or any combination of the above. Nonetheless, alternative response rules to asset sales can be easily accommodated given our methodology's linearity properties.[4]

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[1] The methodology is adapted from Duarte and Eisenbach (2015) and Greenwood, Landier, and Thesmar (2014).

[2] See, e.g., Fabozzi (1999).

[3] E.g., Goldstein, Jiang, and Ng, (2015), Chen, Goldstein, and Jiang (2010), Huang, Wei, and Yan (2007).

[4] At the same time, while it is reasonable to envision strategies other than asset sales in response to idiosyncratic, or even aggregate but mild shocks, the set of feasible strategies during severe macroeconomic, distressed scenarios may be more limited: Extensive disposals of cash buffers may not be optimal as it may be interpreted as a signal of weakness; cross-fund liquidity borrowing may not be available if distress is common across funds, and credit lines may be subject to restrictive covenants in broad distress scenarios.

Asset liquidation rule. We assume that funds sell assets in proportion to their initial holdings, so that their asset allocation remains unchanged. The proportional rule is a sensible assumption to capture average behavior and is consistent with empirical evidence.[5]

Asset liquidity. We follow the literature in assuming that asset sales have a proportional (linear) impact on prices.[6] Thus, if the sale of $10 billion of a given security reduces its price by 10 basis points, then the sale of $100 billion of the same security would reduce the price by 100 basis points.

The literature provides a wide range of possible liquidity estimates for the asset classes in our analysis. We establish a ranking of asset liquidities using the asset weights assigned in the Basel III Liquidity Coverage Ratio (LCR) and the proposals for the Net Stable Funding Ratio (NSFR). More detail is provided in the Methodology section.

We also assume that there are no cross-price effects from asset sales. In other words, the sale of an asset is reflected only in the price of that same asset and not in the prices of other assets.

Computation of the aggregate spillover. The spillover calculation proceeds as follows:

1) The interest rate shock Δr causes fund i with average duration d_i to experience a return of $-d_i \Delta r$ on its bond holdings.
2) With flow-performance sensitivity b_i, the fund suffers outflows $b_i d_i \Delta r$.
3) With total assets a_i and portfolio weight m_{ik} in asset class k, the fund sells $a_i m_{ik} b_i d_i \Delta r$ of asset class k. Across all funds, sales of asset class k are $\sum_i a_i m_{ik} b_i d_i \Delta r$.
4) With asset (il)liquidity ℓ_k, the sales of asset k cause a price drop of $\ell_k \sum_i a_i m_{ik} b_i d_i \Delta r$.
5) The price drop across all asset classes causes fund j to experience a spillover loss of $a_j \sum_k m_{jk} \ell_k \sum_i a_i m_{ik} b_i d_i \Delta r$.
6) Summing across funds, we get a total spillover loss $\sum_j a_j \sum_k m_{jk} \ell_k \sum_i a_i m_{ik} b_i d_i \Delta r$.

Similar to the decomposition in Duarte and Eisenbach (2015), total spillover losses here can be decomposed into three factors:[7]

$$\underbrace{a}_{\text{Agg. assets}} \times \underbrace{b}_{\text{Agg. sensitivity}} \times \underbrace{\sum_k m_k^2 \ell_k \sum_i \gamma_i \mu_{ik} \sigma_i d_i \Delta r}_{\text{Illiquidity concentration}}$$

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[5] See, e.g., Coval and Stafford (2007) and Jotikasthira, Lundblad, and Ramadorai (2012).

[6] See, e.g., Greenwood et al. (2014) and references therein.

[7] We denote by $\gamma_i = a_i / a$ fund i's assets as a share of system assets and by $\sigma_i = b_i / b$ fund i's flow-performance sensitivity relative to aggregate sensitivity. For the portfolio weights we denote by $m_k = \sum_i m_{ik} a_i / a$ the system portfolio weight for asset k and by $\mu_{ik} = m_{ik} / m_k$ fund i's portfolio weight for asset k relative to the system portfolio weight.

Investor redemptions link the initial shock to subsequent asset sales, as appropriate for asset managers. In Duarte and Eisenbach (2015), institutional leverage targeting serves as the link between shocks and asset sales for levered institutions.[8]

Data

Using Morningstar data, we create a quarter-end panel of mutual fund performance characteristics and asset allocations. The dataset records 10,638 unique funds between 2005q1 and 2015q1, and contains 279,390 fund-quarter observations. After screening for outliers (e.g., funds with relatively short life, unreliable data, etc.), the final dataset contains 254,526 observations and 10,511 unique funds.[9]

Fund assets are grouped into 14 asset classes according to Morningstar's asset class categorization.[10] Along with Morningstar's standard equity and bond categories, we account for aggregate cash and a residual asset class which encompasses a cluster of derivative-based instruments.

Methodology

We calculate flow-performance sensitivity at the fund level in two stages. First, for each fund *i* and every month *t*, we regress the fund's monthly returns $R_{i,\tau}$ (net of the risk-free rate) over the previous twelve months $\tau = t - 11, \dots, t$ on the monthly excess returns E_τ of the overall stock market (CRSP value-weighted):

$$R_{i,\tau} \;= \alpha_{i,t} + \beta_{i,t} E_\tau + \varepsilon_{i,\tau} \quad \text{for} \quad \tau = t - 11, \dots, t$$

In this regression, the intercept $\alpha_{i,t}$ measures fund *i*'s average monthly return in excess of the overall stock market over the previous 12 months including month *t*.
Next, for each fund i, we regress the fund's monthly flows $F_{i,t}$ on the fund's estimated α as of month t from the first stage:

$$F_{i,t} = a_i + b_i \, \hat{\alpha}_{i,t} + \epsilon_{i,t}$$

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[8] See also Greenwood et al. (2014).

[9] 17,644 (6%) observations and 99 (1%) funds were dropped by excluding funds with total asset allocations +/- 5 percentage points from 100, and 7,220 (3%) observations and 28 (~%) funds were dropped by removing observations with allocations of +/- 100 percentage points in any given asset class.

[10] The 14 asset classes used were equities (developed economies), equities (emerging economies), equities (not classified), agency MBS, bank loans, corporate bonds, covered bonds, asset backed securities, government bonds, municipal bonds, non-agency residential MBS, commercial MBS, cash, and residual assets.

The coefficient b_i represents the flow-performance sensitivity of fund i: it gives the net inflows into fund i (as a percentage of assets) associated with a 1 percentage point increase in the fund's average extra return (relative to the overall stock market) over the previous 12 months. In contrast to our approach, Goldstein et al. (2015) also control for monthly returns on a bond index in the first-stage regressions to isolate idiosyncratic fund performance above market alternatives. Since our spillover analysis involves a shock to the bond factor, we exclude this control to ensure that the sensitivity estimated in the second-stage regression includes investors' response to fund returns driven by the aggregate bond factor.

Simulation

We set the interest rate shock Δr to be a 100 basis points parallel increase in the yield curve. The shock affects any fund that reports duration for at least some portion of its portfolio holdings. These "bond funds" roughly correspond to four Morningstar fund types: Taxable Bond, Municipal Bond, Allocation and Alternative.

"Equity" funds (i.e. funds that do not report duration for any of their assets) are not subject to the initial interest rate shock. However, they are included, together with all the funds shocked originally, in the calculation of the overall fire sale spillover to the extent that they hold assets the prices of which are affected by the initial asset sales by the shocked funds. This acknowledges the price externality on equity securities that mixed strategy bond funds would impose when proportionately selling equity and fixed income securities.

Table 1 below shows the assumption regarding the relative market liquidity for the asset classes constituting funds' portfolios. As mentioned earlier, the parameters indicate a rank order across asset classes defined using information on the LCR and NSFR weights, selecting conservatively the higher weight between the two when there was discordance. More precisely, one asset class, corporate bonds, was set as the "pivot" category, and for that asset class it was assumed that a \$10 billion sale would correspond to a 10 basis points price decrease.[11] Then the liquidity of every other asset class was set according to its LCR or NFSR weight in relation to the weight assigned to corporate bonds.

We measure aggregate fire sale spillover vulnerability by taking the ratio of spillover losses to direct losses, which indicates how systemic a unit of direct loss can be in units of subsequent spillover losses. The chart in Figure 1 shows this ratio.

Figure 2 shows the decomposition of spillover losses into the three multiplicative factors shown above: aggregate assets, aggregate sensitivity, and illiquidity concentration. The final category is high when relatively illiquid assets are held by funds that are relatively large, have relatively high flow-performance sensitivity, have relatively long duration, or some combination of the three.

[11] This is the conventional assumption in Greenwood et al.(2014), and Duarte and Eisenbach (2015). Jotikasthira et al. (2012) find even larger price impacts for corporate bonds.

Table 1: List of asset classes and liquidities

Asset Class	**Price impact**
Cash	0
Equity – Region developed	$1.57e10^{-13}$
Equity – Region emerging	$2.14e10^{-13}$
Equity – Region unclassified	$2.14e10^{-13}$
Agency MBS	$0.43571e10^{-13}$
Bank Loan	$1.71e10^{-13}$
Corporate Bond	$1e10^{-13}$
Covered Bond	$1.85e10^{-13}$
Asset backed security	$2.85e10^{-13}$
Government and government-related bonds	$0.57e10^{-13}$
Municipal bonds	$2.85e10^{-13}$
Non-agency residential MBS	$2.85e10^{-13}$
Commercial MBS	$2.85e10^{-13}$
Residual assets	0

Notes: A price impact of $1e10^{-13}$ indicates a 10 basis point price decline per $10 billion worth of assets sold. The asset-specific liquidities are based on the liquidity weights given to asset classes in the LCR and NSFR rules produced by Basel III. The asset-specific liquidities were then normalized so that the liquidity of corporate bonds was $1e10^{-13}$ (in accordance with the literature, see above) and all other asset liquidities were defined relative to this benchmark liquidity.

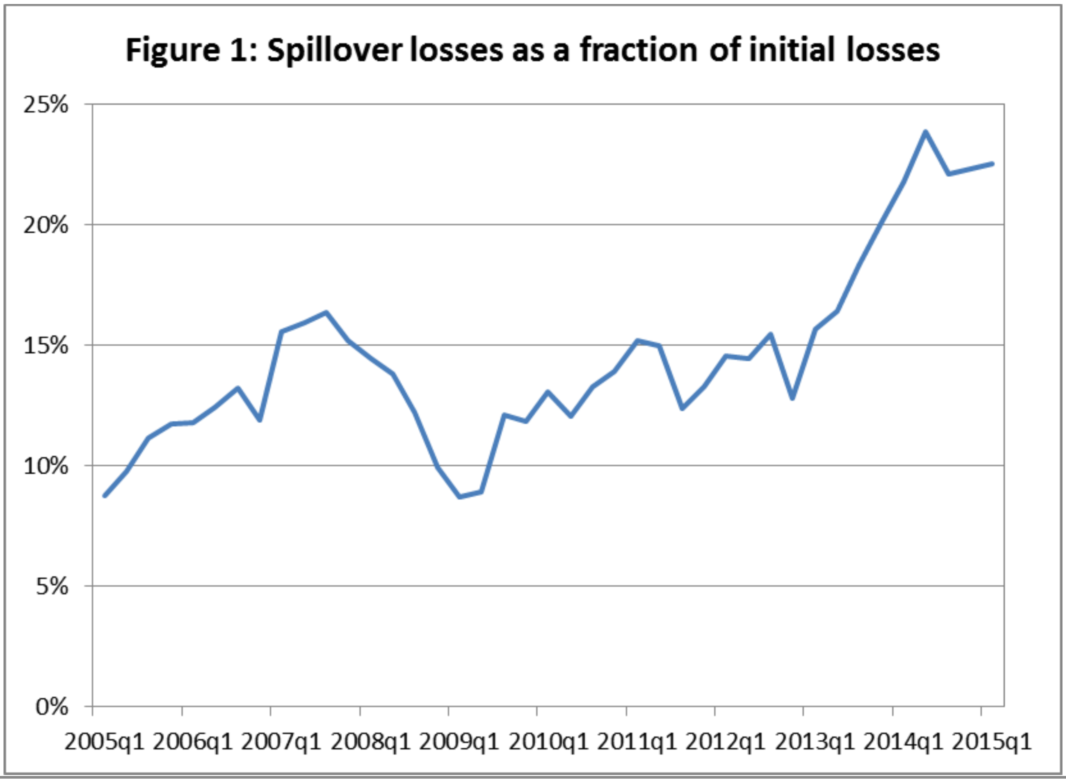
Figure 1: Spillover losses as a fraction of initial losses
25%
20%
15%
10%
5%
0%
2005q1 2006q1 2007q1 2008q1 2009q1 2010q1 2011q1 2012q1 2013q1 2014q1 2015q1

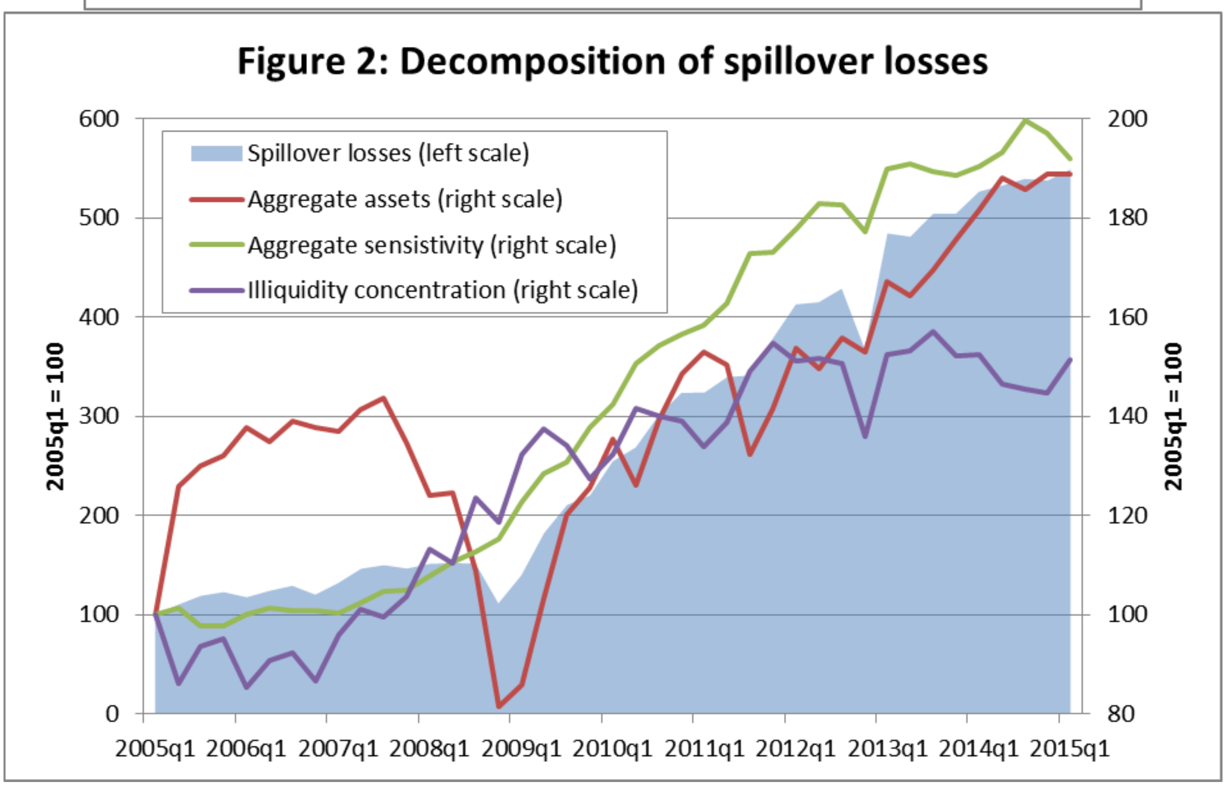
Figure 2: Decomposition of spillover losses
Spillover losses (left scale)
Aggregate assets (right scale)
Aggregate sensistivity (right scale)
Illiquidity concentration (right scale)
2005q1 = 100
600
500
400
300
200
100
0
200
180
160
140
120
100
80
2005q1 2006q1 2007q1 2008q1 2009q1 2010q1 2011q1 2012q1 2013q1 2014q1 2015q1

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