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Abstract

Banks carry significant exposures to nonbanks from direct dealings, but they can also be exposed, indirectly, through losses in asset values resulting from fire-sale events. We assess the vulnerability of U.S. banks to fire sales potentially originating from any of twelve separate nonbank segments and identify network-like externalities driven by the interconnectedness across nonbank types in terms of asset holdings. We document that such network externalities can contribute to very large multiples of an original fire sale, thus suggesting that conventional assessments of fire-sale vulnerabilities can be grossly understated and highlighting the value of treating nonbank financial institutions as one organic whole for monitoring purposes.

Key words: fire sales, network externalities, financial stability, nonbanks, monitoring

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1 Introduction

Non-Bank Financial Institutions' (NBFIs) involvement in credit intermediation activities has grown steadily since the end of the financial crisis of 2007-2008 to more than $60 trillion on a global scale in 2020, with the United States accounting for about a third of this amount (Global Monitoring Report on NBFIs, Financial Stability Board, 2021).[1] NBFIs have also grown increasingly more interconnected, and so have their linkages with banking institutions. As recently reported, bank exposures to NBFIs are "growing in size" and take the form of credit lines and term loans, securities financing and derivatives transactions.[2] As Vice Chair of Supervision Barr stated in a recent speech, "We need to worry, a lot, about non-bank risks to financial stability" because, among other things, "stress in non-bank financial markets is often transmitted to the banking system, both directly and indirectly."[3]

The risk exposures of banks from *direct* links to NBFIs are certainly of first-order importance. The inability of NBFI counterparties to honor their liabilities would cause losses and possible distress, with a potential for further shock propagation. However, banks may also be exposed to NBFIs *indirectly*, simply by virtue of common asset holdings: there may be states of the world where certain nonbanks may experience distress, and as a result they may be forced to sell assets at fire-sale conditions. Such asset sales, in turn, may depress prices and thus impair the net worth of banks that hold similar assets. In addition to recent, prominent examples of fire sales by British pension funds and U.S. money market funds (Li et al., 2021), this behavior has been documented for many other NBFI types, such as insurance companies (Merrill et al, 2021; Ellul et al., 2011; 2015), broker-dealers (see, e.g., Rosengren, 2014; Begalle et al., 2016; Carlson and Macchiavelli, 2020), hedge funds (Edwards, 1999) and equity and bond mutual funds (Coval and Stafford, 2007, Falato et al., 2021).

The importance of fire sales as channels of shock transmission and amplification of systemic instability is well known since the seminal work by Greenwood, Landier and Thesmar (2015, henceforth "GLT"), and Duarte and Eisenbach (2021). These authors, however, have placed their attention to shock transmission within the same industry segment, quantifying the vulnerability of banks to fire sales originated by other

[1] Included in this definition of NBFIs are, e.g., open-end funds, money market funds, finance companies, securities brokers and dealers, insurance companies, securitization vehicles.
[2] Basel Committee for Banking Supervision. "Newsletter on bank exposures to non-bank financial intermediaries," 11/24/2022. https://www.bis.org/publ/bcbs_nl31 htm
[3] "Why Bank Capital Matters." Remarks by Michael S. Barr, Vice Chair for Supervision, Board of Governors of the Federal Reserve System, 12/1/2022. https://www federalreserve.gov/newsevents/speech/barr20221201a.htm

banks. Similarly, Cetorelli, Duarte and Eisenbach (2016) quantified the fire-sale spillovers from poor-performing open-end funds, via outflows, onto other funds. Within-segment fire-sale vulnerabilities are a natural starting point, as institutions of the same type are likely to hold similar asset portfolios. However, asset holding commonalities also exist *across* segments of the broad financial industry, and especially so between banks and NBFIs that are also engaging in financial intermediation activities. Recently, Cetorelli (2021) examined *cross*-segment exposures, evaluating the vulnerabilities of U.S. banking institutions to potential fire sales initiated by open-end funds, documenting meaningful exposures and important consequences for banks' performance as a result of such exposures.

In this paper we explicitly emphasize the NBFI cross-segment dimension. We take a comprehensive approach, evaluating the fire-sale implications from shocks to banks and twelve separate NBFI segments (multiple types of insurance companies, open-end funds, hedge funds, pension funds, securities brokers-dealers, and finance companies). A focus on the cross-segment dimension is justified by the observation that, in distressed states of the world, distress is likely to materialize in the broad financial ecosystem, so that asset sales initiated in a given non-bank segment may not find other nonbanks able to act as "natural buyers" as in normal states of the world. In fact, an initial fire sale in those circumstances may *cascade* and lead to further sales from other nonbanks, either in anticipation of asset price dislocations or as a result of distress caused by the original sales.

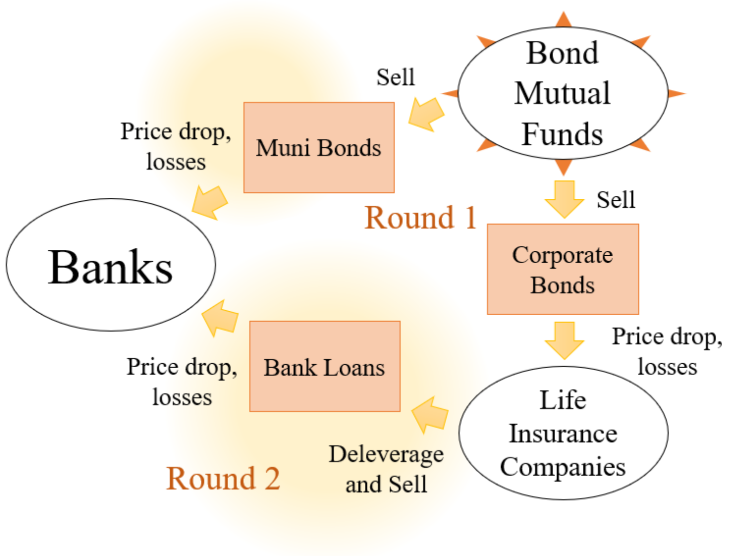
Highlighting whole-system interactions suggests potentially complex spillover channels when distress occurs in the NBFI space. Specifically, a bank may not have direct counterparty exposures to a given non-bank segment, and perhaps not even a close asset holding commonality with entities in that segment. However, a fire sale initiated by those entities may lead to asset sales of *other* non-bank segments whose asset holding profile is closer to that of banks.

Figure 1 uses a concrete, simple example to visualize the complexity of fire-sale spillover channels once the full network of NBFI segments is taken into consideration. Suppose a distress event forces nonbanks of a given segment (for instance, bond mutual funds) to sell a fraction of their assets. In this stylized example, funds sell municipal bonds and corporate bonds, thus potentially dislocating the prices of such asset classes. Let us assume that banks are directly affected by such market price effect only through their portfolios of municipal bonds (of course, banks may and do hold corporate bonds, but for the sake of this illustration we assume they do not). We call this the direct, "first-round" transmission channel of an original fire sale. However, another NBFI segment (for instance, life insurance companies) has large holdings of corporate bonds and is thus affected by bond funds' fire sales through this asset price channel. If life insurance companies need to resort to their own forced asset sales, including a portion of their bank loan holdings – an asset class U.S. insurers increasingly hold – the resulting impact on bank loan prices would in turn affect banks. This additional impact is part of what we call the indirect, "second-round" transmission channel.[4]

Hence, while banks may be directly impacted by bond funds' asset sales, the full impact may be much larger after taking into account the whole network of asset interconnections across all NBFI segments.

In this paper we identify network-like externalities associated with fire-sale events initiated by individual NBFI segments, driven by the interconnectedness across non-bank types in terms of asset holdings. We show that such network externalities can contribute to very large multiples of an original fire sale, thus suggesting that conventional assessments of fire-sale vulnerabilities can be grossly understated. Nonbanks can be legitimately seen as a set of separate segments in normal times, but they should be

Figure 1: Two rounds of fire-sale impact on banks.



considered as parts of an organic whole in analyzing and understanding the transmission and the amplification of stress scenarios in the financial ecosystem.

In our study we shock each NBFI segment separately and trace both its direct, first-round impact on banks and the indirect, second-round effect on banks generated via the first-round effect on all other

[4] We are aware that the terms "first-" and "second-round" suggest a sequential dimension, but in practical terms the fire-sale spillovers we are analyzing can propagate very fast and in fact even simultaneously: entities in a given NBFI segment may resort to asset sales in *anticipation* of losses from another segment's distress.

NBFI segments. By comparing the separate effects from each shock, we identify and rank specific NBFI segments in terms of their direct impact on banks. Finance companies and life insurers are estimated as imposing the largest direct losses on banks, followed by bond mutual funds, hedge funds, and pension funds.

The quantification of the second-round spillover effects identifies a *manifold* of distinct distress paths, themselves amenable to a rank ordering in terms of their importance for banks. Once second-round effects are computed, bond and equity funds appear to be the NBFI segments responsible for the largest overall spillovers on banks, followed by pension funds, life insurers and exchange traded funds. The reshuffling in the rank orderings from first- to second-round effects is driven by, among other factors, the shock originators' degree of asset holding interconnections in the cross-section of segments, and thus by their capacity to propagate and compound an original distress event across the entire ecosystem.

2 Methodology

The methodology builds on recent works (GLT, 2015; Cetorelli et al., 2016; Duarte and Eisenbach, 2021) and lends itself to examining fire-sale cascades triggered by either a price shock or a portfolio shock. A price shock is defined as a drop in the price of every asset in an asset class (expressed as a percent return). A portfolio shock is defined as the partial sale of the portfolios of every institution in a segment (expressed as a list of dollar amounts, one for each asset class, indicating the amounts sold). We refer to the consequences of this original trigger as a "cascade" in the sense that portfolio sales cause further price drops and price drops cause further portfolio sales.[5] Note, however, that we abstract from the cause of the original trigger.

Like our predecessors, we assume that prices react linearly to fire sales (i.e., if the dollar amount sold is twice as large, the percentage drop in price is also twice as large). Our approach thus requires specifying fire-sale elasticities, i.e., the coefficients that map a certain dollar sale to a certain percent drop in price. Our approach also requires the specification of a shock response function for each institution type, which is part of our contribution. The extent to which institutions may resort to asset sales is likely to be heterogenous across segments. We approximate this heterogeneity with a series of linear reaction functions (interchangeably referred to as "reaction coefficients"). While we present our results based on a specific set of assumptions governing the calculation of the loss response functions, the methodology is

[5] Of course, one could conceive *further* knock-on rounds beyond the second, the analysis of which would only reinforce the central message of our contribution.

designed to allow alternative assumptions that could render those response functions more or less “aggressive”. We discuss our assumptions and some possible alternatives in Section 3.3.

We employ our framework for a specific exercise. For each institution type, we assume a 1% portfolio shock, i.e., a uniform sale of 1% of that institution’s portfolio across all asset classes. We then work out the consequences for banks by examining the first-round spillover impact.[6]

We begin with a hypothetical example to illustrate the methodology. Assume that bond mutual funds (segment s) hold an amount $q_{s,a} = \$2{,}500$ billion of corporate bonds (asset a). Because of some adverse event, bond funds are forced to sell a fraction $\alpha = 1\%$ of their holdings, including \$25 billion worth of corporate bonds. The percent impact on bond prices is proportional to the amount sold based on an elasticity coefficient $e_a = 1.00 \cdot 10^{-13}$. Bond prices therefore decline by $\alpha \cdot q_{s,a} \cdot e_a = 0.25\%$. Banks (segment B) hold approximately $q_{B,a} = \$900$ billion of corporate bonds, and thus this drop in bond prices causes market-value losses of $\alpha \cdot q_{s,a} \cdot e_a \cdot q_{B,a} = \$2.25$ billion for banks. We define the first-round spillover impact from s to banks (or any other segment) as the sum of market value losses over all asset classes:

$$L_{1,s\to B} = \sum_a \alpha \cdot q_{s,a} \cdot e_a \cdot q_{B,a}. \qquad (1)$$

Continuing with the above example, suppose that life insurers (segment t) hold $q_{t,a} = \$3{,}200$ billion of corporate bonds. The initial fire sale of corporate bonds by bond funds causes life insurers to sustain a market-value loss of $\alpha \cdot q_{s,a} \cdot e_a \cdot q_{t,a} = \$8$ billion. Aggregating these and other losses over all asset classes, the total first-round spillover loss from bond mutual funds to life insurers is, say, \$10 billion:

$$L_{1,s\to t} = \sum\nolimits_a \alpha \cdot q_{s,a} \cdot e_a \cdot q_{t,a} = \$10 \text{ billion.}$$

We assume for the purposes of this example that life insurers sell $R_t = 10$ dollars of assets for every dollar of market-value losses, i.e., a total of $L_{1,s\to t} \cdot R_t = \$100$ billion worth of assets.[7] Finally, we

[6] We assume a uniform shock set at 1% to facilitate the comparison in the resulting effects across segments and to allow the establishment of meaningful rank orderings. The magnitude of the shock itself is just one parameter that could be modified at will to approximate alternative scenarios. For instance, one could recognize that a “typical” shock would be greater than 1% for some institution types and less than 1% for others, and accordingly assume segment-specific, empirically motivated initial shocks.

[7] As discussed, the actual reaction functions of institutions would be heterogeneous. The present assumption that $R = 10$ for insurance companies is just for the sake of illustration. We make and motivate our assumptions in Section 3 – namely, Section 3.2 for the specific asset class breakdown and related price elasticity coefficients, and Section 3.3 for the institution type breakdown and related response coefficients.

assume that the sales are made proportionally out of a segment's existing portfolio. Thus, for instance, if life insurers hold $q_{t,b} = \$200$ billion of bank loans out of a total overall portfolio of $\sum_a q_{t,a} = \$5{,}000$ billion, they will sell $L_{1,s\to t} \cdot R_t \cdot (q_{t,b}/\sum_a q_{t,a}) = \$100$ billion $\cdot\ (200/5{,}000) = \$4$ billion worth of bank loans.

The effect of this sale on bank loan prices is, once again, proportional to the amount sold and to the elasticity of bank loan prices which we assume to be (again for the purposes of the current example) $e_b = 2 \cdot 10^{-13}$. The total loss caused for banks by this sale is then equal to the percent drop in bank-loan prices times the amount held by banks (say, $q_{B,b} = \$4{,}000$ billion), i.e.,

$$L_{2,s\to t\to B,b} = L_{1,s\to t} \cdot R_t \cdot (q_{t,b}/\textstyle\sum_a q_{t,a}) \cdot e_b \cdot q_{B,b} = \$3.2 \text{ billion.}$$

Finally, to compute the grand total second-round spillover impact of bond mutual funds onto banks, we sum the above expression over all assets b and all segments t (other than the shock originator itself, s, and the ultimate shock receiver, B), obtaining

$$L_{2,s\to B} = \sum_{t\notin\{s,B\}} \sum_b L_{2,s\to t\to B,b} = \sum_{t\notin\{s,B\}} \sum_b \left(\sum_a \alpha q_{s,a} e_a q_{t,a} \right) R_t \frac{q_{t,b}}{\sum_a q_{t,a}} e_b q_{B,b},$$

or, rearranging,

$$L_{2,s\to B} = \alpha \sum_{t\notin\{s,B\}} R_t \frac{1}{\sum_a q_{t,a}} \left(\sum_a q_{s,a} e_a q_{t,a} \right) \left(\sum_b q_{t,b} e_b q_{B,b} \right). \tag{2}$$

This expression highlights the five factors that contribute to the size of the second-round spillover impact from a segment to another (bond mutual funds to banks, in this case). The first one is α, the size of the initial portfolio shock. The next four factors are inside the summation over all intermediate segments (i.e., excluding the shock originator and the shock receiver). For each segment, the second factor is R_t, that segment's response coefficient, the specific nature of which we describe below. The third factor is the inverse of the size of the intermediate segment. For a given initial dollar shock, a larger intermediate segment will be less impacted and therefore transmit less. The fourth and fifth factors (the two summations in parentheses) are the sizes of the first-round impact of, respectively, the shock originator on the intermediate segment and the intermediate segment on the shock receiver.

Note that we exclude the "self-links" (the shock originator, s, and the ultimate shock receiver, B) because our aim is to capture the amplification effect of an initial shock to a given NBFI entity type through the impact on every other type.

3 Inputs

Our computation requires three inputs: portfolio holdings, fire-sale elasticity coefficients (mapping a fire-sale amount to a percent drop in price), and loss response coefficients (mapping a loss to a fire-sale amount).

3.1 Portfolio holdings

In order to assess spillover risk, we need to know which financial institutions hold which assets. Given the broad, cross-sectional scope of our study, we do not conduct the analysis using entity-specific data, as is done in the extant literature. Instead, we use aggregate, segment-specific information, thus trading off granularity in exchange for breadth. We discuss this tradeoff in greater detail below in Section 3.2. We obtain this information from the quarterly Financial Accounts of the United States (Z.1) issued by the Federal Reserve Board, commonly known as the Flow of Funds (FoF). These tables contain, among other information, dollar holdings by holder entity type and asset class. We use data for the period from 2007q1 to 2021q4.

The FoF identifies several entity types. We include eleven entity types that we consider relevant for an analysis of fire sales: *Private Depository Institutions* (or *Banks*),[8] *Property-Casualty Insurance Companies* (or *P&C Insurers*), *Life Insurance Companies: General Accounts* (or *Life Insurers*), *Money Market Funds* (or *MMFs*), *Mutual Funds*, *Exchange-Traded Funds* (or *ETFs*), *Mortgage REITs*, *Security Brokers and Dealers* (or *Broker-Dealers*), *Hedge Funds*, *Defined Benefit (DB) Pension Funds* (both *Private* and *State and Local Government*) and *Finance Companies*.[9] (Throughout the paper, capitalized and italicized labels indicate specific entity types as defined for the purpose of our analysis, whereas non-italicized labels indicate a looser definition.) We exclude *Equity REITs*, which do not hold meaningful financial assets, and other categories for which we do not immediately identify a mechanism that would

[8] *Private Depository Institutions* includes all banks and bank-like entities such as thrifts and credit unions. It also includes foreign banking offices in U.S., but it does not include bank holding companies (BHCs) and intermediate holding companies (IHCs) which are included under *Holding Companies*. Holding companies are the unconsolidated filers of forms Y-9LP and Y-9SP and they are excluded from this version because they do not hold significant assets subject to fire sales. See *Z.1: Financial Accounts of the United States – All Table Descriptions* (henceforth "Guide"), L.131.
[9] Form G-20 filers. To learn more, see https://www.federalreserve.gov/releases/g20/current/g20.htm

lead to fire sales: *Life Insurance Companies: Separate Accounts*,[10] *Government-Sponsored Enterprises (or GSEs)*, *Agency- and GSE-Backed Mortgage Pools*, *Issuers of ABS*, *Holding Companies*, and *Other Financial Business*.[11]

Since most mutual funds are specialized to one type of holdings, grouping all mutual funds under one monolithic institution type is likely to overestimate the spillover effects. For instance, corporate bond fire sales *per se* are unlikely to cause losses for equity funds, and so forth. To reflect this fact, we further subdivide the *Mutual Funds* category into *Mutual Funds (Equity)*, *Mutual Funds (Bonds)*, and *Mutual Funds (Hybrid)*, bringing the total number of institution types to thirteen. We allocate the total assets reported in the FoF under *Mutual Funds* among these three constructed institution types proportionally to the amounts reported for the same three institution types in the Total Net Assets data from the Investment Company Institute (ICI). While the ICI data totals do not always correspond to the FoF totals, they are always in the same order of magnitude and follow a comparable trend. We also allocate cash and short-term paper proportionally, then assume that the balance of equity funds is equity and the balance of bond funds is a mix of noncash long-term fixed income assets. Finally, hybrid funds are credited with the remaining assets in all categories.

The FoF also identifies many asset types. We include eight asset types: Equity (30641), Agency MBS (30617), Bank Loans (40230), Open Market Paper (30691), Corporate and Foreign Bonds (30630), Government Bonds (30611), Municipal Bonds (30620), and Cash (the sum of various cash and cash-like instruments). Except for cash, these asset types are selected according to a few criteria. First, they are tradable and thus possibly subject to fire sales. Second, they are held by more than one entity type. We exclude: (i) non-tradable, institution-specific assets like "policy payables"; and (ii) mutual fund shares. The latter include both traditional mutual fund investments and money-market mutual fund shares held as investments by other institutions. Mutual fund shares can only be redeemed, not sold, and thus do not have an own price, distinct from that of the underlying assets, that can be affected by fire sales. Table 1 shows the most recent cross-holding matrix by institution type and asset from the 2021q4 FoF. As the

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[10] *Life Insurance Companies: Separate Accounts* include the assets that back variable annuities. These could behave like mutual funds and be subject to outflows following bad performance. They are excluded now but could be included in a future version.

[11] Regardless of whether *GSEs* are included, *Agency- and GSE-Backed Mortgage Pools* should remain excluded as they are consolidated under *GSEs*. See the footnotes to tables L.125 and L.126 or the Guide.

table shows, asset classes are broadly held across segments, thus suggesting a potential for diffused shock transmission across the entire network of institution types.

Table 1. Cross-holding matrix from the 2021q4 Flow of Funds, adjusted to break Mutual Funds down into three subtypes. Definitions are in the text.

Amounts in $ billion	Equity	Agency MBS	Bank Loan	Open Market Paper	Corp Bond	Gov Bond	Muni Bond	Cash	Total
Banks	54	3,883	12,631	0	888	1,641	643	4,221	23,962
P&C Insurers	643	136	28	4	702	188	289	142	2,133
Life Insurers	133	231	808	23	3,266	175	222	141	4,998
Money Market Funds	0	410	0	226	7	1,815	111	2,640	5,208
Mutual Funds (Equity)	14,270	0	0	26	0	0	0	190	14,486
Mutual Funds (Bonds)	0	492	131	10	2,485	1,447	900	73	5,537
Mutual Funds (Hybrid)	1,264	49	13	3	250	145	90	24	1,840
Exchange-Traded Funds	5,804	0	0	0	800	331	83	39	7,057
Mortgage REITs	0	168	0	0	12	0	0	17	197
Broker-Dealers	234	54	0	16	15	99	13	1,396	1,827
Finance Companies	0	0	1,026	0	99	0	0	57	1,182
Hedge Funds	1,140	8	181	0	474	165	15	227	2,210
Pension Funds	4,932	321	23	44	1,312	695	0	666	7,993
Total	28,475	5,753	14,840	354	10,308	6,701	2,367	9,832	

3.2 Estimating price impact of asset sales

The methodology follows the literature in assuming that the sale of assets has a proportional (linear) impact on prices. This means that 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. During a systemic event it seems likely that this assumption would not hold, and that in fact the asset sales may be occurring at a time when all these institutions would be on the same side of the market, i.e., when "natural buyers" are less willing or able to absorb the excess demand by the very definition of a fire sale (See, e.g., Shleifer and Vishny, 2011). In that sense, the results can be interpreted as a conservative approximation of the actual disruption that could be observed during generalized distress scenarios.

Besides linearity, it is assumed that different asset classes exhibit different degrees of liquidity. Reliable point estimates of asset market liquidity are not available in the literature. However, the methodology can impose a reasonable rank order in the degree of illiquidity of various asset classes. The ordering is established using information contained in the weights assigned to different assets in the calculation of the Basel III Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR) using the procedure described in Duarte and Eisenbach (2015). Some degree of judgment was introduced in the case of asset classes that did not perfectly map into the asset classes listed in the LCR and NSFR documentation (see, e.g., Cetorelli et al, 2016, Duarte and Eisenbach, 2021).

Our challenge is to map the Basel asset classes to the ones listed in the FoF. Some asset classes have a direct correspondence: *Agency MBS*, *Bank Loans*, *Government Bonds*, and *Municipal Bonds*. Others do not have a perfect correspondence:

- *Corporate Bonds*: Corporate and Foreign Bonds in the FoF includes foreign government bonds and Non-agency MBS and ABS. These three categories have three different firesale elasticities. We assume that the large majority of Corporate and Foreign Bonds are *Corporate Bonds* and apply that firesale elasticity.
- *Equity*: Equity in the FoF is aggregated, whereas in the LCR and NSFR rules it is subdivided by region ("developed", "emerging", and "unclassified"), with different firesale elasticities. We assume that all equity shown in the FoF is developed.
- *Open Market Paper*: Open market paper (commercial paper and bankers' acceptances) does not have a coefficient. We assume the coefficient to be half that of *Corporate Bonds*.
- *Bank Loans*: The FoF provides a granular breakdown of Bank Loans (into residential mortgages, commercial mortgages, consumer loans, etc.). However, currently, we only have one elasticity coefficient, so we lump all these categories together.

The asset classes we examine are therefore the following: *Equity*, *Agency MBS*, *Bank Loans*, *Open Market Paper*, *Corporate Bonds*, *Government and Related Bonds*, *Municipal Bonds*, and *Cash*. Here, too, italicized labels indicate the specific asset categories as defined for the purpose of our analysis.

This asset-class classification, partly driven by the data structure of the Flow of Funds, is admittedly fairly coarse, disregarding the existence of meaningful sub-categories within each class. For instance, bank loans include, among others, both commercial and industrial loans and home mortgages, municipal bonds include general obligation bonds and revenue bonds, etc. Similar to previous work, we treat each asset class as a homogeneous whole and therefore implicitly assume significant price correlations within each asset class, so that sales of a given sub-category are expected to have a diffuse impact *within* that asset class. Also in line with previous work, it is assumed that there are no cross-price effects *across* asset classes. This amounts to assuming, e.g., that the sale of a corporate bond has the same effect on all corporate bonds, but it does not affect the price of municipal bonds. This last example highlights that coarseness and granularity result, respectively, in overestimation of within-class spillovers and underestimation of across-class spillovers, so that the net effect of additional coarseness or granularity is not univocal.

3.3 Loss response coefficients

The last ingredient is a loss response coefficient for each institution type, i.e., the fraction of the portfolio sold for a given percent loss in portfolio value. The mechanisms that induce different institution types to resort to fire sales are heterogeneous, but we identify two main classes: fund outflows and deleveraging.

Institutions subject to outflows include all mutual funds and other unlevered collective investment vehicles like ETFs that tend to experience outflows in response to poor performance. For these institutions, we thus assume a flow-performance relationship as in Cetorelli et al. (2016) and assume that the resulting outflows translate roughly one-to-one into asset sales.[12]

Institutions subject to deleveraging, on the other hand, include banks, finance companies, broker-dealers, and roughly speaking also hedge funds and insurance companies.[13] For these institutions, we use a target leverage rule as in Duarte and Eisenbach (2021) and GLT (2015), i.e., we assume that the main response mechanism is deleveraging to restore the pre-shock leverage ratio. While this is our assumption, there is also evidence that the extent of such adjustments are not uniform across firms. Banks and other leveraged institutions can also react to a loss with a mix of capital conservation via cutting distributions, job cuts, and simply tolerating a temporarily lower leverage ratio. In our analysis we abstract from these considerations and assume full adjustment as a benchmark. Other papers (e.g., Duarte and Eisenbach, 2021) use a partial adjustment mechanism, whereby the firm responds to the initial shock by disposing of assets in an amount equal to a fraction of the initial shock. This assumption can be either interpreted as a partial adjustment rule or that the adjustment is complete but that it is not done instantaneously but rather over an extended period, and we are just capturing the effect over the first adjustment period. It is easy to define and apply a partial adjustment rule. Under such a rule, our analysis would be bound to produce

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[12] In the case of ETFs, asset sales result when authorized participants (APs) arbitrage price differences by redeeming underpriced shares and liquidating the underlying assets. Although this is only one of many ways an AP may react to an arbitrage opportunity, there is evidence that on average this is what happens (see, e.g., Pan and Zheng, 2020). We thus roughly assimilate ETFs to other collective funds.

[13] While hedge fund can be subject to *both* outflows *and* deleveraging, they rarely offer demand liquidity to investors, substantially reducing the importance of the former mechanism. Similar to banks, insurance companies are subject to both market and regulatory capital constraints. We thus assimilate both institution types to leveraged institutions.

more conservative results than those under a full leverage adjustment rule. This could, in turn, affect our relative ranking of levered institution types and unlevered ones, such as mutual funds.

The relevant coefficients can be assumed based on a mix of estimates from the literature and a priori knowledge of the mechanism that drives the firesale for that entity type. This methodology is ad hoc, but transparent and defensible and lends itself easily to sensitivity analysis, one instance of which is in the Appendix. In the rest of this subsection we provide specific detail on our assumptions.

3.3.1 Banks, other lenders, and levered investment funds

For banks and other levered lenders (including *Banks*, *Finance Companies*, and *Broker-Dealers*), and for *Hedge Funds*, the main response mechanism is deleveraging. Namely, an institution may react to an initial shock, and resulting increase in leverage, with asset sales in order to return to pre-shock leverage levels. There is evidence in the literature of such "active" balance sheet management, suggesting that financial firms target an optimal leverage level and adjust asset size accordingly every time the balance sheet experiences a departure from such target (e.g., Adrian and Shin, 2010).

We define the leverage ratio (LR) as total capital over total assets. For banks we can assume, as in Duarte and Eisenbach (2021), that banks attempt to sell assets to return to the pre-shock leverage level. Thus, the response coefficient is[14]

$$R = 1 / LR - 1. \qquad (3)$$

For banks and other levered lenders, we use an LR of 0.08, thus obtaining a response coefficient R = 11.5. This value is a rough approximation of banks' actual raw leverage ratio. For instance, according to the most recent (2022q1) FRBNY Research report on bank holding companies (BHC), total equity is $2.5T and total assets are $27.5T, for a raw leverage ratio of 9%. However, banks with assets greater than $750B have $1.15T in equity and hold $14.3T in assets, for a raw leverage ratio of 8%.[15]

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[14] A bank with $10 of assets and $2 of equity has a leverage ratio of 2 / 10 = 0.2. If a shock wipes out $1 of assets, the bank is left with $1 of equity and $9 of assets. At the pre-shock leverage level, the bank's equity can now support assets worth $1 / 0.2 = $5, and thus the bank should sell assets worth $4 = (1 / 0.2 – 1), hence the above formula.

[15] Quarterly Trends for Consolidated U.S. Banking Organizations, Federal Reserve Bank of New York (https://www.newyorkfed.org/research/banking_research/quarterly_trends). Similarly, according to the most recent (2022q3) data for FDIC-Insured Commercial Banks and Savings Institutions, total assets are $23.6T (FRED QBPBSTAS) and total equity is $2.1T (FRED QBPBSTLKTEQKTBKEQK) for a raw leverage ratio of 8.9%.

We use this coefficient for *Banks*, but also for *Security Brokers and Dealers*, which engage in lending and are also subject to a kind of capital regulation, and for *Finance Companies*. These other leveraged lenders have different balance sheets and face different rules than banks. However, as a simplification, we use the same coefficient as *Banks* because these institutions engage in business of a similar nature as banks.[16]

For *Hedge Funds*, we compute leverage including information on derivatives. Namely, we define the leverage ratio as the ratio of (Total Assets – Total Liabilities)/(Total Assets + Derivatives Long Exposure), i.e., dollars of net worth divided by total dollars at risk.[17] While this definition is arbitrary and hides a great heterogeneity in the use of derivatives among hedge funds, we believe it is the most meaningful definition that is feasible using FoF data.[18] Based on this definition, we compute the R coefficient for hedge funds for every quarter in which data is available (2012q4 to 2021q4). The R coefficient over this period is reasonably stable and thus we adopt the average value throughout the period, R=1.28.[19]

Note that this R coefficient only represents the lender's own deleveraging response following losses induced by fire sales. As banks and other lenders engage in maturity and liquidity transformation, additional asset sales could be induced by the drying up of the lender's funding sources, such as short-term borrowings and, for banks, deposits.

3.3.2 Insurance companies

Similar to lenders, we assume that, after a shock, insurance companies attempt to return to the pre-shock level of regulatory capital, as measured by the Risk-Based Capital (RBC) ratio.[20] While the effect of

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[16] For the sake of comparison, at 2021Q4, Broker-Dealers had approximately $300B equity (FRED) and $4200B total assets (FoF) or a 7% raw leverage ratio. Finance Companies had $250B equity (FRED) and $1700B total assets (FoF) or a 15% raw leverage ratio.

[17] To the best of our understanding, the "Derivatives Long Exposure" item in the FoF is obtained from SEC Form PF information. The derivatives long exposure reported in those forms is generally delta-adjusted, so it is effective (as opposed to notional) exposure.

[18] In the FoF, hedge funds are typically aggregated together with other household assets and liabilities. However, the aggregate balance sheet of hedge funds is available among supplemental materials (Table b101 f).

[19] Barth, Hammond and Monin (2020) use disaggregated SEC Form PF data to examine the cross-section of hedge-fund leverage. The measures they report imply an R coefficient between 0.6 and 2.7, depending on the exact definition of leverage used. This range provides some confidence in our rough estimate of 1.28.

[20] The complex regulatory capital calculus of insurance companies is described, for instance, in Ellul et al (2011, 2015). One important aspect of this calculus are the "mark-to-market" rules that determine whether declines in the market value of investments should be immediately recognized as losses. Even when these rules allow delayed recognition, the ability of

market-value losses on regulatory capital ratios is complex and not always instantaneous, there are several forces (including the institution's own risk management processes) that push towards such an outcome. In practice, during the 2007 financial crisis, insurance companies have engaged in substantial fire sales of residential mortgage-backed securities (Merrill et al, 2021) and bonds (Ellul et al., 2011; 2015).

We obtain separate coefficients for *Life Insurance Companies* and *Property-Casualty Insurance Companies* as:

$$R = 1 / (RBC\ Ratio * Average\ Factor), \qquad (4)$$

Where, for each institution type, $RBC\ Ratio$ is the value-weighted average RBC Ratio (sum of numerators / sum of denominators across all companies) and the $Average\ Factor$ is the aggregate portfolio-weighted National Association of Insurance Commissioners (NAIC) capital charge on the bond holdings of each institution type. We use the pre-2021 rules based on coarse rating,[21] so that, e.g., the capital charge for NAIC 1 rated bonds (AAA to AA corporates) is 0.30% and the charge for NAIC 6 rated bonds (C and below) is 19.50% for Life and 30% for P&C. Together with current RBC Ratios of 8.83x and 5.79x, respectively, we thus obtain coefficients of R = 13.28 and R = 23.35.

As is for banks, the R coefficient only represents the firm's own "deleveraging" (or "de-risking") response, and we exclude other sources of risk such as funding risk. For life insurance companies, surrender risk creates a problem akin to bank deposit flight. Although life insurance and annuity products are generally considered to be relatively long-term liabilities, a substantial portion of these liabilities are available for discretionary withdrawal with little or no penalty and therefore can, in practice, turn out to be short-term liabilities. This risk is likely underestimated (see, e.g., Burkhart, 2018, or Koijen and Yogo, 2022).

3.3.3 Unlevered collective investment funds

Finally, for unlevered collective investment funds (all *Mutual Funds*, *Money Market Funds*, and *Exchange-Traded Funds*), the main mechanism relates to outflows following negative performance. To

financial firms to access debt or equity in markets will depend on the market value of the firm. In the 2007 financial crisis, regulatory and book capital ratios for many firms did not show signs of distress, yet the ability of these firms to access funding markets was severely limited and many insurance companies accessed government facilities to raise funds.

[21] In July of 2021, the NAIC adopted new risk-based weights based on more granular ratings. Using these newer weights does not result in a materially different R coefficient.

estimate these flows, we can rely on published estimates of the flow-performance relationship together with the a priori knowledge that outflows cause funds to sell in an approximate 1:1 ratio with the size of the outflows, as in Cetorelli et al. (2016). It is important to note that most published estimates measure the flow relationship to the fund's abnormal performance ("alpha") and not to absolute performance (see, e.g., Huang et al., 2007; Chen et al., 2010). One paper that attempts to measure the overall flow-performance relationship with a macro view is Anadu et al. (2020). We thus adopt the coefficients from this paper (R = 0.035 for equity funds and R = 0.785 for bond funds).[22] We apply the former coefficient to *Equity Mutual Funds*, and the latter to *Bond Mutual Funds*, and *Money Market Funds*. For *Hybrid Mutual Funds* and *Exchange-Traded Funds*, whose holdings include both bonds and equity, we compute a composite coefficient equal to the value-weighted average of bonds and equity held by each fund type. The percentages of equity in each fund are, respectively, 70% and 83%, resulting in coefficients R = 0.258 and R = 0.160, respectively.

3.3.4 Non-redeemable collective funds: defined benefit pension funds and mortgage REITs

As shown by the recent (2022) UK episode, a combination of adverse market movements and regulations can force pension funds to sell assets. On one hand, to the best of our understanding, US pension fund rules seem to insulate US pension funds from market movements to a large degree. On the other hand, however, regulation and other forces can cause pension funds to experience a sudden, idiosyncratic need to reallocate their portfolio. We thus include *Pension Funds* because of their size and potential to be the initiators of fire sales, but we set their R coefficient (i.e., their ability to transmit shocks) to zero. Similar considerations apply to *Mortgage REITs*.

4 Results: fire-sale threat to banks

Fire-sale spillover risk is interesting from a broad financial stability perspective, but also from a more traditional bank safety and soundness perspective. More precisely, the applications of this methodology demonstrate how a monitoring framework centered on NBFI entities and their activities can provide unique insights to enhance the supervisory process for banking institutions. It is thus interesting to apply our framework to identify which NBFI segments present the greatest fire-sale spillover risks *for banks*.

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[22] This coefficient is obtained by summing the estimated regression coefficients on *Return[t]* (row 3) and *Return[t-1]* (row 4) from their Table 2 on p. 12. Note that, other than Anadu et al (2020), the rest of the literature measures much higher coefficients for equity funds (0.67-0.70). As a conservative robustness check, we also run our exercise using a coefficient of R = 0.785 for all funds. The results are reported in the Appendix.

To this end, as anticipated in Section 2, for each institution type we assume a 1% portfolio shock (i.e., a fire sale of 1% of the institutions' portfolio applied proportionally across all asset classes) and then compute the consequences for bank capital through the fire-sale channel.[23] We compute both the direct, first-round effects of each segment's fire sales on banks, and the matrix of second-round effects through the knock-ons onto the entire cross section of segments. A general note on the interpretation of the results: the absolute values of the estimated losses are not immediately interpretable, as they are determined by the chosen set of parametric assumptions governing the simulations, presented in Section 3. Consequently, we cannot say whether a given effect is "small" or "large" in an absolute sense.[24]

However, since the assumptions remain the same across the simulations, we can legitimately interpret the results in a relative sense, thus assessing whether an effect is smaller or larger than another one. Consequently, the insights from the analysis are mainly presented in terms of *rank orderings* within the cross section of segments and between the first and the second rounds.

Table 2 shows the results from first-round and second-round effects from the assumed fire sales. The first column in the table indicates in each row the institution type that originates the fire sale. The second column reports the aggregate balance sheet size of each institution type. The third to fifth columns display the first-round effects, expressing the relative degree of vulnerability of *Banks* to hypothetical NBFI fire sales: respectively, the dollar loss on the aggregate balance sheet, the loss as a percentage of aggregate equity capital, and the rank order of each NBFI institution type by loss size. *Finance Companies* and *Life Insurance Companies* are nearly tied for first place, followed by *Mutual Funds (Bonds)*, *Hedge Funds*, and *Pension Funds*. Similar to the analysis in GLT (2015), an institution's importance to banks (their "systemicness") depends on multiple factors: size (how many *dollars* of assets does it sell, given that we assume a 1% *percent* portfolio liquidation), interconnectedness (does it hold asset classes that banks also hold), and liquidity of holdings (for a given sale amount, more illiquid assets will have a greater price impact, resulting in greater losses for holders of those assets). Both life insurance companies and finance companies hold bank loans, which are relatively illiquid and obviously also a large fraction of banks' portfolios. Life insurers are much larger than finance companies, but their

[23] We are writing the paper with a focus on banks on the receiving end of shocks, but clearly the considerations related to the network of asset holding commonalities apply more generally across the whole cross section of NBFI segments, which we examine in Section 5.

[24] This observation applies equally to any of the contributions to fire-sale vulnerabilities that are based on the GLT (2015) original methodology. The methodology however is amenable to specific, *ad hoc*, calibrations to gauge the scale of the specific impact of hypothetical fire sales, as done, e.g. in the work summarized in Cetorelli and Sarkar (2023).

holdings are much more diversified, including asset classes like equities that are not generally held by banks.

Various types of collective investment funds (*Mutual Funds (Bonds)*, *Hedge Funds*, and *Pension Funds*) take the next few spots in the ranking. Note that both *Hedge Funds*' and *Pension Funds*' holdings are concentrated in equities. Since equities are relatively liquid, and since *Banks* hold very little in equities, they should be relatively unaffected by equity fire sales. However, because of their size and leverage, *Hedge Funds* and *Pension Funds* still manage to rank fourth and fifth overall, above *Money Market Funds*.

We can also show the breakdown of the first-order losses by asset classes. Table 3 shows the contribution to total bank capital loss of the shock on each asset class, as a result of the first-round fire sales of each shocked institution (the row sums equal the totals in column 4 of Table 2). The table shows that losses are very concentrated on bank loans for the top two institution types (*Life Insurance Companies* and *Finance Companies*) and for *Hedge Funds*, and dispersed among several fixed-income asset classes for the other runners-up (*Mutual Funds (Bond)* and *Pension Funds)*. Note that the *Cash* column contains all zero values because *Cash* does not give rise to losses.

Table 2: First- and second-round losses for Banks

		First-Round Loss			Second-Round Loss			
Institution Type	Size ($B)	$B	% Bank Capital	Rank	$B	% Bank Capital	Rank	Network Multiplier
Banks	23,962							
P&C Insurers	2,133	-2.2	-0.12%	7	-18.6	-0.97%	7	89%
Life Insurers	4,998	-21.3	-1.11%	2	-45.9	-2.39%	4	68%
Money Market Funds	5,208	-2.6	-0.14%	6	-2.9	-0.15%	10	53%
Mutual Funds (Equity)	14,486	-1.2	-0.06%	9	-60.3	-3.15%	2	98%
Mutual Funds (Bonds)	5,537	-8.9	-0.46%	3	-68.6	-3.58%	1	89%
Mutual Funds (Hybrid)	1,840	-1.0	-0.05%	10	-12.3	-0.64%	8	93%
Exchange-Traded Funds	7,057	-1.7	-0.09%	8	-43.4	-2.27%	5	96%
Mortgage REITs	197	-0.3	-0.02%	11	-0.4	-0.02%	12	57%
Broker-Dealers	1,827	-0.2	-0.01%	12	-1.5	-0.08%	11	86%
Finance Companies	1,182	-22.3	-1.16%	1	-10.3	-0.54%	9	32%
Hedge Funds	2,210	-4.6	-0.24%	4	-23.6	-1.23%	6	84%
Pension Funds	7,993	-3.3	-0.17%	5	-52.8	-2.75%	3	94%

Source: Authors' calculations on data from Financial Accounts of the United States and Investment Company Institute.
Note: This table presents the spillover losses suffered by private depository institutions based on the scenario that a particular NBFI institution type experiences 1% portfolio shock. The table shows both the first-round and second-round losses. The second column presents the total amount of assets (in billions) for each institution type. The following columns report the first and second round separately as dollar amount (in billions), as proportion (in percent of bank capital), and as rank (#1 indicates the greatest loss). The last column shows the "Network Multiplier," defined as the ratio of second-round loss over total (first- plus second-round) loss.

Table 3: Asset class heatmap of the first-round losses of Banks

	Equity	Agency MBS	Bank Loan	Open Market Paper	Corp Bond	Gov Bond	Muni Bond	Cash
P&C Insurers	0.00%	-0.01%	-0.03%	0.00%	-0.03%	-0.01%	-0.03%	0.00%
Life Insurers	0.00%	-0.02%	-0.91%	0.00%	-0.15%	-0.01%	-0.02%	0.00%
Money Market Funds	0.00%	-0.04%	0.00%	0.00%	0.00%	-0.09%	-0.01%	0.00%
Mutual Funds (Equity)	-0.06%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Mutual Funds (Bonds)	0.00%	-0.04%	-0.15%	0.00%	-0.12%	-0.07%	-0.09%	0.00%
Mutual Funds (Hybrid)	-0.01%	0.00%	-0.01%	0.00%	-0.01%	-0.01%	-0.01%	0.00%
Exchange-Traded Funds	-0.03%	0.00%	0.00%	0.00%	-0.04%	-0.02%	-0.01%	0.00%
Mortgage REITs	0.00%	-0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Broker-Dealers	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Finance Companies	0.00%	0.00%	-1.16%	0.00%	0.00%	0.00%	0.00%	0.00%
Hedge Funds	-0.01%	0.00%	-0.20%	0.00%	-0.02%	-0.01%	0.00%	0.00%
Pension Funds	-0.02%	-0.03%	-0.03%	0.00%	-0.06%	-0.03%	0.00%	0.00%

We now consider the losses incurred by every institution type, and their resulting second-round fire sales. Before displaying the full second-order effects, it is helpful to visualize the intermediate steps, represented by the entire matrix of first-round effects, showing the impact of an original shock to each segment on every other segment. This matrix is reported in Table 4. (Table A.6 in the Appendix contains the matrix of second-round effects and is accompanied by some methodological notes.)

The *Banks* column shows the direct impact on banks and the figures correspond to column 4 of Table 2. The $(N-1)\times(N-1)$ submatrix that excludes the *Banks* row and column instead reports the effect of a shock to each NBFI segment on every other NBFI segment. Visual inspection and analysis of the network characteristics of this submatrix provides insight into the calculation of the second-round effects, but more importantly, it affords a view and an understanding of NBFIs from an integrated, ecosystem-wide perspective. For example, we can assess the "cohesion" within the NBFI space as shown by the density of the submatrix, i.e., the frequency of non-zero cells. Although many cells in the table appear to be zero because of rounding, 97 percent of the cells are non-zero, with an average impact across all non-zero cells equal to -0.75. Note that, since the computed magnitudes depend on our assumptions, non-zero cells imply a qualitatively different degree of cohesion than zero cells. The high cohesion of this network, at least for 2021q4, is a direct indication of the need to consider NBFI segments as an organic whole, at least when it comes to an understanding of their role as shock transmitters.

Likewise, the matrix allows the identification of the relative "centrality" of each segment, both in their role as transmitters and as receivers. On the receiving end, both *P&C* and *Life Insurers* appear to be very central, as their columns in the submatrix display a balance sheet vulnerability to shocks originating from

Table 4: Whole-network analysis. First-round effect as a percentage of target equity.

Values in Percent		**Final shock received by…**												
		Banks	P&C	Life	MMF	MFE	MFB	MFH	ETFs	REIT	B&D	FinCo	HF	PF
Shock originates from…	Banks		-2.5	-6.1	0	0	-0.2	-0.1	0	-0.2	-0.2	-23.5	-0.5	0
	P&C Insurers	-0.1		-0.8	0	-0.1	0	-0.1	-0.1	0	-0.2	-0.1	-0.2	-0.1
	Life Insurers	-1.1	-3.1		0	0	-0.2	-0.1	-0.1	0	-0.1	-1.8	-0.2	-0.1
	Money Market Funds	-0.1	-0.4	-0.1		0	0	0	0	0	-0.1	0	0	0
	Mutual Funds (Equity)	-0.1	-16.4	-0.9	0		0	-1.5	-1.8	0	-3.6	0	-2.6	-1.4
	Mutual Funds (Bonds)	-0.5	-3.1	-2.6	0	0		-0.1	0	0	-0.1	-0.5	-0.1	0
	Mutual Funds (Hybrid)	-0.1	-1.8	-0.3	0	-0.2	0		-0.2	0	-0.3	-0.1	-0.2	-0.1
	Exchange-Traded Funds	-0.1	-7.4	-1.1	0	-0.9	0	-0.6		0	-1.5	-0.1	-1.1	-0.6
	Mortgage REITs	0	0	0	0	0	0	0	0		0	0	0	0
	Broker-Dealers	0	-0.3	0	0	0	0	0	0	0		0	0	0
	Finance Companies	-1.2	-0.1	-0.5	0	0	0	0	0	0	0		0	0
	Hedge Funds	-0.2	-1.7	-0.6	0	-0.2	0	-0.1	-0.2	0	-0.3	-0.4		-0.1
	Pension Funds	-0.2	-6.8	-1.6	0	-0.8	-0.1	-0.6	-0.7	0	-1.3	-0.2	-1.0	

almost every other NBFI segment. On the origination side, *Pension Funds*, *Equity funds*, but also *Exchange Traded Funds* seem to have the potential to impose losses on the largest cross section of segments (as shown by their respective rows in the submatrix).

Finally, the submatrix also allows to differentiate the role of the different segments in terms of their ability to be a "hub" of shock propagation for specific segments or subset of segments. For example, maintaining the focus on banks' vulnerability, while it is the case that both *P&C* and *Life Insurers* appear to have a highly central position in the network, for their diffused asset commonality with every other NBFI segment, it is also the case that, *from the perspective of Banks*, *Life Insurers* are much more important hubs of shock impulses, given their much higher direct impact on *Banks*.

Importantly, these network-related properties are time-dependent, thus lending themselves to be tracked over time to yield updated monitoring priorities.

We can now discuss the results of the impact on banks of the second-round sales, shown in Table 2. *Mutual Funds (Bonds)* are the highest ranked as shock originators, followed by *Mutual Funds (Equity),* *Pension Funds and Life Insurers.* What, besides the large size of these segments, accounts for the rank ordering reshuffling? Intuitively, it must be driven by the ability of these sectors to affect many sectors in the whole NBFI space (so that the resulting induced effects on banks add up to large losses) or impose important asset losses on specific sectors that in turn can affect banks more severely. Our quantitative analysis shows that both mechanisms are at play: *Mutual Funds (Bonds)* hold mostly *Corporate Bonds,* which are the most broadly held asset class, which explains why *Mutual Funds (Bonds)* can impose diffused first-round losses across the segments (see its corresponding row in Table 4). Hence, an original firesale concentrated in bonds has large second-round effects. At the same time, equity assets may not be as broadly held in the cross-section of segments, but *Mutual Funds (Equity)*'s fire sales have a significant, concentrated effect on specific sectors, such as *P&C Insurers* and *Hedge Funds* (see *Mutual Funds (Equity)*'s row in Table 4), which in turn translates in large second-round effects through a combination of size and asset overlap with *Banks*. At the other extreme, *Finance Companies*' rank drops from first to seventh. While their loan sales can hurt banks directly, due to their portfolio concentration they are less likely to hurt others, and thus the additional induced fire sales are relatively less severe. Table 5 shows the corresponding heatmap by shocked institution and bank holding type. Losses are still concentrated, but not as in the first round, and the table shows large values for *Equity*, *Bank Loans*, and *Corporate Bonds*.

Table 5: Heatmap of the second-round losses of Banks. The Cash column is filled with zero values because cash does not generate losses.

	Equity	Agency MBS	Bank Loan	Open Market Paper	Corp Bond	Gov Bond	Muni Bond	Cash
P&C Insurers	-0.06%	0.00%	-0.07%	0.00%	-0.77%	-0.01%	-0.06%	0.00%
Life Insurers	-0.02%	0.00%	-1.61%	0.00%	-0.73%	0.00%	-0.03%	0.00%
Money Market Funds	0.00%	-0.02%	0.00%	0.00%	-0.01%	-0.09%	-0.03%	0.00%
Mutual Funds (Equity)	-3.15%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Mutual Funds (Bonds)	0.00%	-0.02%	-0.31%	0.00%	-2.91%	-0.07%	-0.26%	0.00%
Mutual Funds (Hybrid)	-0.28%	0.00%	-0.03%	0.00%	-0.30%	-0.01%	-0.03%	0.00%
Exchange-Traded Funds	-1.27%	0.00%	0.00%	0.00%	-0.95%	-0.02%	-0.03%	0.00%
Mortgage REITs	0.00%	-0.01%	0.00%	0.00%	-0.01%	0.00%	0.00%	0.00%
Broker-Dealers	-0.05%	0.00%	0.00%	0.00%	-0.02%	-0.01%	0.00%	0.00%
Finance Companies	0.00%	0.00%	-0.43%	0.00%	-0.11%	0.00%	0.00%	0.00%
Hedge Funds	-0.22%	0.00%	-0.43%	0.00%	-0.56%	-0.01%	0.00%	0.00%
Pension Funds	-1.09%	-0.01%	-0.05%	0.00%	-1.56%	-0.04%	0.00%	0.00%

Finally, the last column of Table 2 shows the "network multiplier", defined as the ratio of the second-round loss over the total (first- plus second-round) loss. This share is the result of a combination of connectedness, leverage, and holdings illiquidity: for a given asset class held by banks, the same volume of fire sales can have different effects if the asset class is illiquid, and if it is also held by leveraged non-bank investors. As the column shows, the network multipliers are estimated to be very large, often over eighty percent. Thus, if we only focus on the direct effect of a given NBFI segment onto banks, we are missing an important and potentially dominant component of the total effect.

We dig deeper in the analysis of the second-round effects. Specifically, we would like to know the relative contribution of each NBFI type to the total second-round effect of a given NBFI type. The results are in Table 6.

The rightmost "Total" column contains the same numbers as column 7 of Table 2 (second-round percent loss). These totals are decomposed in the rest of each row. For instance, the effect on bank capital of a 1% sale by *Mutual Funds (Bonds)* (-3.58%, fifth row) is largely transmitted via the *Life Insurance Companies* channel (-2.68%) and in minor part via the *Property-Casualty Insurance Companies* and *Finance Companies* channels (-0.34% and -0.54%, respectively). The table also reveals that the effect of *Life Insurance Companies* (-2.39%, second row) is largely transmitted, because of loan sales, via *Finance Companies* (-1.96%).

Table 6: Relative second-round contribution from different intermediate shocks transmitters (in column), given an initial 1% portfolio shock hitting an institution type (in row).

Values in Percent	P&C	Life	MMF	MFE	MFB	MFH	ETFs	REIT	B&D	FinCo	HF	PF	Total
P&C Insurers		-0.79	0.00	0.00	-0.02	0.00	0.00	0.00	0.00	-0.13	-0.02	0.00	-0.97
Life Insurers	-0.34		0.00	0.00	-0.06	0.00	0.00	0.00	0.00	-1.96	-0.03	0.00	-2.39
Money Market Funds	-0.04	-0.09		0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.15
Mutual Funds (Equity)	-1.82	-0.88	0.00		0.00	-0.02	-0.03	0.00	-0.04	0.00	-0.36	0.00	-3.15
Mutual Funds (Bonds)	-0.34	-2.68	0.00	0.00		0.00	0.00	0.00	0.00	-0.54	-0.02	0.00	-3.58
Mutual Funds (Hybrid)	-0.20	-0.35	0.00	0.00	-0.01		0.00	0.00	0.00	-0.05	-0.03	0.00	-0.64
Exchange-Traded Funds	-0.82	-1.16	0.00	0.00	-0.02	-0.01		0.00	-0.02	-0.09	-0.15	0.00	-2.27
Mortgage REITs	0.00	-0.02	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	-0.02
Broker-Dealers	-0.03	-0.04	0.00	0.00	0.00	0.00	0.00	0.00		0.00	-0.01	0.00	-0.08
Finance Companies	-0.01	-0.51	0.00	0.00	0.00	0.00	0.00	0.00	0.00		-0.01	0.00	-0.54
Hedge Funds	-0.19	-0.61	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	-0.41		0.00	-1.23
Pension Funds	-0.76	-1.61	0.00	0.00	-0.03	-0.01	-0.01	0.00	-0.01	-0.19	-0.13		-2.75
Total	-4.56	-8.74	-0.01	0.00	-0.15	-0.04	-0.04	0.00	-0.09	-3.38	-0.76	0.00	

The bottom row of Table 6 presents another kind of "Total": the aggregate second-round contribution of each institution type across the whole network. For instance, *Life Insurance Companies* (-8.74%, the bottom row) contributes the most to the transmission of the second-round spillovers from other institution types to *Banks*, with the majority contribution (-2.68%) via transmitting the initial 1% sale by *Mutual Funds (Bonds)*. *Property-Casualty Insurance Companies* come next (-4.56%), and their impact comes largely from transmitting the initial portfolio shock from *Mutual Funds Equity* (-1.82%) to *Banks*. These results show that insurance companies, and especially life insurers, are a central hub in the network of financial institution types because of their diversified holdings.

As discussed in Section 2, our analysis excludes self-links. As a form of robustness check, Tables A.3-A.5 in the Appendix reproduce the analysis of Tables 2, 5, and 6, this time including the effect of the shock originator upon itself.

5 Whole-network analysis

Our analysis so far has focused on firesale spillovers from NBFIs onto banks. Our methodology, however, can be applied to any segment – bank or non-bank – of the financial system and thus enables us to obtain a global view of the system by mapping the potential for firesale spillovers throughout the entire network of financial institutions. We do so by examining the network multipliers of every institution type vis-à-vis every other institution type. While no single table can express the entirety of information embedded in this complex and interconnected network, we believe that the network multipliers capture the least obvious aspect of interconnectedness: the type of connections that are not visible without running an exercise like ours. Since the network multiplier is defined as second-round loss divided by total (first- plus second-round) loss, a large share between two segments signifies that the second-round interaction between the two segments (i.e., the interaction that is mediated by third segments) is large compared to the direct interaction.

The matrix of network multipliers is shown in Table 7. By construction, this matrix is symmetric.[25] The main diagonal entries are blank because, as elsewhere, we do not focus on the effect of segments on themselves.

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[25] The symmetry stems from the fact that the matrix of *dollar* losses (both first- and second-round) is itself symmetric, as can be easily seen from the expressions for $L_{1,s\to B}$ and $L_{2,s\to B}$ (equations 1 and 2) in Section 2. The reason is that our framework is

Table 7. Second-round share matrix. The table shows the second-round dollar *loss divided by total (first- and second-round) loss. The second-round share matrix is symmetric.*

Values in Percent						Final shock received by...							
Shock originates from...	Banks	P&C	Life	MMF	MFE	MFB	MFH	ETFs	REIT	B&D	FinCo	HF	PF
Banks		89	68	53	98	89	93	96	57	86	32	84	94
P&C Insurers	89		54	66	36	74	50	44	80	45	97	61	53
Life Insurers	68	54		92	94	66	84	85	87	90	93	83	81
Money Market Funds	53	66	92		100	60	82	89	62	55	100	88	81
Mutual Funds (Equity)	98	36	94	100		100	55	51	100	53	100	55	55
Mutual Funds (Bonds)	89	74	66	60	100		89	93	83	88	97	89	90
Mutual Funds (Hybrid)	93	50	84	82	55	89		57	91	58	98	63	61
Exchange-Traded Funds	96	44	85	89	51	93	57		96	55	98	59	58
Mortgage REITs	57	80	87	62	100	83	91	96		73	100	95	87
Broker-Dealers	86	45	90	55	53	88	58	55	73		100	61	59
Finance Companies	32	97	93	100	100	97	98	98	100	100		94	98
Hedge Funds	84	61	83	88	55	89	63	59	95	61	94		63
Pension Funds	94	53	81	81	55	90	61	58	87	59	98	63	

The matrix highlights certain interesting properties of the inter-segment network. First, and rather unsurprisingly, banks have large multipliers, showing their interconnectedness to the rest of the financial system. Second, finance companies have very large multipliers with all other institution types except banks. The low multiplier does not mean that they are disconnected from banks; instead, their strong asset commonality with banks connects them, via banks, to the rest of the financial system. Similarly, equity and bond open-end funds do not have, almost by definition, first-round effects on one another. However, via their common connections (e.g., life insurers) they can have substantial spillovers on one another. Finally, the fact that the estimated multipliers are quite large (the mean is 77 percent, and the

linear, and thus the loss from a firesale is directly proportional to both the amount sold (i.e., the shock originator's holding) and to the amount held (i.e. the shock receiver's holding). Note that the symmetry in dollar losses implies very different outcomes when measured as a percent of the shock receiver's equity, the approach we took above. Thus, for instance, the dollar loss suffered by *Banks* from *Finance Companies*' fire sales is the same as that suffered by *Finance Companies* from *Banks*' fire sales; however, that dollar number is a much smaller percentage of *Banks*' capital than it is of *Finance Companies*' capital. In calculating the network multiplier, however, the denominators cancel out, leaving a symmetric matrix.

lowest quartile is still 59 percent) further corroborates the highly cohesive nature of the NBFI network, and thus of the capacity for shocks to propagate diffusely independently of the original source.

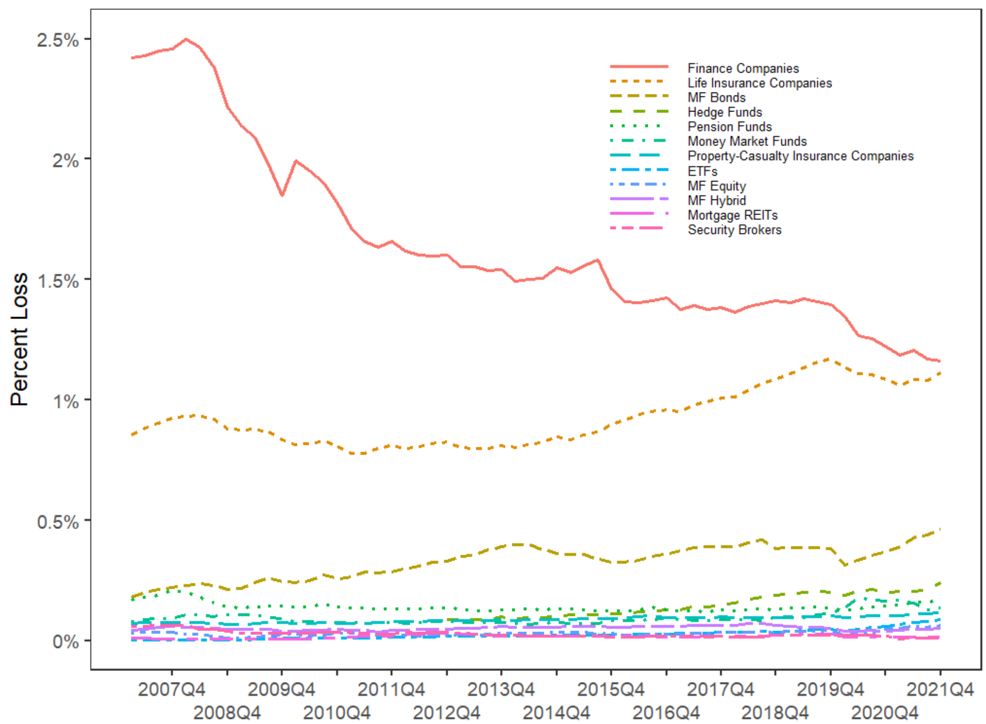
6 Time series analysis

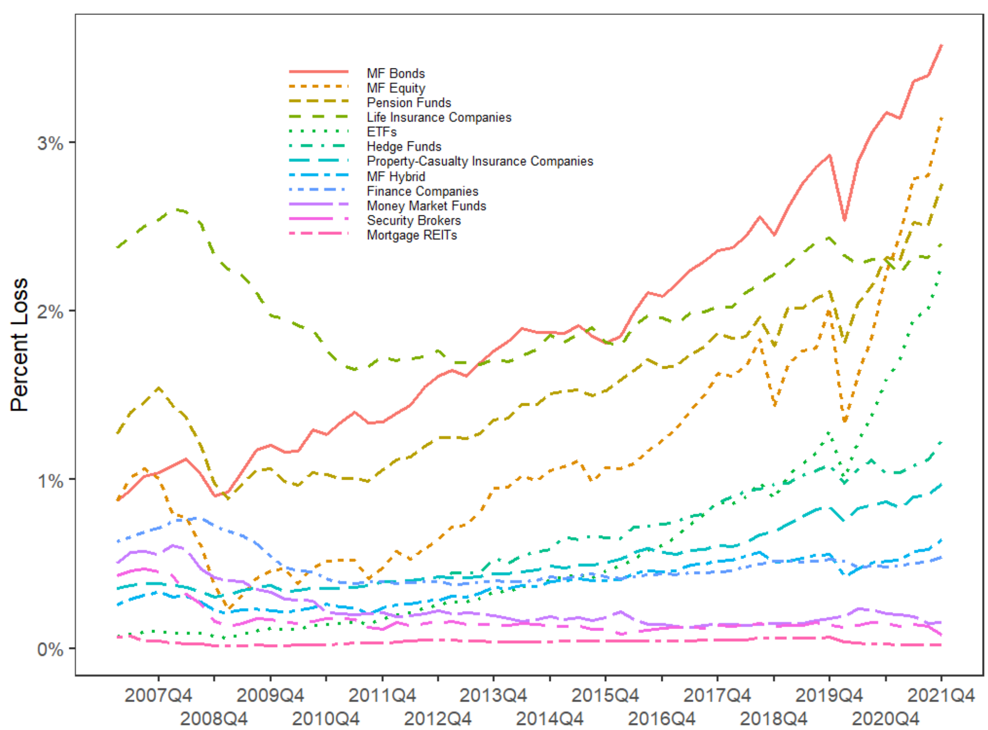
The results reported so far were based on the Flow of Funds snapshot at 2021q4. Important additional insights can be extracted from the time series analysis of the first- and second-round effects. We perform this computation for each quarter between 2007q1 and 2021q4.

Figure 2 shows loss as percent of bank capital. The top panel shows the loss due to direct (Round 1) firesale exposure. The bottom panel shows the indirect (Round 2) exposure. The Round 1 ranking is very stable in time. *Finance Companies,* due to their asset similarity to banks, are consistently first. *Life Insurance Companies* and *Mutual Funds (Bonds)* are consistently second and third. This ranking stability, however, masks substantial variation. *Finance Companies*' effect shrinks by about half over the sample period, while its initially large lead over life insurers shrinks to almost nothing. *Life Insurance Companies*, in turn, remain relatively stable, while *Mutual Funds (Bonds)* grow more than twofold in importance over the sample period.

The Round 2 ranking is far less stable. While their loss level is stable and they are consistently among the most important institutions, *Life Insurance Companies* go from first to fourth rank over the sample period. *Finance Companies* follow a similar trajectory, going from fifth at the beginning of the sample to eighth at the end. Their overall low rank is due to a lack of network amplification. Conversely, *Mutual Funds (Bonds)* grow fourfold over time and rise from third to first. *Mutual Funds (Equity)* start third (on par with their bond counterparts) and finish second, but this apparent relative stability masks substantial variation: their current rank is attained only very recently after having ranked as low as seventh during

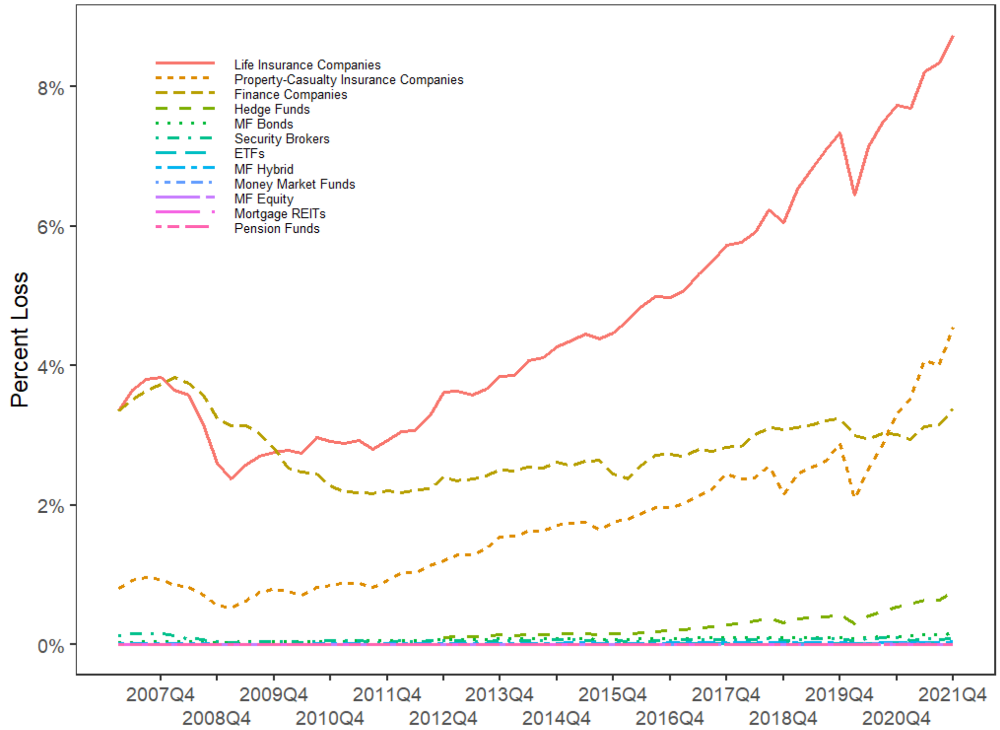
Figure 2. Historical evolution of loss as percent of bank capital. Above: Round 1 (direct) effect. Below: Round 2 (indirect) amplification via the NBFI network. Legend is sorted by most recent quarter value.





the sample period. *Pension Funds* begin second and finish third showing substantial amount of second-round spillover effects. Finally, due to their exponential growth, *ETFs* go from virtually nothing at the beginning of the sample to fifth at the end, within sight of the top three. Overall, the increasing impact trend of all these funds is explained by their growth in size relative to other segments, and especially relative to insurance, and by their steady degree of interconnectedness. The latter trend can be seen in the time-series of the matrix of first-round effects (as in Table 4), which we do not show for brevity.

Figure 3. Historical evolution of the aggregate relative contribution of an NBFI type to second-round bank losses, as a percent of bank capital, initiated by every other NBFI type.



Finally, Figure 3 (like the bottom row of Table 6) shows the historical evolution of each institution's aggregate contribution to second-round bank losses across the network. Only three institution types stand out. *Life Insurance Companies* are by far the highest, followed by *Property-Casualty Insurance Companies* and *Finance Companies*. Until recently, *Property-Casualty Insurance Companies* were a relatively distant third, but their importance in the network rose rapidly in recent quarters. In general, the contribution of both insurer types grows throughout the sample. Their growth is mainly attributable to a combination of two factors. One is their broadly diversified asset portfolios, and thus their ability to transmit shocks from fast-growing NBFIs (ETFs and, to a lesser degree, mutual funds). The other is the increase in insurers' portfolio shares of *Equity* and *Corporate Bonds*, asset classes also held by these growing NBFIs. A third candidate factor – growth in asset size – can be ruled out because asset size has been relatively stable for both insurer types compared to other institution types.

In the Appendix we also show the time series of the network multipliers for the impact of nonbanks on banks. As in the last column of Table 2, most network multipliers are over 80% and they remain stable throughout the sample, indicating that the high cohesion of the NBFI network is a persistent feature.

7 Conclusion

Nonbanks continue to grow in scale and as providers of financial intermediation services. Not surprisingly, banking institutions have seen a steady increase in their direct exposures to nonbanks, from credit lines to securities financing and derivatives transactions. However, banks can be vulnerable to nonbanks indirectly, because of common asset holdings and the resulting exposure to potential asset fire sales. Moreover, banks may be constrained in their ability to manage such exposures, since the asset profile of a banking organization is driven by underlying business scope strategic decisions, as well as by regulation.

We have built and expanded over the methodology proposed by GLT (2015) to quantify fire-sale spillovers originating from any of twelve NBFI segments. We have documented significant, and rising, exposures by U.S. banks to potential asset fire sales from nonbanks. Moreover, we have shown that banks are exposed to specific segments, even in the absence of meaningful asset portfolio overlaps. The reason is that the twelve non-bank segments display a significant degree of cohesion in terms of their own cross-vulnerabilities. A shock originating from any of the non-bank segments is likely to propagate and amplify diffusely in the entire ecosystem through a complex web of knock-on effects.

The analysis has allowed us to rank order the twelve NBFI segments along separate dimensions: First, in terms of the relative ability to impose direct, first-round losses on banks. Finance companies and life insurers are at the top of this ranking, because of their size and direct asset overlap with banks. Second, on the basis of segments' capacity to impose aggregate losses, once the knock-on, second-round effects are taken into account. Bond and equity funds, but also pension funds, rise at the top of the ranking because they can impose diffused first-round losses across all segments or concentrated losses on segments highly influential on banks. Third, we also rank segments for their role as vectors of shock propagation. Along this dimension, life insurers and P&C insurers are at the top of the ranking because of their very diversified asset portfolios, which make them especially vulnerable to first-round losses originating from a diverse cross-section of other segments.

Hence, banks are vulnerable to nonbanks through complex, indirect channels. The complexity might look overwhelming; nevertheless, this analysis has provided the instruments to enhance the monitoring of such exposures. Moreover, besides the bank-specific insights, considering the full network of NBFI segments has allowed us to uncover important network externalities associated with fire-sale events, which can be responsible for very significant amplifications of original financial distress. These conclusions suggest innovative implications for financial stability: while nonbanks are made up of a set of very separate, distinct segments, operating according to distinct business models, they should be considered *as a more homogeneous whole* in analyzing and understanding the transmission and the amplification of stress scenarios in the financial ecosystem. The matrices of cross-segment effects, and the associated network characteristics can be utilized to develop macro-prudential surveillance tools, amenable to monitoring over time, with differences from one quarter to the next pointing to emerging risks.

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8 Appendix: robustness checks

8.1 Alternative loss response coefficients

As discussed in Section 3, as a robustness check, we also consider alternative loss response coefficients. We assume slightly higher loss response coefficients for *Mutual Funds (Equity)*, *Mutual Funds (Hybrid)* and *ETFs* (0.785 for all the three types of institutions), compared to the assumption in the baseline analysis. These alternative loss response coefficients do not affect the first-round losses for banks but result in slightly different second-round losses for bank as reported in Tables A.1 and A.2, which parallel Tables 2 and 5. Rankings are unvaried.

8.2 Second-round effect including self-link

Tables A.3-A.5 parallel Tables 2, 5, and 6, but including the self-link, i.e., the second-round effect of a given institution type on itself. Note that, in our original analysis, the second-round effect for institution type A onto *Banks* excludes two paths:

1) A → A → *Banks*
2) A → *Banks* → *Banks*

The first path is excluded because our aim is to capture the amplification effect of an initial shock to a given NBFI entity type through the impact on every other type. The second path is excluded because our focus is the effect of NBFIs on Banks, and not possibly spillovers from Banks onto themselves. In the alternative specification in this appendix, we include #1 (the self-link) but continue to exclude #2, as shown in Figure A.1.

Both definitions of spillover (including and excluding the self-link) are used in the network-effects literature, depending on the situation.[26] Changes are minor except for *Life Insurers* and *Finance Companies*. Life insurance companies are now the highest-ranked by a large margin. The self-link makes an important difference because of their size, and then affects banks because of their high connectedness.

8.3 Network multiplier

Figure A.2 shows the network multiplier (as in the last column of Table 2) for the whole sample.

[26] Both definitions have been often considered in the literature studying spillovers. For example, Acemoglu et al. (2016) do not consider the self-links but Pace and LeSage (2014) do.

Table A.1: First- and second-round losses for Banks based on alternative loss response coefficients

Institution Type	Size ($B)	First-Round Loss $B	First-Round Loss % Bank Capital	First-Round Loss Rank	Second-Round Loss $B	Second-Round Loss % Bank Capital	Second-Round Loss Rank	Second-Round Share
Banks	23,962							
P&C Insurers	2,133	-2.2	-0.12%	7	-18.8	-0.98%	7	89%
Life Insurers	4,998	-21.3	-1.11%	2	-46.0	-2.40%	4	68%
Money Market Funds	5,208	-2.6	-0.14%	6	-2.9	-0.15%	10	53%
Mutual Funds (Equity)	14,486	-1.2	-0.06%	9	-63.0	-3.29%	2	98%
Mutual Funds (Bonds)	5,537	-8.9	-0.46%	3	-68.7	-3.58%	1	89%
Mutual Funds (Hybrid)	1,840	-1.0	-0.05%	10	-12.7	-0.66%	8	93%
Exchange-Traded Funds	7,057	-1.7	-0.09%	8	-44.6	-2.33%	5	96%
Mortgage REITs	197	-0.3	-0.02%	11	-0.4	-0.02%	12	57%
Broker-Dealers	1,827	-0.2	-0.01%	12	-1.6	-0.08%	11	87%
Finance Companies	1,182	-22.3	-1.16%	1	-10.3	-0.54%	9	32%
Hedge Funds	2,210	-4.6	-0.24%	4	-24.0	-1.25%	6	84%
Pension Funds	7,993	-3.3	-0.17%	5	-54.4	-2.84%	3	94%

Table A.1. Source: Authors' calculations on data from Financial Accounts of the United States and Investment Company Institute.

Table A.2: Heatmap of the second-round losses of Banks based on alternative loss response coefficients

	Equity	Agency MBS	Bank Loan	Open Market Paper	Corp Bond	Gov Bond	Muni Bond	Cash
P&C Insurers	-0.07%	0.00%	-0.07%	0.00%	-0.77%	-0.01%	-0.06%	0.00%
Life Insurers	-0.02%	0.00%	-1.61%	0.00%	-0.73%	0.00%	-0.03%	0.00%
Money Market Funds	0.00%	-0.02%	0.00%	0.00%	-0.01%	-0.09%	-0.03%	0.00%
Mutual Funds (Equity)	-3.29%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Mutual Funds (Bonds)	0.00%	-0.02%	-0.31%	0.00%	-2.92%	-0.07%	-0.26%	0.00%
Mutual Funds (Hybrid)	-0.30%	0.00%	-0.03%	0.00%	-0.30%	-0.01%	-0.03%	0.00%
Exchange-Traded Funds	-1.33%	0.00%	0.00%	0.00%	-0.95%	-0.02%	-0.03%	0.00%
Mortgage REITs	0.00%	-0.01%	0.00%	0.00%	-0.01%	0.00%	0.00%	0.00%
Broker-Dealers	-0.06%	0.00%	0.00%	0.00%	-0.02%	-0.01%	0.00%	0.00%
Finance Companies	0.00%	0.00%	-0.43%	0.00%	-0.11%	0.00%	0.00%	0.00%
Hedge Funds	-0.24%	0.00%	-0.43%	0.00%	-0.56%	-0.01%	0.00%	0.00%
Pension Funds	-1.17%	-0.01%	-0.05%	0.00%	-1.56%	-0.04%	0.00%	0.00%

Figure A.1: Second-round effect including self-link

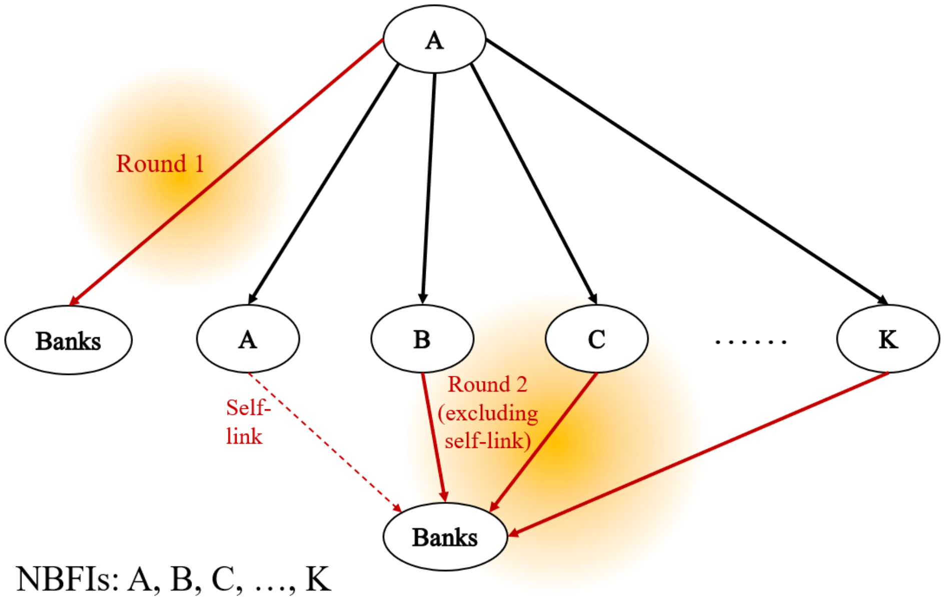


Table A.3: First- and second-round losses for Banks, including self-link (i.e, including the effect of the shocked institution type on itself)

Institution Type	Size ($B)	First-Round Loss $B	First-Round Loss % Bank Capital	First-Round Loss Rank	Second-Round Loss $B	Second-Round Loss % Bank Capital	Second-Round Loss Rank	Second-Round Share
Banks	23,962							
P&C Insurers	2,133	-2.2	-0.12%	7	-22.0	-1.15%	8	91%
Life Insurers	4,998	-21.3	-1.11%	2	-113.8	-5.94%	1	84%
Money Market Funds	5,208	-2.6	-0.14%	6	-3.0	-0.16%	10	53%
Mutual Funds (Equity)	14,486	-1.2	-0.06%	9	-60.4	-3.15%	3	98%
Mutual Funds (Bonds)	5,537	-8.9	-0.46%	3	-69.8	-3.64%	2	89%
Mutual Funds (Hybrid)	1,840	-1.0	-0.05%	10	-12.4	-0.65%	9	93%
Exchange-Traded Funds	7,057	-1.7	-0.09%	8	-43.6	-2.28%	6	96%
Mortgage REITs	197	-0.3	-0.02%	11	-0.4	-0.02%	12	57%
Broker-Dealers	1,827	-0.2	-0.01%	12	-1.5	-0.08%	11	87%
Finance Companies	1,182	-22.3	-1.16%	1	-49.5	-2.58%	5	69%
Hedge Funds	2,210	-4.6	-0.24%	4	-24.2	-1.26%	7	84%
Pension Funds	7,993	-3.3	-0.17%	5	-52.8	-2.75%	4	94%

Source: Authors' calculations on data from Financial Accounts of the United States and Investment Company Institute.

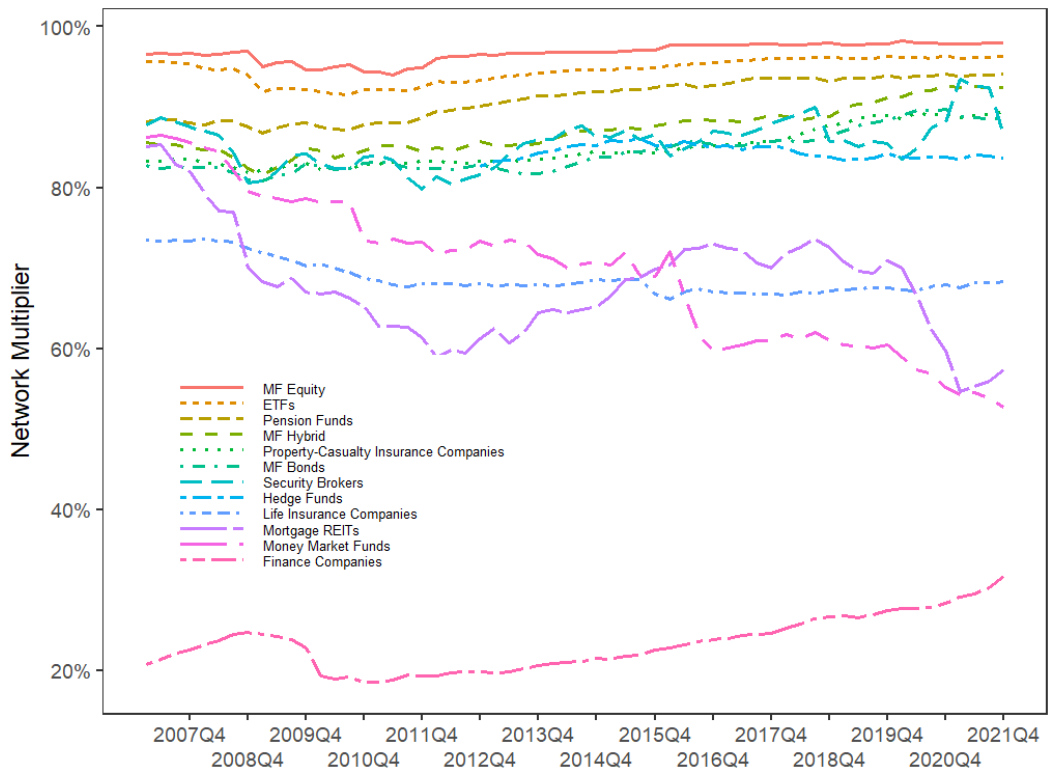
Table A.4: Heatmap of the second-round losses of banks, including self-link.

	Equity	Agency MBS	Bank Loan	Open Market Paper	Corp Bond	Gov Bond	Muni Bond	Cash
P&C Insurers	-0.14%	-0.01%	-0.07%	0.00%	-0.84%	-0.01%	-0.09%	0.00%
Life Insurers	-0.03%	-0.01%	-1.94%	0.00%	-3.88%	-0.01%	-0.07%	0.00%
Money Market Funds	0.00%	-0.02%	0.00%	0.00%	-0.01%	-0.10%	-0.03%	0.00%
Mutual Funds (Equity)	-3.15%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Mutual Funds (Bonds)	0.00%	-0.02%	-0.31%	0.00%	-2.95%	-0.08%	-0.28%	0.00%
Mutual Funds (Hybrid)	-0.28%	0.00%	-0.03%	0.00%	-0.30%	-0.01%	-0.03%	0.00%
Exchange-Traded Funds	-1.28%	0.00%	0.00%	0.00%	-0.95%	-0.02%	-0.03%	0.00%
Mortgage REITs	0.00%	-0.01%	0.00%	0.00%	-0.01%	0.00%	0.00%	0.00%
Broker-Dealers	-0.05%	0.00%	0.00%	0.00%	-0.02%	-0.01%	0.00%	0.00%
Finance Companies	0.00%	0.00%	-2.46%	0.00%	-0.12%	0.00%	0.00%	0.00%
Hedge Funds	-0.25%	0.00%	-0.43%	0.00%	-0.56%	-0.01%	0.00%	0.00%
Pension Funds	-1.09%	-0.01%	-0.05%	0.00%	-1.56%	-0.04%	0.00%	0.00%

Table A.5: Relative second-round contribution from different intermediate shocks transmitters (in column), given an initial 1% portfolio shock hitting an institution type (in row), including self-link.

Values in Percent	P&C	Life	MMF	MFE	MFB	MFH	ETFs	REIT	B&D	FinCo	HF	PF	Total
P&C Insurers	-0.18	-0.79	0.00	0.00	-0.02	0.00	0.00	0.00	0.00	-0.13	-0.02	0.00	-1.15
Life Insurers	-0.34	-3.54	0.00	0.00	-0.06	0.00	0.00	0.00	0.00	-1.96	-0.03	0.00	-5.94
Money Market Funds	-0.04	-0.09	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.16
Mutual Funds (Equity)	-1.82	-0.88	0.00	0.00	0.00	-0.02	-0.03	0.00	-0.04	0.00	-0.36	0.00	-3.15
Mutual Funds (Bonds)	-0.34	-2.68	0.00	0.00	-0.06	0.00	0.00	0.00	0.00	-0.54	-0.02	0.00	-3.64
Mutual Funds (Hybrid)	-0.20	-0.35	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	-0.05	-0.03	0.00	-0.65
Exchange-Traded Funds	-0.82	-1.16	0.00	0.00	-0.02	-0.01	-0.01	0.00	-0.02	-0.09	-0.15	0.00	-2.28
Mortgage REITs	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.02
Broker-Dealers	-0.03	-0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	-0.08
Finance Companies	-0.01	-0.51	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-2.04	-0.01	0.00	-2.58
Hedge Funds	-0.19	-0.61	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	-0.41	-0.03	0.00	-1.26
Pension Funds	-0.76	-1.61	0.00	0.00	-0.03	-0.01	-0.01	0.00	-0.01	-0.19	-0.13	0.00	-2.75
Total	-4.73	-12.28	-0.01	-0.01	-0.22	-0.04	-0.05	0.00	-0.09	-5.43	-0.79	0.00	

Figure A.2: Time series of the network multiplier for the total impact of nonbanks on Banks



9 Appendix: additional whole-network tabulations

Table A.6 shows the second-round impact of fire-sale spillovers as a percentage of equity of the receiving segment (same as Table 4, but for the second round). As in Table 4, equity is estimated as "implied equity" as follows. For non-leveraged intermediaries (*Money Market Funds*, *Mutual Funds (Equity)*, *Mutual Funds (Bonds)*, *Mutual Funds (Hybrid)*, *Exchange-Traded Funds*, *Mortgage REITs*, and *Pension Funds*), $Equity = Total\ Assets$. For leveraged intermediaries (*Banks*, *P&C Insurers*, *Life Insurers*, *Broker-Dealers*, *Finance Companies*, and *Hedge Funds*), $Equity = Total\ Assets\ /\ (1 + R)$, where R is the response coefficient and Total Assets is the figure from the Flow of Funds. Unlike Table 7 in the paper, which is symmetric, Table 4 and Table A.6 are not symmetric. Thus, for instance, *Banks* and *Finance Companies* have a large effect on each other, which is the same in dollar terms, but this same effect is a much larger percentage of the capital of *Finance Companies* relative to *Banks*.

Table A.6: Whole-network analysis. Second-round effect as a percentage of target equity.

Values in Percent	Final shock received by…												
Shock originates from…	Banks	P&C	Life	MMF	MFE	MFB	MFH	ETFs	REIT	B&D	FinCo	HF	PF
Banks		-21.2	-13.1	-0.1	-0.4	-1.2	-0.7	-0.6	-0.2	-1.0	-10.9	-2.4	-0.7
P&C Insurers	-1.0		-0.9	0.0	-0.1	-0.1	-0.1	-0.1	0.0	-0.1	-3.9	-0.3	-0.1
Life Insurers	-2.4	-3.5		-0.1	-0.3	-0.3	-0.3	-0.3	-0.2	-0.8	-24.5	-1.1	-0.3
Money Market Funds	-0.2	-0.7	-1.1		0.0	-0.1	0.0	0.0	0.0	-0.1	-3.2	-0.1	0.0
Mutual Funds (Equity)	-3.1	-9.1	-13.9	-0.1		-1.0	-1.8	-1.9	-0.2	-4.0	-5.4	-3.2	-1.7
Mutual Funds (Bonds)	-3.6	-8.8	-5.1	-0.1	-0.4		-0.4	-0.4	-0.2	-0.9	-14.8	-1.2	-0.4
Mutual Funds (Hybrid)	-0.6	-1.8	-1.8	0.0	-0.2	-0.1		-0.2	0.0	-0.5	-2.0	-0.4	-0.2
Exchange-Traded Funds	-2.3	-5.8	-6.6	-0.1	-0.9	-0.6	-0.8		-0.1	-1.8	-5.0	-1.6	-0.8
Mortgage REITs	0.0	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0		0.0	-0.4	0.0	0.0
Broker-Dealers	-0.1	-0.2	-0.3	0.0	0.0	0.0	0.0	0.0	0.0		-0.4	-0.1	0.0
Finance Companies	-0.5	-4.2	-6.6	-0.1	0.0	-0.3	-0.1	-0.1	-0.2	-0.2		-0.6	-0.1
Hedge Funds	-1.2	-2.8	-2.9	0.0	-0.2	-0.2	-0.2	-0.2	-0.1	-0.5	-6.4		-0.2
Pension Funds	-2.8	-7.8	-6.8	-0.1	-0.9	-0.6	-0.9	-0.9	-0.1	-1.8	-7.4	-1.7	

10 Appendix: alternate notation

For computational purposes, our framework can be more succinctly specified using the following notation. Given M asset classes and N institution types, define the matrix Q $(N \times M)$ whose (n, m)-th cell contains the portfolio holdings of entity type n for asset m. Assume an exogenous price shock S_0^P $(M \times 1)$ (expressed in percent) or portfolio shock S_0^Q $(N \times M)$ (expressed in dollars). Also assume a vector of firesale elasticities E $(M \times 1)$, where the m-th cell contains the percent change in that asset class's price per aggregate dollar sold. Finally, assume a vector of loss response coefficients R $(N \times 1)$, whose n-th cell contains the fraction of portfolio sold for a given percent loss in portfolio value. Upon a price shock S_t^P, the resulting portfolio shock is

$$S_t^Q = PctQ \cdot \left[R \cdot (Q\, S_t^P)\mathbf{1}_{(1\times M)}\right],$$

where the symbol $\cdot$ is the element-wise product and $PctQ$ indicates the normalized Q, where the (n, m)-th cell contains the percent of entity type n's portfolio held in asset m.

The first-round portfolio shock then triggers a second-round price shock

$$S_{t+1}^P = \left[\left(S_t^Q\right)^{\mathsf{T}} \mathbf{1}_{(N\times 1)}\right] \cdot E,$$

etc., and vice versa.[27]

Our methodology also makes it possible to characterize S_∞ (the sum of the sequence of all successive shocks). In principle, S_∞ represents the overall effect of the fire-sale cascade. In practice, however, for S_∞ to be identified, some stringent conditions on R and E must be verified. These conditions are generally not verified in our situation, resulting in an explosive cascade. This is not necessarily an incorrect result or an undesirable property of our model. However, for the time being, we only focus on the first two rounds.

[27] For the purpose of highlighting critical nodes, under regularity conditions, this methodology defines a mapping from price shock to price shock ($S_t^P \rightarrow S_{t+1}^P \rightarrow \cdots S_{t+k}^P$) or, equivalently, from portfolio shock to portfolio shock ($S_t^Q \rightarrow S_{t+1}^Q \rightarrow \cdots S_{t+k}^Q$).