

ANALYSIS

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Private Credit & Systemic Risk

The private credit market has expanded rapidly in recent years, becoming an established source of corporate loans to middle-market firms, a key financing tool for private equity transactions, and a testing ground for new lending strategies. Private credit has thus grown in systemic importance as it takes on a larger role in corporate finance and develops linkages across the financial system while remaining less transparent, less liquid, and more reliant on structures that make its risks more difficult to evaluate than those of other types of credit intermediaries.

The growing interconnectedness between private credit funds and other financial institutions can amplify financial instability, as evidenced by higher correlation and network connectivity during periods of stress. While the scale of private credit is still small and fund leverage appears modest, the direction of travel points toward greater systemic importance as it expands beyond middle-market corporate lending and taps public-market funding.

Regulators and central banks should thus consider expanding the regulatory perimeter to include significant private credit funds and to monitor risk concentrations, including leverage and liquidity mismatches. Transparency and data gaps must be addressed through improved reporting requirements for private credit funds and borrowers, enabling better monitoring of exposures and interconnectedness.

Macroprudential policies should carefully consider private credit dynamics, including accounting for rapid nonbank credit growth when setting countercyclical buffers and ensuring central banks are prepared to manage liquidity or credit crunches that could arise from stress in private credit markets. These measures can help mitigate systemic risks while ensuring the benefits of this growing source of credit.

In this paper, we explore the private credit market in depth, assess the extent of its interconnectedness in the financial system using well-known reduced-form econometric measures of systemic risk, and conclude with high-level policy implications and recommendations.

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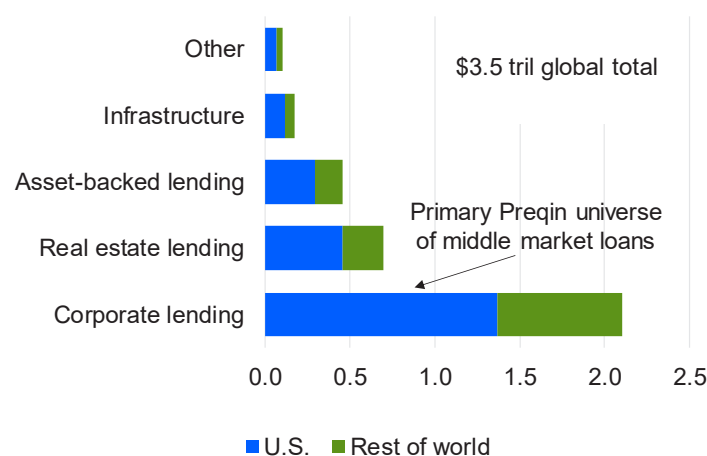
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SUMMARY

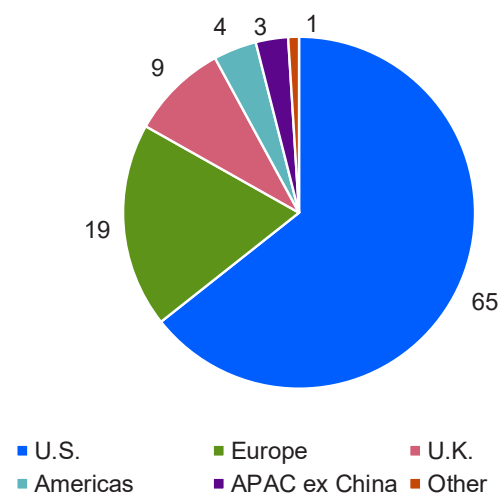
The private credit market has rapidly expanded in recent years, becoming an established source of corporate loans to middle-market firms, a key financing tool for private equity transactions, and a testing ground for new lending strategies. A broad measure of global private credit assets across a range of investment asset classes, and including committed funds that have not yet been invested—so-called dry powder—has surged to an estimated \$3.5 trillion globally as of late 2025 (see Chart 1).

Chart 1: The Private Credit Universe Covers a Range of Asset Classes

2025 estimate of private credit funds committed, \$ tril



Domicile of PC investments as of 2025, % of total



Sources: Prequin, AIMA, Moody's Analytics

Commonly reported figures that put the size of private credit closer to \$1.7 trillion refer narrowly to corporate private loans, but this understates the industry's more recent moves into other lending areas. Approximately two-thirds of total private credit assets are in the U.S., putting private credit well ahead of the high-yield corporate bond and syndicated leveraged loan markets in size.

As private credit expands into new markets such as asset-backed finance, infrastructure project finance, and various forms of real estate lending, its role in providing credit has substantially increased. And as its footprint increases, any vulnerabilities that it poses will become more consequential for borrowers and investors and potentially for the broader financial system, with implications for how it should be regulated.¹

Since this paper was first published in June 2025, the private credit market has experienced significant stress. A wave of redemption requests has recently hit semi-liquid and evergreen private credit funds, forcing major managers—including Blackstone, Apollo, Morgan Stanley, Carlyle, Blue Owl and Ares—to invoke contractual redemption gates limiting quarterly withdrawals to 5% of net asset value. Redemption requests at some funds exceeded 10% to 15% of outstanding shares in a single quarter. The stress has been concentrated in funds with significant exposure to software and technology borrowers facing artificial intelligence-driven disruption, compounded by elevated interest rates that compressed borrower interest

¹ International Monetary Fund (2024).

coverage ratios, and fanned by increasing private credit defaults, which are approaching a record 10%.² This episode motivates the updated results and expanded policy discussion.

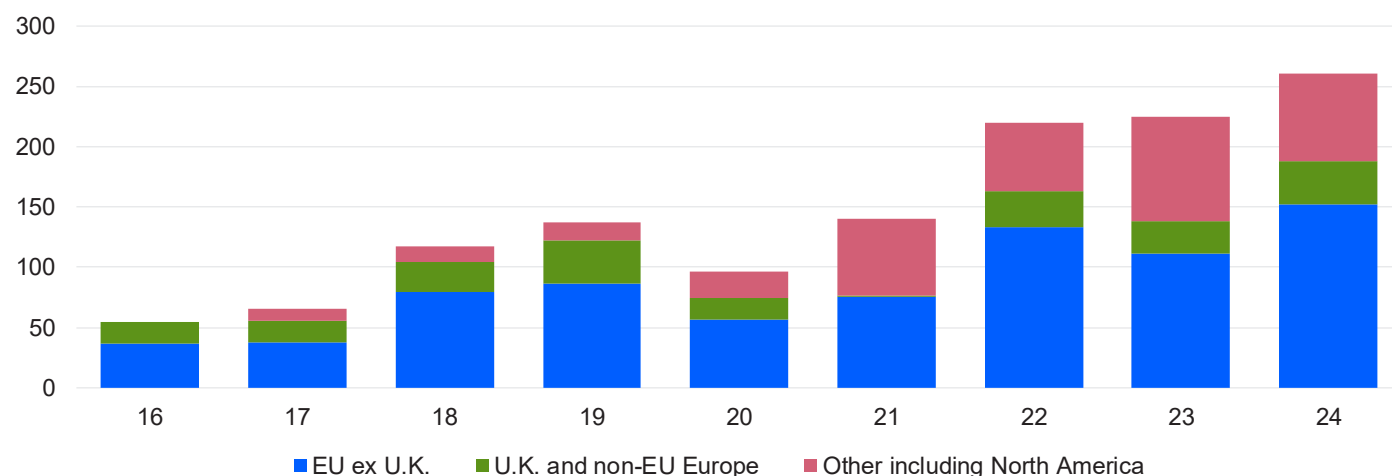
Private credit investments are typically structured through closed-end funds with committed capital and multiyear lockups, matching the illiquidity of the underlying loans. Operating largely outside the traditional banking system and public markets, such funds offer limited transparency about their holdings and exposures, making it difficult to assess the underlying risks. The asset class has delivered equity-like returns over time, attracting strong investor interest despite its opaque risk profile.

As private credit has grown, regulators have raised reasonable concerns about its rapid expansion, increasingly aggressive competition, and a shift toward riskier borrowers and more complex deal structures—all of which could erode returns and amplify risks as the market matures.³

Beyond its growth and opacity, a key systemic concern is private credit’s deepening ties—and interconnectedness—with traditional banks and a broad range of nonbank financial intermediaries. Banks are increasingly involved in private credit and other NBFIs through partnerships, fund financing, and structured risk transfers, allowing them to maintain economic exposure to credit markets while shifting assets off balance sheet. Global SRT issuance, which is concentrated in Europe but often covers global credit loss exposures, has grown sharply, from approximately €50 billion in 2016 to more than €250 billion in 2024, reflecting the increasing use of this mechanism for regulatory capital relief (see Chart 2).⁴ While such arrangements may offer capital efficiency, they can also obscure the true distribution of risk, prompting regulatory scrutiny over potential capital requirement arbitrage. Meanwhile, U.S. banks have rapidly expanded lines of credit to NBFIs, including private credit funds.⁵

Chart 2: Global Banks Rely on Structured Risk Transfer for Capital Relief

Issuance of new SRT pools, € bil



Sources: AICPM, Moody’s Analytics

² Fitch Ratings (2026).

³ See, for instance, [Federal Reserve \(2023\)](#). Also, see [Cai and Haque \(2024\)](#) and [Degerli and Monin \(2024\)](#).

⁴ [Basel Committee on Banking Supervision \(2026\)](#)

⁵ [Acharya, Cetorelli, and Tuckman \(2024\)](#), [Levin and Malfroy-Camine \(2025\)](#), [Fritzdixon and Lu \(2026\)](#).

At the same time, private credit channels have significant exposure to institutional investors, including pension funds, insurers, and sovereign wealth funds, who are attracted by higher yields but may become exposed to liquidity strains during periods of market stress due to the illiquid and bespoke nature of the debt. Moreover, large asset managers are becoming more active in private credit, traditionally via closed-end institutional funds but increasingly through newer vehicles targeting retail and wealth channels. These structures, such as interval and evergreen funds, offer some degree of liquidity for redemptions despite holding illiquid assets. They may rely on tools such as credit lines or net asset value lending to manage redemptions, creating emerging links to short-term funding markets. While still modest in scale, these structures introduce potential channels for the transmission of financial shocks, warranting closer oversight as retail participation expands.

In this paper, we propose an approach to quantify the extent of interconnectedness in the financial system using well-known reduced-form econometric measures of systemic risk. More specifically, we use principal component analysis and Granger-causality network modeling to analyze stock returns and market-implied expected default frequencies for financial institutions across four industry groups. We find that the degree of interconnectedness, as captured by PCA, and the directionality of such relationships and contagion, as captured by Granger-causality analysis, become highly magnified during periods of market stress.⁶

Moreover, we observe a shift in the structure of these linkages: Banks have become less central, while business development companies, our proxy for private credit, and other NBFIs have grown more important in terms of their interconnectedness. This is particularly the case in times of crisis, as evidenced by comparing the COVID-19 pandemic to the Global Financial Crisis. The PCA results suggest the network has become denser overall, but its structure has shifted away from a bank-centered core, with private credit and other NBFIs now markedly more prominent.

This shift likely reflects the rise of private credit in the post-GFC era and regulatory changes that have altered the role of banks, despite the limited extent of banks' and other nonbanks' direct exposures to private credit. The indirect linkages through funding lines, shared borrowers, investor overlaps, and overall market sentiment mean stress can quickly propagate.

OUR PRINCIPAL FINDINGS ARE:

1. Private credit, once a niche asset class, has grown in systemic importance as it takes on a larger role in corporate finance and develops linkages across the financial system while remaining less transparent, less liquid, and more reliant on structures that make its risks more difficult to evaluate than those of other types of credit intermediaries.
2. Reforms implemented in the wake of the GFC have shifted nonfinancial corporate debt off bank balance sheets, reducing banks' leverage but creating new transmission channels via nonbanks. The network of interconnections in the financial system has more dispersed nodes with denser connections than it did pre-crisis, when the system operated more like a "hub and spoke" model with banks at the center of the network and nonbanks at the periphery.

⁶ Our approach is similar to that of [Billio, Getmansky, Lo, and Pelizzon \(2012\)](#), which has been summarized in the Appendix for completeness. PCA captures the aggregate extent of simultaneous common variation across firms, providing measures of overall interconnectedness and how tightly individual firms or industries are linked to the common variation. In contrast, Granger-causality network analysis identifies directed, time-varying firm-to-firm links, allowing us to interpret observed linkages as spillover effects in returns and default risk. In the presence of market frictions, these spillovers are indicative of contagion, in the spirit of models of financial network contagion like those by [Gai, Haldane, and Kapadia \(2011\)](#) and [Acemoglu, Ozdaglar, and Tahbaz-Salehi \(2015\)](#).

3. While a more distributed network of financial institutions may enhance efficiency and capital allocation in normal times, the increased number of connections can act as a shock amplifier during periods of market stress. The same linkages that facilitate risk-sharing in calm conditions can become conduits for contagion under strain, especially when involving more opaque parts of the network—such as private credit—where risks are harder to monitor. This dynamic is evident in periods of elevated correlation and tighter network connectivity when markets come under pressure.
4. While the scale of private credit is still small and fund leverage appears modest, the direction of travel points toward growing systemic importance as it expands into new lending strategies and prepares to tap retail funding and explore liquidity features that could create fragility. That will warrant a commensurate increase in focus from a financial stability perspective.

Regulators and central banks should thus consider expanding the regulatory perimeter to include significant private credit funds and to monitor risk concentrations, including leverage and liquidity mismatches. Transparency and data gaps should be addressed through improved reporting requirements for private credit funds and borrowers, enabling better monitoring of exposures and interconnectedness. Macroprudential policies should carefully consider private credit dynamics, including accounting for rapid nonbank credit growth when setting countercyclical buffers and ensuring central banks are prepared to manage liquidity or credit crunches that could arise from stress in private credit markets. These measures can help mitigate systemic risks while ensuring the benefits to borrowers and investors alike of this growing source of credit.

The recent stress episode underscores the urgency of these recommendations and suggests several additional priorities. First, the gating events revealed that, notwithstanding the risk disclosures, investors in semi-liquid fund structures may not have fully appreciated the liquidity constraints; regulators should consider requiring enhanced liquidity risk disclosures for these vehicles and proceed cautiously with modifications to the “accredited investor” standard. The Department of Labor’s recently proposed rule on inclusion of investment alternatives in the \$10 trillion 401(k) market is a particular concern.

Second, the concentration of private credit portfolios in technology and software sectors (approaching one-half of recent deal volume) represents correlated risk that should be monitored through improved reporting on sectoral exposures. Third, the growing use of structured risk transfers by global banks creates additional bank-nonbank linkages that warrant coordinated supervision between securities regulators and prudential authorities. Fourth, European insurers and pension funds are significant limited partners in global private credit funds, creating cross-border transmission channels that macroprudential frameworks should take into account.

The nature of systemic linkages in credit provision, in both corporate markets and, increasingly, others too, has changed since the GFC. We have arguably reduced the relative systemic centrality of banks but increased the complexity and opacity of the broader credit network. Private credit’s rise is emblematic of this shift—it has improved credit access for nonfinancial firms and the distribution of risk across the system. At the same time, it has added complexity and opacity to an already intricately connected system, in which stress can propagate in unforeseen ways. The net effect is that systemic risk has not disappeared; it has evolved, requiring updated tools and vigilant monitoring.

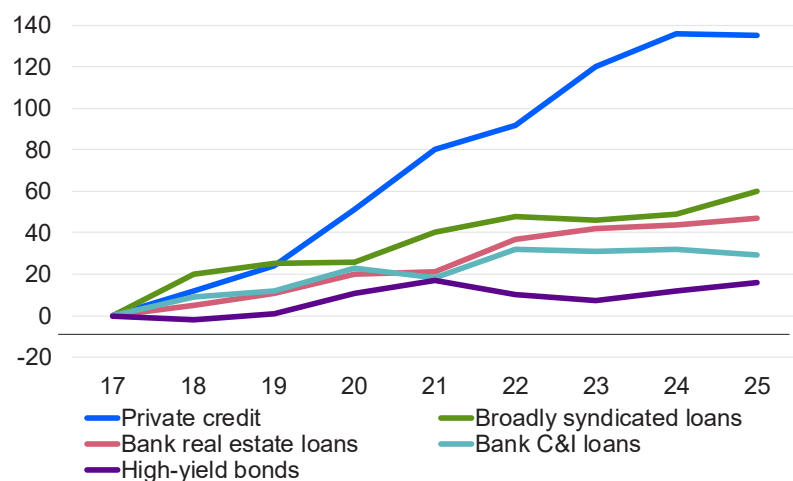
In this paper, we explore the size and characteristics of the private credit market in depth, describe our analysis and results, and conclude with policy implications and recommendations.

SIZING UP PRIVATE CREDIT

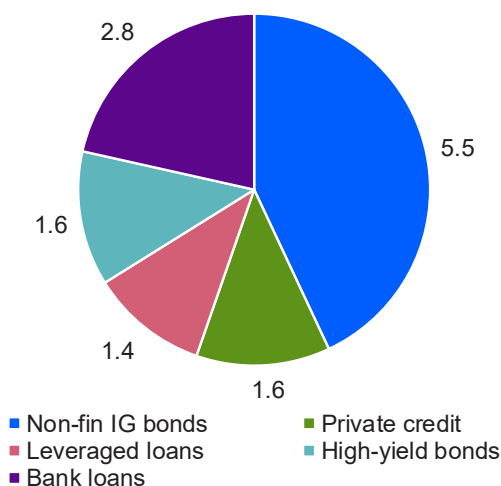
Outstanding U.S. nonfinancial corporate debt has reached record levels, exceeding \$14 trillion across investment-grade bonds, high-yield bonds, leveraged loans, and bank and private credit, almost doubling over the past decade. The fastest growth has occurred in the riskier, non-investment-grade segments, including leveraged loans, high-yield bonds, and, by a wide margin, private credit (see Chart 3). This reflects a structural shift in corporate credit provision. Post-GFC banking reforms imposed tighter capital and liquidity requirements, constraining traditional bank lending and paving the way for institutional capital to fill the gap. Private credit, especially direct lending, expanded rapidly in this space.

Chart 3: Private Credit Is a Big Player in the Corporate Debt Market

Change in outstanding credit since 2017, %



U.S. corporate debt, \$ tril



Sources: IMF, Krugman (2026), Pitchbook, Federal Reserve, Moody's Analytics

Approximately half of private credit's global assets, including those of BDCs, are in direct loans to middle-market firms that typically generate \$50 million to \$1 billion in revenue. Their debt needs generally are too small for public bond markets or leveraged loans, and some borrowers of that size report difficulty securing conventional bank loans (see Chart 4). Compared with bank lenders, direct lenders offer speed and customized terms, including more repayment flexibility and fewer disclosures, in exchange for receiving a higher interest rate than typical bank loans.

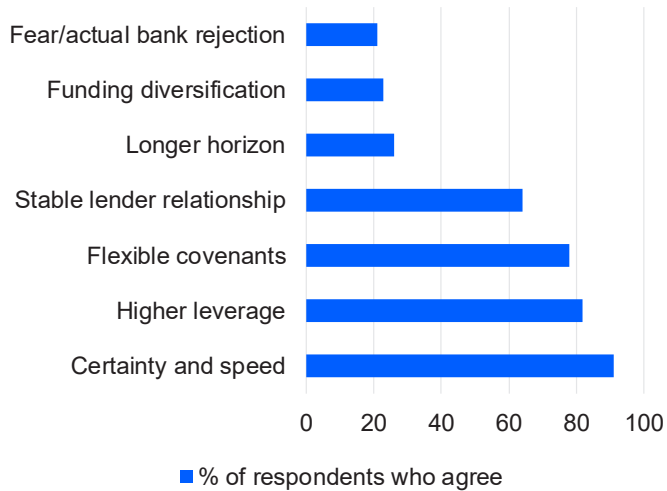
Beyond direct lending, private credit managers are pushing into specialty finance and asset-based lending, including equipment leasing, litigation finance and consumer loans, with a similar flexibility pitch to borrowers. Though this subset is much smaller, it represents one of the least transparent and fastest-growing areas.⁷

A notable feature of private credit portfolios is their heavy concentration in information technology, which accounts for nearly half of recent private credit deal volume (see Chart 5). Healthcare is the second-largest sector. This concentration poses risks: The rapid advance of generative AI has begun to erode the competitive positions of mid-market software firms,

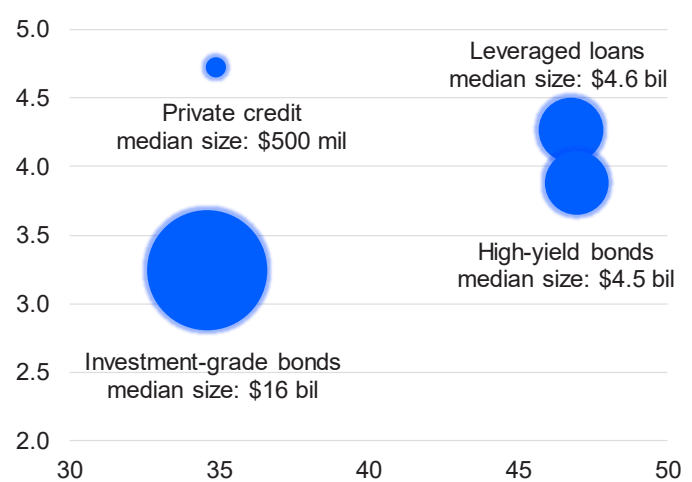
⁷ Wyman (2024a) and McKinsey (2024).

Chart 4: Borrower-Friendly Structure Means Higher Returns & Risks

Reasons U.S. borrowers prefer private over bank loan



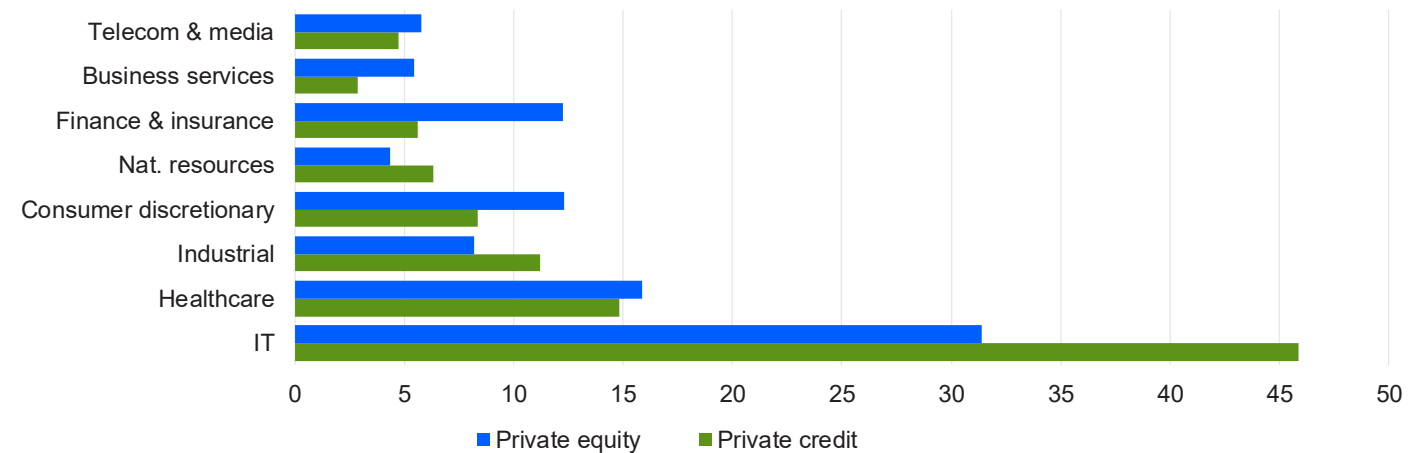
X-axis: Debt-to-asset ratio, %; Y-axis: Debt-to-EBITDA ratio



Sources: Univ. of Chicago, IMF, Moody's Analytics

Chart 5: IT and Healthcare Dominate Private Credit Investments

Industry distribution of 2020-2024 private asset deals, % of total



Sources: Preqin, NBER, Moody's Analytics

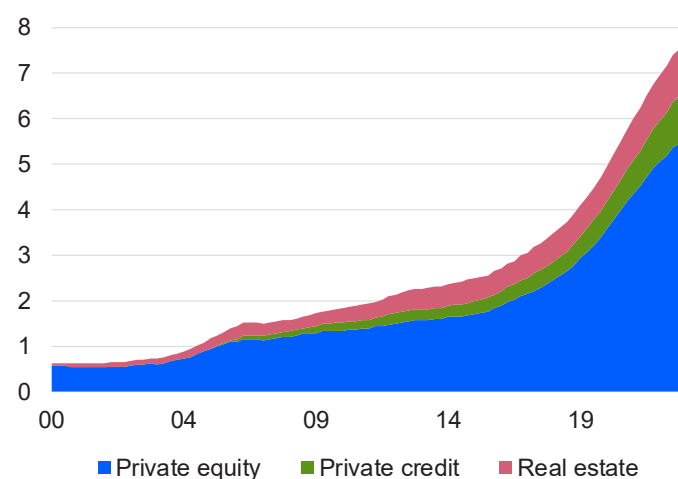
which comprise a significant share of private credit loan books. As AI disruption reduces the enterprise value of these borrowers, the collateral underpinning billions in loans has come under pressure—a risk that was not widely anticipated at the time of the original analysis.

STRUCTURE, FUNDING AND LEVERAGE

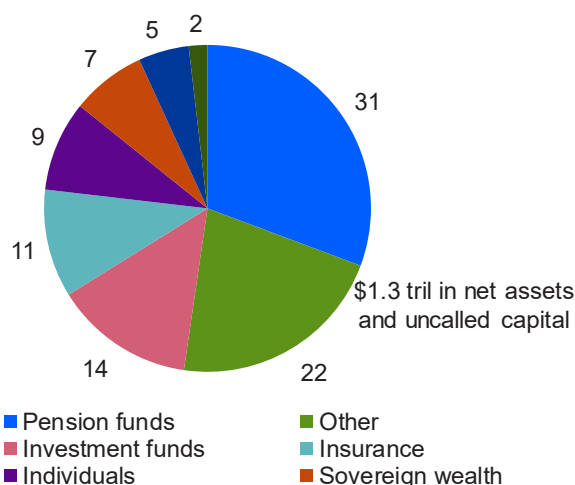
Private credit investments are primarily structured as closed-end funds, often organized as limited partnerships or LLCs, similar to private equity vehicles. General partners manage these funds on behalf of limited partners—typically institutional investors—who commit capital for a set term. By locking up investor capital for a set period, the closed-end structure reduces redemption pressure and aligns the fund’s timeline with the long-term, illiquid loans it holds. Consequently, the asset class has attracted patient investors such as pension funds, insurers, endowments, and sovereign wealth funds (see Chart 6).

Chart 6: What Is Behind the Private Credit Boom?

U.S. private market assets, \$ tril



Investors in U.S. private credit funds, % of total



Notes: The “other” category includes foreign fund of funds, corporations, family offices, investment advisers, general partners and employees, and others
Sources: Boston Fed, Brookings, IMF, Office of Financial Research, Moody’s Analytics

The use of leverage varies considerably across funds. While some direct lending funds maintain conservative profiles with modest or no fund-level borrowing, others extensively use credit facilities—including subscription lines, NAV lending, and hybrid structures with banks and, in some cases, nonbank lenders—to enhance returns. In some cases, the combined effect of fund-level borrowing and portfolio-company-level leverage results in total leverage profiles that resemble those of complex structured finance vehicles. This layered structure introduces risk dynamics and interdependencies that differ from more traditional credit strategies. The use of swaps and other derivatives to hedge or transfer risk—or to enhance returns—has also expanded, introducing further potential for leverage, interconnectedness and complexity. Variability in leverage use reflects differing investor mandates, risk tolerances, and return targets across the industry.

In addition to using fund-level leverage, private credit managers are increasingly financing their loan portfolios through private collateralized loan obligation structures, with well over \$100 billion of private credit CLOs outstanding in 2023.⁸ Traditionally associated with syndicated corporate

⁸ International Monetary Fund (2024) and Standard and Poor’s (2026).

loans, CLOs are now being adapted to warehouse and securitize portfolios of middle-market direct loans. Private credit issuance has been soaring, with middle-market issuance approaching \$40 billion annually in 2025. Banks may find senior CLO tranches attractive investments that expose them to private credit with sufficient protection to check regulatory boxes. These private credit CLOs provide managers with an additional funding source, often at lower cost, and allow them to scale lending without requiring new equity capital. However, this introduces another layer of leverage and structural complexity that is not always visible to end investors, further complicating risk assessment across the private credit market.

Several recent studies document this structure of private credit funds in detail: Private credit funds are typically highly capitalized, with equity accounting for 65% to 80% of total assets, and exhibit limited maturity mismatch.⁹ Collateralized lending with bank ties is on the rise, and closed-end fund structures are reshaping refinancing and liquidation incentives.

TRANSPARENCY AND LIQUIDITY

Private credit's lack of standardization in lending terms and limited disclosures about borrowers complicate efforts to monitor fund risks. Unlike public markets, most private credit offers no real-time pricing, relies on bespoke contracts, and has floating-rate exposure, which can become burdensome during periods of rising interest rates, such as the Federal Reserve's tightening starting in 2021. How burdensome depends on the financial condition of the borrowers, however, and that information is best known to the fund's insiders. Even the public BDCs provide little information about the financial condition of the individual borrowers.

As the private credit market evolves, a growing number of funds have adopted semi-liquid structures to accommodate investor demand for redemption options and broaden their investor base.¹⁰ Even among ostensibly closed-end vehicles, some funds permit periodic redemptions subject to notice periods, gates or manager discretion, which tempers—but does not eliminate—the insulation from liquidity pressures. These models introduce a duration mismatch. Funds commit to holding long-dated, illiquid assets while offering investors periodic liquidity, supported by credit lines or cash buffers. This mismatch is not incidental. It enables funds to extract an illiquidity premium while presenting an appearance of flexibility to investors—but it also creates a structural vulnerability if investor redemption demands outpace the cash flows of the underlying assets.

Alongside these structures, BDCs have long offered a more liquid alternative for investors to acquire a stake in middle-market loans. Created by Congress in 1980 to support small and midsize businesses, BDCs are usually publicly traded and subject to specific regulatory requirements, including disclosure requirements and a 2:1 debt-to-equity leverage limit.¹¹ Most BDCs employ leverage to align their target returns with market expectations for equity-like investments. Many BDCs, particularly non-traded ones, voluntarily offer redemption options subject to gates to prevent disruptive withdrawals. Prices of listed BDC funds tend to follow general equity market movements.

⁹ Matvos, Piskorski, and Seru (2026), Doerr and Aldasoro (2025), and Albuquerque and Zawadowski (2025). Ivashina (2025) provides a broader overview of the private credit literature.

¹⁰ Goldman (2024) and Wyman (2024b).

¹¹ At year-end 2023, there were 132 BDCs with total net assets of \$159 billion, according to ICI's 2024 [Investment Factbook](#), corresponding to total assets under management in excess of \$300 billion (see [LSTA, 2025](#)). BDCs may be listed on stock exchanges or may be unlisted, with about an even split in terms of assets under management. Unlisted BDCs may be nontraded or private. Nontraded BDCs can be available to retail investors and operate under regular redemptions. Private BDC investors can liquidate their shares only when the BDC goes public, during specified liquidity events, or if it chooses to unwind its portfolio and liquidate the fund. Unlike other closed-end funds, BDCs are not registered under the Investment Company Act of 1940 but instead elect to be subject to certain provisions of the act. For more on BDCs, see [Horowitz and Gaines \(2019\)](#).

While still closed-end funds holding similarly illiquid and opaque loans, BDCs provide retail and institutional investors with greater liquidity and transparency than other private credit vehicles. Many private credit firms operate BDCs, accounting for approximately \$300 billion of private credit assets in total, offering a window into this opaque world. However, differences in fee structures, leverage limits, and investor liquidity attributes mean that stress in BDCs may manifest differently than in the private funds. In particular, disclosure requirements may make riskier lending exposures and structures less attractive to BDCs than other funds.

While BDCs represent only a fraction of the private credit market, sharp drawdowns in their valuations may serve as a stress signal—one that casts a shadow over less-transparent vehicles. As in past episodes, from structured credit in 2008 to U.K. pensions in 2022, the trigger is not necessarily realized losses but the suspicion of them.

STRUCTURAL FEATURES AMPLIFY VALUATION UNCERTAINTY

The relevance of private credit for financial stability lies less in the likelihood of immediate borrower insolvency than in how the structure of the funds affects transparency, comparability, and the timing of loss recognition for end investors. As private credit has expanded, the combination of bespoke contracts, layered leverage, sectoral concentration, and deferred cash flow features has increased dispersion across borrowers and obscured the mapping from underlying credit fundamentals to reported valuations. These characteristics do not, by themselves, imply systemwide fragility, but they raise the probability that, when shocks occur, they are transmitted through valuation uncertainty, funding responses, and confidence effects rather than through realized defaults.

Inherent traits of commercial lending to small private institutions include the lack of an active secondary market for individual loans and infrequent, lower-quality financial reporting. Valuation is necessarily ad hoc and model-based. Mark-to-model assets are vulnerable to swings in market confidence. In leveraged or liquidity-sensitive institutions, that shift in perception can become self-reinforcing, prompting sharp asset markdowns and investor redemptions well before the underlying loans default.

Features such as payment-in-kind arrangements, which allow borrowers to defer interest payments by adding them to the loan's principal, offer short-term relief but bring additional risks. If not managed carefully, they can rapidly increase debt levels, potentially exacerbating financial strain. Moody's Ratings has noted that the rising use of PIK loans in private credit mirrors a broader trend across corporate lending toward distressed exchanges, in which companies restructure debt to avoid a payment default, potentially resulting in larger ultimate losses for investors (see Chart 7).¹² In a stress environment, the transition from PIK income to realized impairment can be abrupt, leading to discrete valuation jumps.

While many private credit vehicles are insulated from immediate market repricing, they are not immune to broader market dynamics, particularly in a stress environment. Investor sentiment and capital allocation decisions can shift quickly, leading to fundraising challenges in evergreen vehicles or spillovers into other asset classes as investors rebalance. Funds that use leverage or offer redemptions may face margin calls or lose access to funding lines. Even without daily NAVs or immediate withdrawal risk, other effects—such as heightened counterparty scrutiny, unrealized losses on illiquid holdings, or sudden repricing in related exposures—can trigger liquidity pressures across an asset manager's holdings. In times of stress, the mere suspicion that opaque or illiquid assets may conceal losses can undermine confidence in the manager's broader portfolio, prompting counterparties to retrench or

¹² Hamilton and Su (2025).

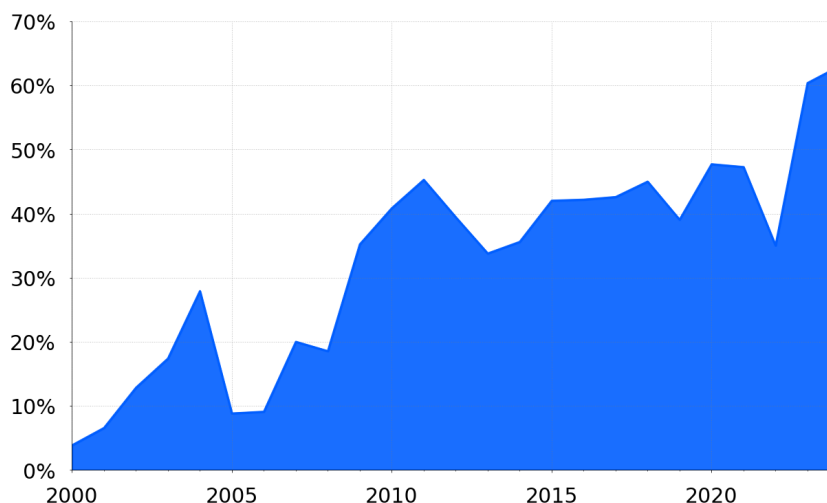
investors to redeem from more liquid vehicles. This, in turn, can force asset sales and amplify contagion across otherwise unrelated asset classes.

Chart 7: Distressed Exchanges Are on the Rise

Distressed exchanges, % of total defaults

Restructuring a debt contract by extending maturities and modifying other terms, especially under financial duress, is often considered a default.

Rather than resulting in defaults such as missed payments or bankruptcies, the expected heightened default risk is more likely to show itself in more distressed restructurings.



Sources: Moody's Ratings, Moody's Analytics

SYSTEMIC RISK TRANSMISSION VIA VALUATION SHOCKS

As noted above, recent empirical work emphasizes that the balance-sheet structure of private credit funds differs fundamentally from that of banks, reducing exposure to classic run-based fragility.¹³ Higher capitalization and more limited maturity transformation lower reliance on runnable short-term liabilities, so losses are initially borne by equity investors rather than by short-term creditors. From this perspective, private credit is less susceptible to a run, in which uncertainty about asset values makes it individually rational for depositors or other short-term creditors to withdraw funding en masse after it becomes uncertain that an institution has sufficient liquid funds to meet all redemption requests.¹⁴

A more likely channel for systemic transmission of private credit risks arises through valuation shocks—changes in expectations about the realizable future value of an asset—amplified by opaque balance sheets, asymmetric information and correlated exposures. Even absent widespread runs, shocks can propagate through asset-price declines, balance-sheet interactions, and synchronized reductions in risk-bearing capacity.¹⁵ When financing conditions depend on model-based rather than continuously priced valuations, uncertainty about true asset values can amplify shocks through abrupt repricing and balance-sheet adjustments and, if severe enough, could trigger default dynamics and runs.¹⁶

A useful way to think about the rise of private credit, much like private equity, is that it has matched an investor base willing to tolerate bespoke contracts, limited transparency, and infrequent price discovery. For ordinary shocks, this structure can be stabilizing: Shifting

¹³ Matvos, Piskorski, and Seru (2026).

¹⁴ Diamond and Dybvig (1983).

¹⁵ Bernanke and Gertler (1989).

¹⁶ Kiyotaki and Moore (1997).

part of corporate lending away from maturity-transforming banks toward vehicles funded with longer-horizon capital reduces exposure to forced liquidation and run dynamics. The trade-off is that more system-level credit risk shifts into parts of the financial system where information is less transparent and exposures are harder to infer in real time.¹⁷

This matters in part because there is no clean segmentation between banks and private credit. Using administrative bank loan data matched to private debt deals, recent evidence shows that dual borrowing is common and economically meaningful (see Chart 8).¹⁸ For these borrowers, private lenders tend to provide larger, riskier, and more junior term loans at higher spreads, while banks supply revolving credit lines that function as liquidity insurance. In stress, this structure can transmit shocks back to banks through drawdowns, shared borrower risk, and correlated credit exposures, even if the private credit funds themselves do not face runs.

Opacity becomes systemically relevant when it raises uncertainty about the size, distribution and recoverability of losses following adverse shocks. In private credit markets, bespoke structures and limited transparency constrain the production and aggregation of information about underlying exposures. As a result, adverse information can trigger sharp and correlated revisions in risk assessments, as asymmetric information and limited verifiability push investors toward conservative worst-case pricing even in the absence of forced selling or widespread runs.¹⁹ Publicly traded BDCs offer a limited but informative window into this mechanism: During the BDC stress that began in late 2025, the wedge between market prices and reported NAVs widened sharply, illustrating how quickly investor perceptions of risk and required discounts can change when uncertainty spikes, even when underlying assets are illiquid and not continuously traded (see Chart 9).

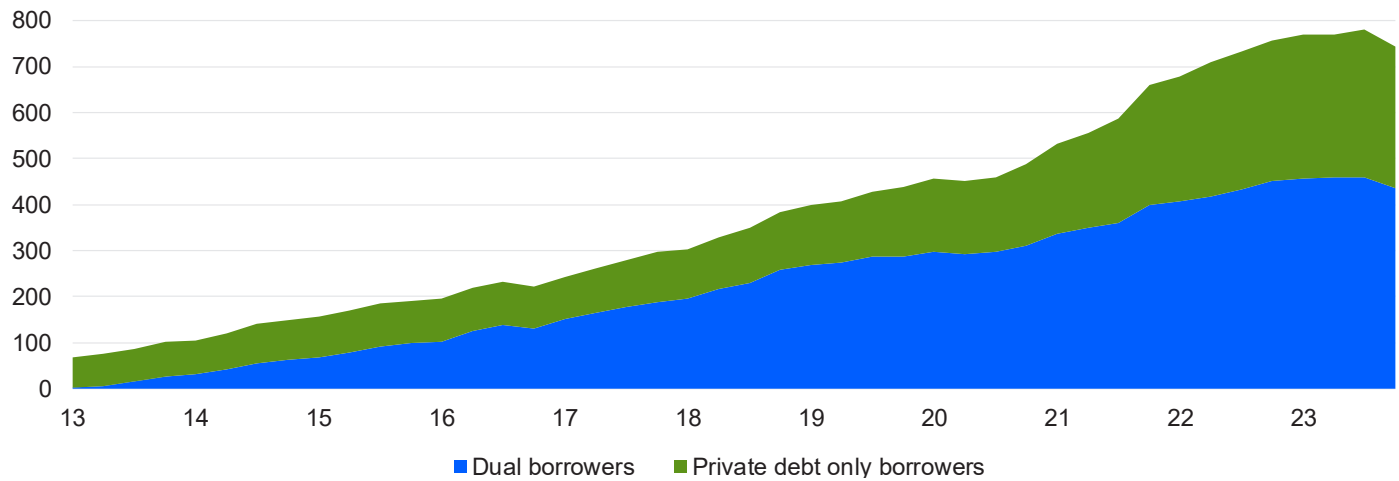
¹⁷ Dang, Gorton, and Holmström (2020).

¹⁸ Haque, Mayer, and Stefanescu (2025).

¹⁹ Brunnermeier and Pedersen (2009).

Chart 8: Many PC Borrowers Are Also Bank Borrowers

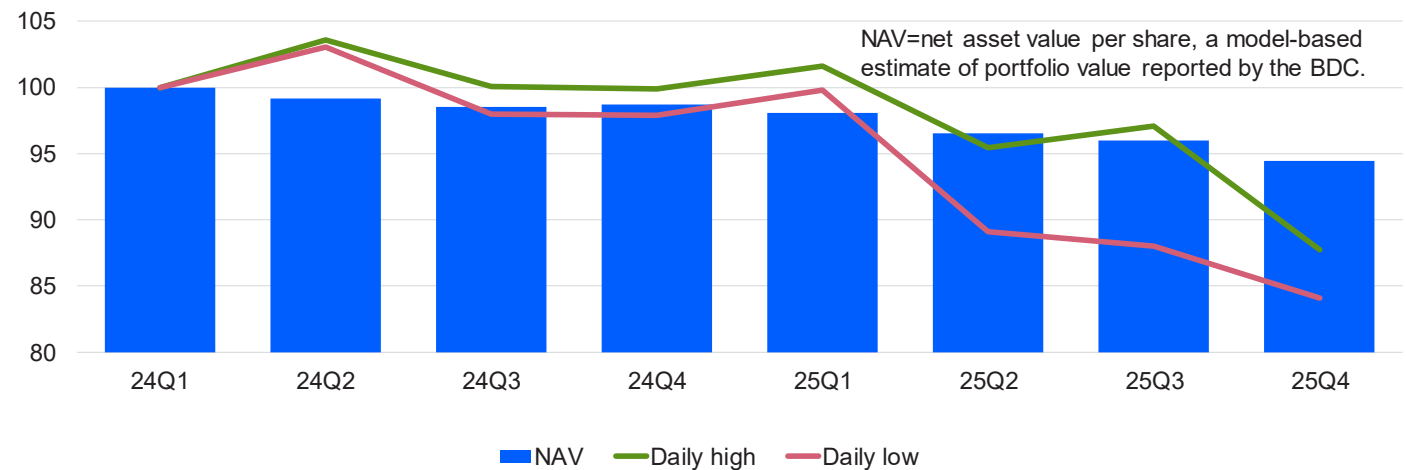
Outstanding debt, \$ bil



Sources: FDIC, Moody's Analytics

Chart 9: Traded BDC Prices Fall More Sharply Than Reported NAV in Stress

Quarterly high/low of daily closing price vs. qtr-end NAV, % of 2024Q1 values; avg of 10 largest traded BDCs



Source: Moody's Analytics

Historical experience from the early phases of the GFC shows that sharp valuation declines in illiquid assets can impair balance sheets and generate prolonged contractions in credit supply even without depositor runs. For banks and other leveraged intermediaries, valuation losses or rising funding costs can prompt balance-sheet contraction and tighter underwriting, reinforcing wider spreads and tighter financial conditions. Lower maturity mismatch in private credit reduces exposure to run-driven instability at origination, but growing links between banks and private credit mean that valuation shocks in opaque credit markets can still propagate back into the banking system through direct funding exposures and shared borrower risk. Crucially, losses on these exposures need not be realized to generate bank stress: Uncertainty about their size and distribution can be sufficient to pressure bank debt and equity valuations and raise counterparty concerns.

ASSESSING THE SYSTEMIC RISK OF PRIVATE CREDIT

Private credit is becoming increasingly relevant to the broader financial system, but its rapid evolution, structural complexity and limited transparency make it difficult to directly observe the extent to which it poses a systemic threat. Instead, we use market-based signals—from the pricing of BDCs and other financial firms—to statistically infer the interconnectedness of private credit with the broader financial system and assess potential risk transmission channels.

More specifically, to gauge interconnectedness over time, we apply PCA to market-based measures of financial institutions' default risks and stock returns. This technique determines whether common or idiosyncratic factors drive firm-level financial shocks. We also employ Granger-causality network modeling of firm default risks and stock returns, which allows us to detect how distress at one group of institutions might spill over to others over time. See the Appendix for technical details.

Our analysis draws on matched monthly data for 60 large U.S.-domiciled financial institutions from January 2004 through March 2026, grouped into commercial banks, including global systemically important banks, insurers, BDCs, and other NBFIs. The other NBFI category includes large U.S. asset managers, broker-dealers, financial data providers, exchanges, and specialty finance companies. We use two market measures across these firms: five-year expected default frequency from the Moody's public company database and total stock returns from the Center for Research in Securities Prices.²⁰

Using both measures allows us to capture complementary aspects of firm-level risk and interconnectedness, with stock returns reflecting real-time equity market shocks and EDFs capturing forward-looking credit risk shocks. BDCs serve as our proxy for the private credit market because private closed-end funds do not provide public market signals. We focus on firms with continuous data coverage since at least 2007, just prior to the GFC, when BDC representation in our sample stabilizes, and apply standard transformations to ensure stationarity and comparability across firms.

Table 1 summarizes key characteristics of the institutions in our sample, including average default risk and stock return behavior. While institutions vary in size—banks and insurers are notably larger than BDCs and other NBFIs—all sectors exhibit meaningful financial risk. Across the sample, equity returns and volatilities are broadly similar, except for somewhat lower average returns for banks. Default risk, measured by five-year EDFs, shows sectoral differences that persist over time. However, all sectors experienced pronounced spikes in default risk and severe losses during crisis periods, with some differences between the GFC and the COVID-19 shock. These similarities and divergences motivate our exploration of how interconnectedness amplifies distress.

²⁰ Moody's (2020).

Table 1: Summary Statistics for the EDF and Stock Return Datasets

	Banks	BDCs	Other NBFIs	Insurers
Count	15	15	15	15
Total assets in sample (\$ bil, 2024)	17,000	50	1,300	3,000
Representative assets in universe (\$ bil, 2024)	20,000	1,100*	20,000*	8,500
5-year EDF (%)				
Avg 2005M1-2025M3	0.48	1.67	0.97	0.55
Std. dev of EDF (monthly %)	0.5	0.47	0.68	0.33
Avg GFC peak (2009M2)	4.62	3.62	3.42	2.89
Avg COVID-19 peak (2020M9)	0.49	2.13	0.49	0.95
Stock returns (%)				
Avg annualized return 2005M1-2025M3	8.0	10.3	10.9	10.7
Std. dev of return (monthly %)	7.0	6.1	6.3	6.8
Avg GFC peak loss (2008M1-2009M2)	-63.1	-44.1	-54.3	-64.5
Avg COVID-19 peak loss (2020M1-2020M3)	-36.6	-44.6	-29.2	-33.6

*BDCs include entire USD private credit assets; other NBFIs include custodial assets of asset managers.

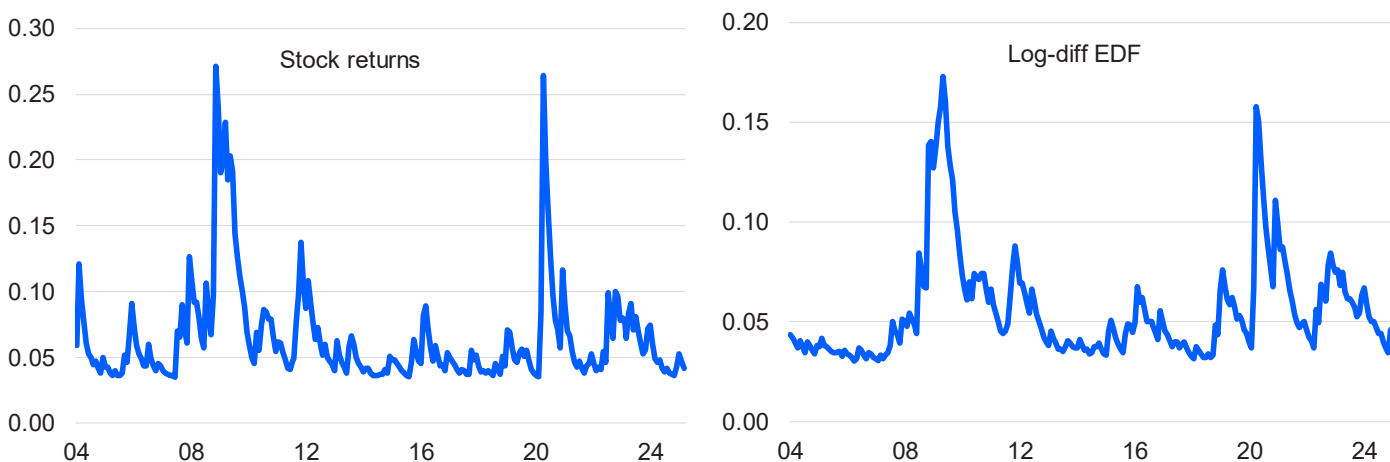
Source: Moody's Analytics

VARIANCE OF THE SYSTEM

We first estimate the system's variance using a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (1,1) model (see Chart 10).²¹ We compute these estimates separately for the cross-sectional average of stock returns (left) and the log-differenced EDFs (right).

Chart 10: Aggregate Return Volatility Spikes in Crisis Periods

GARCH (1,1) estimate of return and EDF conditional variances at the portfolio level



Source: Moody's Analytics

Overall system conditional volatility rises during financial stress, signaling potential systemic instability. As expected, both series show clear spikes during the GFC (2008-2009) and the onset of the COVID-19 pandemic (2020). We also observe smaller upticks around 2012 (potentially reflecting the euro area crisis and U.S. monetary interventions), 2016 (coinciding with a sharp decline in oil prices), and 2022 (aligned with rapid monetary tightening).

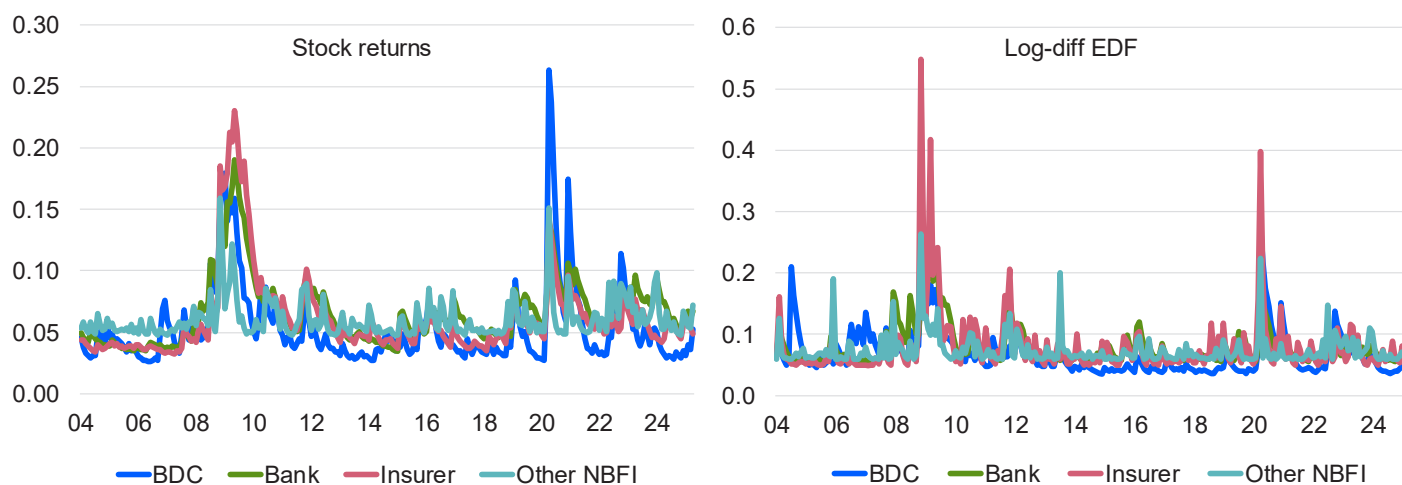
²¹ We calculate the average of returns and EDF percentage changes for all 60 firms in the study and estimate a GARCH (1,1) model on the resulting time series over the time period from January 2004 through March 2026.

These patterns underscore the common exposure of large U.S. financial institutions to systemic shocks.

Additionally, the GARCH-driven estimates allow us to observe how volatility dynamics have evolved across sectors over time (see Chart 11). During the GFC, volatility spikes were more pronounced for banks and NBFIs, reflecting that period's systemic risks and financial instability. In contrast, during the COVID-19 pandemic, banking sector volatility decreased, likely due to improved capital and liquidity regulation and more resilient risk management, while NBFIs experienced higher volatility. This shift indicates how the types of risks and their impact on specific sectors changed between the two crises.

Chart 11: BDC Volatility Shocks More Prominent in COVID-19 Than GFC

GARCH (1,1) sector-specific variance based on stock returns and EDF



Source: Moody's Analytics

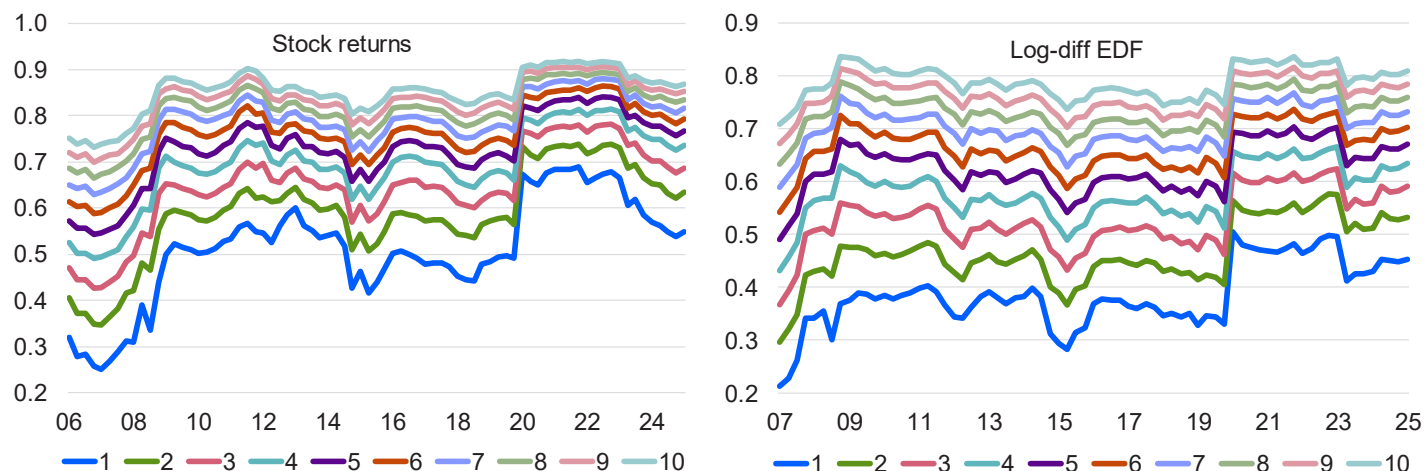
ASSESSING INTERCONNECTEDNESS USING PCA

We then employ PCA to decompose the returns and, separately, the EDFs into a set of uncorrelated factors. PCA helps identify the underlying common sources of risk that affect multiple institutions simultaneously. By focusing on the first few principal components, which capture the largest share of variance, we can discern how much of the risk in the system is driven by common factors. Conceptually, the greater the explanatory power of these principal components, the more interlinked the institutions are, and the higher the potential for contagion during periods of stress.

The PCA decomposition shows that the first few principal components dominate during crises. The first principal component (PC1) is highly dynamic, and both return-based and EDF-based PC1s explain only a modest fraction of the total variance, suggesting the importance of idiosyncratic factors (see Chart 12). However, in the GFC and COVID-19 periods, the variance explained by PC1 and the first few top principal components rises sharply. In these stressed environments, the financial system becomes highly interconnected, and a single systemic factor explains a much larger share of the risk across firms as correlations between different sectors approach unity.

Chart 12: Leading PCAs More Important Over Time and in Crises

Cumulative 3-yr total variance explained by first 10 principal components, %



Source: Moody's Analytics

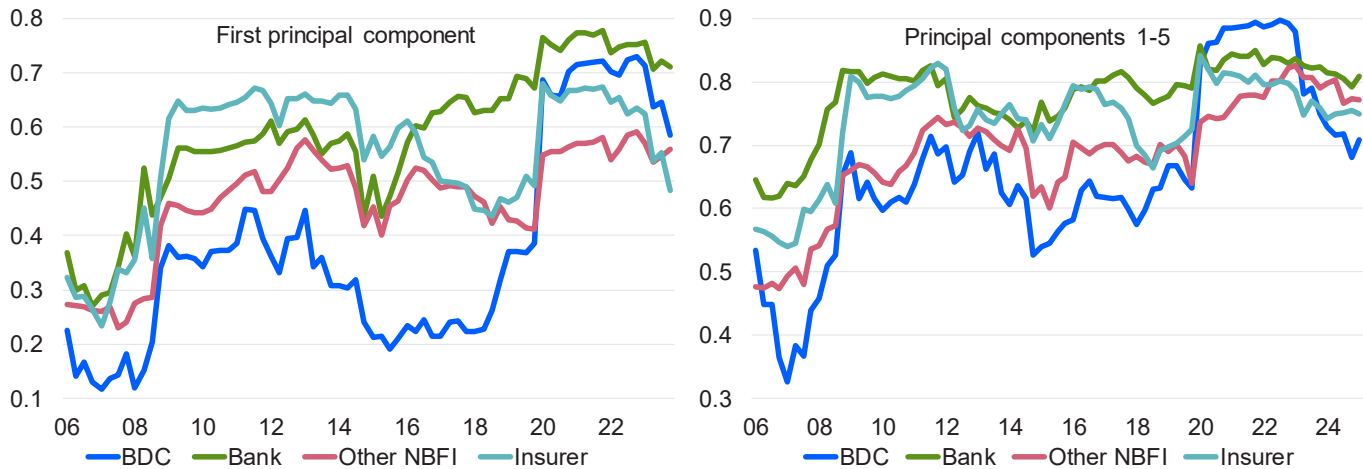
Moreover, our principal component analysis illustrates that the explanatory power of the first few principal components has increased over the past 20 years for stock returns and, to a lesser extent, for EDFs, suggesting that the financial system has generally become more highly interconnected. Specifically, we note that PC1 after the COVID-19 shock explains a higher fraction of total variance (risk) in the system compared with the fraction of risk captured by PC1 in the GFC period.

To explore how strongly individual firms are associated with common PCA components, we regress each firm's returns, or EDF changes, on the leading principal components—typically the first, or the first five—and record the average R-squared across firms within each sector over time (see Charts 13 and 14). These results indicate how much firm-level variation can be explained by common, systemwide factors in each period. A higher average R-squared within a sector indicates stronger co-movement with the dominant sources of systemic risk and points to higher exposure to common shocks and contagion potential. We observe that average R-squares for all groups were low during the pre-GFC years and spiked sharply during the crisis, consistent with a systemwide liquidity and solvency shock. However, BDCs and other NBFIs were significantly less affected. By contrast, BDCs displayed a marked increase in their common factor explained variance during COVID-19. Moreover, this effect persists post-pandemic, suggesting that BDCs are increasingly sensitive to systemic risk factors.

This growing co-movement of private credit firms with the key PCA components suggests that the expansion of private credit is contributing to a more interconnected financial system, and that the level of connectedness could become more consequential during periods of market stress.

Chart 13: BDCs Increasingly Linked to Principal Components

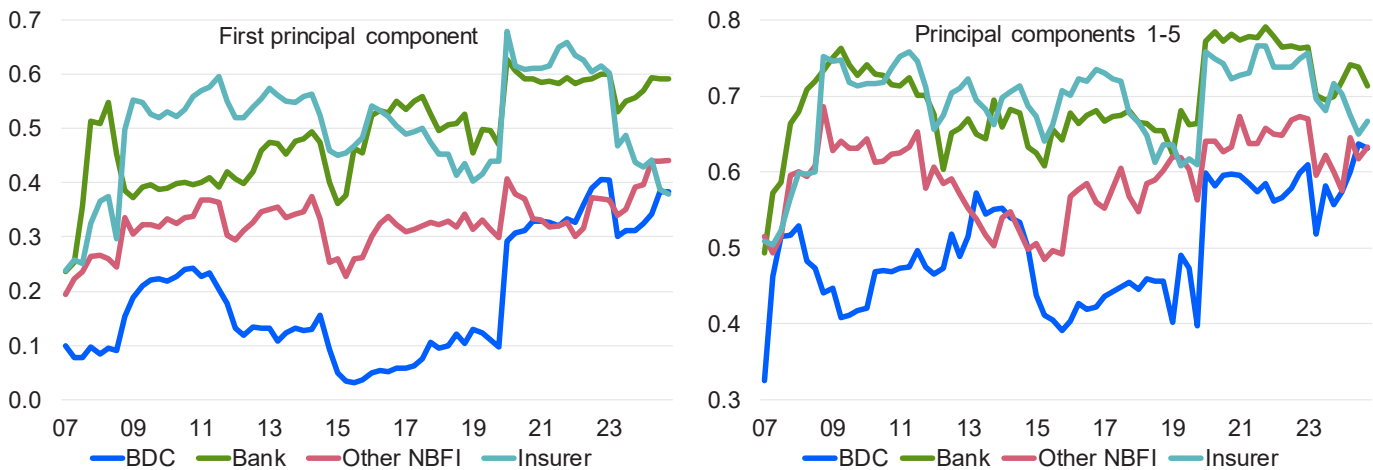
Avg share of company stock return variance in each sector explained, %



Source: Moody's Analytics

Chart 14: EDF Variation Explained by System Principal Components

Avg share of company log-differenced EDF variance in each sector explained, %



Source: Moody's Analytics

ASSESSING CONTAGION USING GRANGER CAUSALITY

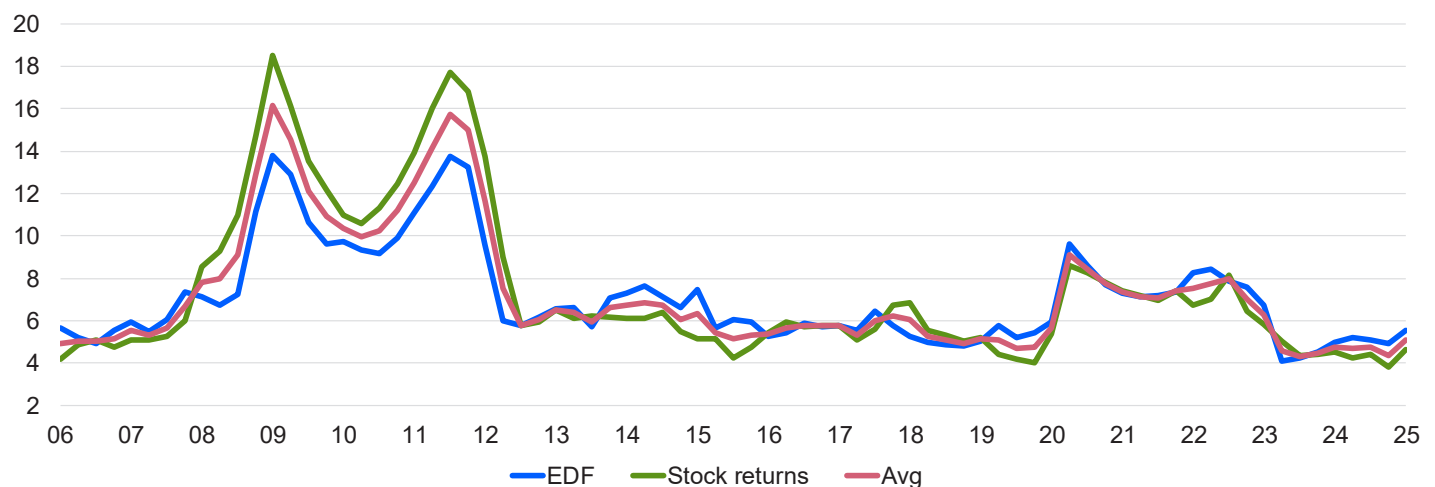
We measured the degree of interconnectedness between firms using PCA. We now use Granger-causality analysis to investigate the directionality of these relationships and to identify evidence of spillovers during periods of market stress. We construct a Granger-causality network to map how risk transmission channels across financial institutions evolve over time, showing that, post-GFC, BDCs have become relatively more central and banks relatively less central in the network during periods of market stress. That, of course, is an observation about evolving interconnectivity, not necessarily about systemic impact: U.S. banks remain a central pillar of the financial system, providing \$19 trillion in credit, several magnitudes higher than that offered by private credit funds directly.

In brief, for three-year rolling windows across our sample, we perform pairwise Granger-causality tests on monthly EDF time series and stock return series for all institutions. For each pair of firms A and B, A is said to Granger-cause B if a predictive model of the returns of B on the prior month's value of A and B is statistically more predictive than a model without A's return included. Each significant Granger-causal relationship is treated as a directed edge, or connection, in a network graph with "source" and "target" firm nodes. We further classify the connection as forcing (increasing the target's risk) or dampening (reducing the target's risk). By rolling this analysis through time, we can track how densely connected the network is and which sectors are hubs of contagion. Both EDFs and stock returns yield qualitatively similar connectedness trends.

The results reveal that the financial system's network connectivity rises dramatically during stress, within and across sectors. For example, in the runup to the GFC, less than 5% of all possible firm-to-firm risk linkages were statistically significant, which is indistinguishable from the statistical noise floor that, just by chance, 5% of firms would be found to be Granger-caused by each other. During the crisis, however, the share of significant linkages jumped into the double digits, with many institutions predicting the subsequent returns or EDFs of others (see Chart 15). In our PCA results, we see elevated connectivity during periods of stress, along with more general signs of rising interconnectivity over time. In contrast, the Granger-causality results show pronounced interconnection that appears only during periods of stress. We view the difference between Granger and PCA results as being symptomatic of the Granger results capturing contagion effects, loss spillovers from one firm to another, that turn otherwise benign interconnection into something more harmful.

Chart 15: Financial Institutions Interconnected in Periods of Stress

Number of Granger linkages (3-yr window ending at indicated period), % of total possible linkages



Source: Moody's Analytics

The same pattern holds across and within different types of institutions, where linkages consistently strengthen during market stress (see Table 2). As of January 2020, just before the pandemic hit, the fraction of significant group-to-group Granger connections—bank-to-BDC, bank-to-insurer, etc.—was at or below the 5% noise floor. But between 2020 and 2021, the network had become significantly more interconnected, with connection rates averaging just shy of 10% across all possible group pairings.

Table 2a: Within- and Cross-Group Connections Rise During Crisis Periods

Number of Granger connections as a % of total possible connections (3-yr window ending at indicated period)

2006M12		Pre-financial crisis (stock returns)			
All		4.54			
	To	Bank	BDC	Other	Insurer
From					
Bank		2.86	5.56	7.56	4.89
BDC		3.33	3.33	2.22	4.44
Other NBFI		3.11	6.67	5.24	3.56
Insurer		6.22	5.56	4.44	2.86

2009M3		Peak financial crisis (stock returns)			
All		18.82			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		26.19	27.22	13.78	28.89
BDC		17.78	13.64	12.22	17.78
Other NBFI		10.67	13.33	10.00	13.78
Insurer		25.33	25.56	17.33	26.19

2009M12		Financial crisis recovery (stock returns)			
All		12.22			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		17.62	13.33	8.44	17.78
BDC		10.26	8.97	9.74	10.26
Other NBFI		8.89	7.18	8.10	10.67
Insurer		14.67	16.92	16.44	14.76

2019M12		Pre-COVID-19 (stock returns)			
All		4.07			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		4.29	4.89	7.56	3.11
BDC		8.89	4.76	6.67	1.78
Other NBFI		1.78	1.33	5.71	1.78
Insurer		3.56	4.00	3.56	1.43

2020M6		COVID-19 crisis (stock returns)			
All		8.70			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		10.95	11.56	12.00	6.22
BDC		10.67	10.48	8.89	6.22
Other NBFI		8.44	6.22	5.24	7.56
Insurer		4.44	16.44	4.44	9.52

2021M12		COVID-19 recovery (stock returns)			
All		7.46			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		7.14	12.00	7.56	8.44
BDC		2.67	15.24	7.11	5.78
Other NBFI		5.33	10.22	3.33	4.00
Insurer		5.33	15.11	3.56	6.67

2026M3		COVID-19 recovery (stock returns)			
All		4.72			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		3.33	3.11	5.78	2.22
BDC		4.44	1.90	3.56	2.67
Other NBFI		4.00	6.22	6.67	6.67
Insurer		4.00	6.22	7.56	7.14

2006M12		Pre-financial crisis (EDF)			
All		5.69			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		8.10	4.76	4.00	6.67
BDC		2.86	7.14	4.76	4.76
Other NBFI		4.44	6.67	7.14	4.89
Insurer		4.89	2.86	6.67	8.10

2009M3		Peak financial crisis (EDF)			
All		13.16			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		17.14	12.82	8.00	21.78
BDC		5.13	9.62	6.67	7.18
Other NBFI		17.78	6.67	5.24	17.33
Insurer		20.00	14.36	14.22	22.38

2009M12		Financial crisis recovery (EDF)			
All		9.29			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		14.76	12.44	5.78	12.89
BDC		9.78	4.29	8.44	5.33
Other NBFI		16.00	5.33	7.62	7.56
Insurer		13.33	8.00	8.00	9.05

2019M12		Pre-COVID-19 (EDF)			
All		5.03			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		7.62	5.78	5.78	5.33
BDC		7.11	4.29	3.11	4.00
Other NBFI		2.67	4.00	3.33	6.67
Insurer		5.33	6.67	4.89	3.81

2020M6		COVID-19 crisis (EDF)			
All		10.00			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		14.29	11.11	16.89	13.78
BDC		10.22	6.67	8.44	4.44
Other NBFI		8.89	7.11	11.43	9.78
Insurer		5.33	9.78	11.56	10.48

2021M12		COVID-19 recovery (EDF)			
All		7.71			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		13.33	5.33	12.44	12.00
BDC		9.33	6.19	8.00	8.89
Other NBFI		4.89	4.00	5.24	8.44
Insurer		6.22	4.00	9.78	5.24

2026M3		COVID-19 recovery (EDF)			
All		6.38			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		4.76	8.44	5.33	3.56
BDC		5.33	4.29	4.89	8.00
Other NBFI		7.11	7.11	6.19	7.56
Insurer		10.67	8.00	5.78	4.76

Notes: Numbers in bold represent statistically significant connection rates following the bootstrap procedure described in the Appendix.

Source: Moody's Analytics

Table 2b: Within- and Cross-Group Connections Rise During Crisis Periods

Number of Granger connections as a % of total possible connections (3-yr window ending at indicated period)

2006M12		Pre-financial crisis (connection rate)			
All		5.12			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		5.48	5.16	5.78	5.78
BDC		3.10	5.24	3.49	4.60
Other NBFI		3.78	6.67	6.19	4.22
Insurer		5.56	4.21	5.56	5.48

2009M3		Peak financial crisis (connection rate)			
All		15.99			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		21.67	20.02	10.89	25.33
BDC		11.45	11.63	9.44	12.48
Other NBFI		14.22	10.00	7.62	15.56
Insurer		22.67	19.96	15.78	24.29

2009M12		Financial crisis recovery (connection rate)			
All		10.76			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		16.19	12.89	7.11	15.33
BDC		10.02	6.63	9.09	7.79
Other NBFI		12.44	6.26	7.86	9.11
Other NBFI		14.00	12.46	12.22	11.90

2019M12		Pre-COVID-19 (connection rate)			
All		4.55			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		5.95	5.33	6.67	4.22
BDC		8.00	4.52	4.89	2.89
Other NBFI		2.22	2.67	4.52	4.22
Insurer		4.44	5.33	4.22	2.62

2020M6		COVID-19 crisis (connection rate)			
All		9.35			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		12.62	11.33	14.44	10.00
BDC		10.44	8.57	8.67	5.33
Other NBFI		8.67	6.67	8.33	8.67
Insurer		4.89	13.11	8.00	10.00

2021M3		COVID-19 recovery (connection rate)			
All		7.59			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		10.24	8.67	10.00	10.22
BDC		6.00	10.71	7.56	7.33
Other NBFI		5.11	7.11	4.29	6.22
Insurer		5.78	9.56	6.67	5.95

2026M3		COVID-19 recovery (connection rate)			
All		5.55			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		4.05	5.78	5.56	2.89
BDC		4.89	3.10	4.22	5.33
Other NBFI		5.56	6.67	6.43	7.11
Insurer		7.33	7.11	6.67	5.95

2006M12		Pre-financial crisis (ratio to all)			
All		100			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		1.07	1.01	1.13	1.13
BDC		0.61	1.02	0.68	0.90
Other NBFI		0.74	1.30	1.21	0.83
Insurer		1.09	0.82	1.09	1.07

2009M3		Peak financial crisis (ratio to all)			
All		100.00			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		1.36	1.25	0.68	1.58
BDC		0.72	0.73	0.59	0.78
Other NBFI		0.89	0.63	0.48	0.97
Insurer		1.42	1.25	0.99	1.52

2009M12		Financial crisis recovery (ratio to all)			
All		100.00			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		1.51	1.20	0.66	1.43
BDC		0.93	0.62	0.85	0.72
Other NBFI		1.16	0.58	0.73	0.85
Insurer		1.30	1.16	1.14	1.11

2019M12		Pre-COVID-19 (ratio to all)			
All		100.00			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		1.31	1.17	1.47	0.93
BDC		1.76	0.99	1.07	0.63
Other NBFI		0.49	0.59	0.99	0.93
Insurer		0.98	1.17	0.93	0.58

2020M6		COVID-19 crisis (ratio to all)			
All		100.00			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		1.35	1.21	1.54	1.07
BDC		1.12	0.92	0.93	0.57
Other NBFI		0.93	0.71	0.89	0.93
Insurer		0.52	1.40	0.86	1.07

2021M3		COVID-19 recovery (ratio to all)			
All		100.00			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		1.35	1.14	1.32	1.35
BDC		0.79	1.41	1.00	0.97
Other NBFI		0.67	0.94	0.57	0.82
Insurer		0.76	1.26	0.88	0.78

2021M3		COVID-19 recovery (ratio to all)			
All		100.00			
	To	Bank	BDC	Other NBFI	Insurer
From					
Bank		0.53	0.76	0.73	0.38
BDC		0.64	0.41	0.56	0.70
Other NBFI		0.73	0.88	0.85	0.94
Insurer		0.97	0.94	0.88	0.78

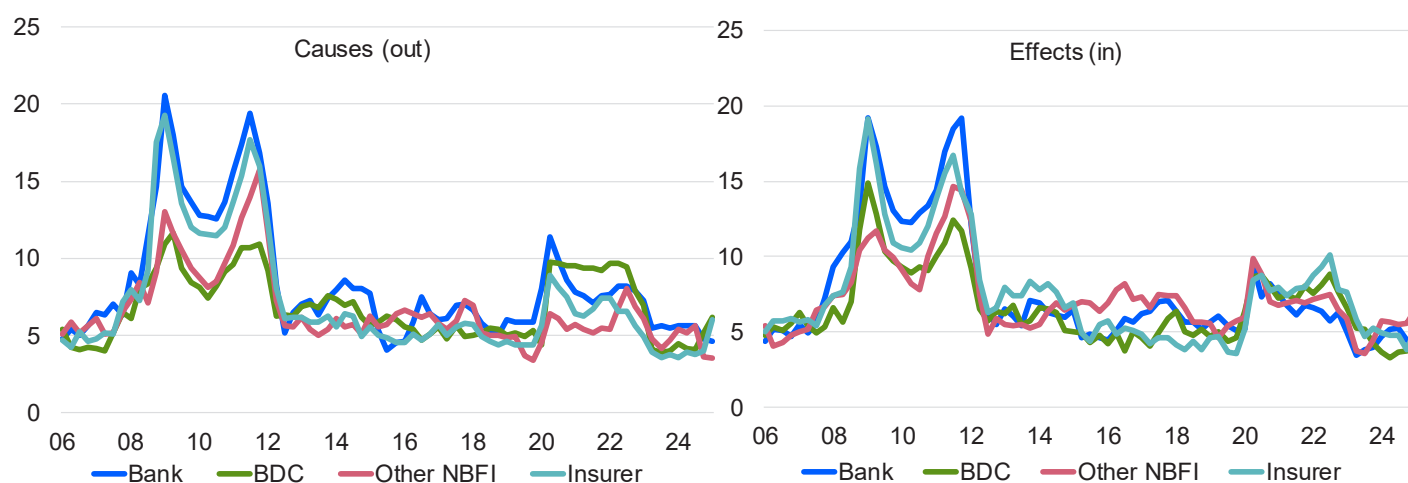
Notes: Numbers in bold represent statistically significant connection rates following the bootstrap procedure described in the Appendix.

Source: Moody's Analytics

Moreover, comparing the GFC period with the post-pandemic period that began in 2022, Table 2 shows that BDCs have become more prominent in the network, while banks have become less so. Specifically, BDCs Granger-cause a larger percentage of banks and nonbanks during the latest stages of the crisis and are Granger-caused to a larger extent by banks and nonbanks during the more recent crisis episode. In absolute terms, the GFC shock was a significantly larger source of financial market stress than the COVID-19 shock, with higher average rates of interconnectedness across all sectors (see Chart 16). But while banks, and to a lesser extent, insurers, were relatively more important in the GFC, in the COVID-19 shock, the connectedness was more evenly spread across sectors in the network. During the GFC, banks and insurers were most likely both sources and destinations of stress. During the COVID-19 shock, we see banks and BDCs slightly more likely to be sources of spillovers (causes), and insurers and other nonbanks somewhat more likely to be destinations of spillovers (effects).

Chart 16: BDC and Other NBFI Links Rise in Pandemic Period From GFC

Number of Granger linkages, % of total possible linkages, EDF and returns avg (3-yr rolling windows)



Source: Moody's Analytics

The growing dispersion of connectivity in relative terms can also be seen in the rightmost column of Table 2, comparing the March 2009 and June 2020 matrix of cross-sector connection rates relative to the average connection rate in those periods, with a much more even spread across the matrix in 2020 than the bank and insurance tilt in 2009, including relatively more interconnections across the nonbanks.

Another striking finding is the changing topography of the networks through time (see Charts 17-19). While banks dominated the network during the GFC in a hub-and-spoke pattern, the financial network during the pandemic more closely resembled a web, with banks, insurers, BDCs and other NBFIs taking on more equal roles. And in periods of calm, the network becomes less interconnected.

Chart 17: Banks Dominated the System During the GFC

Size of node=degree of forcing connections

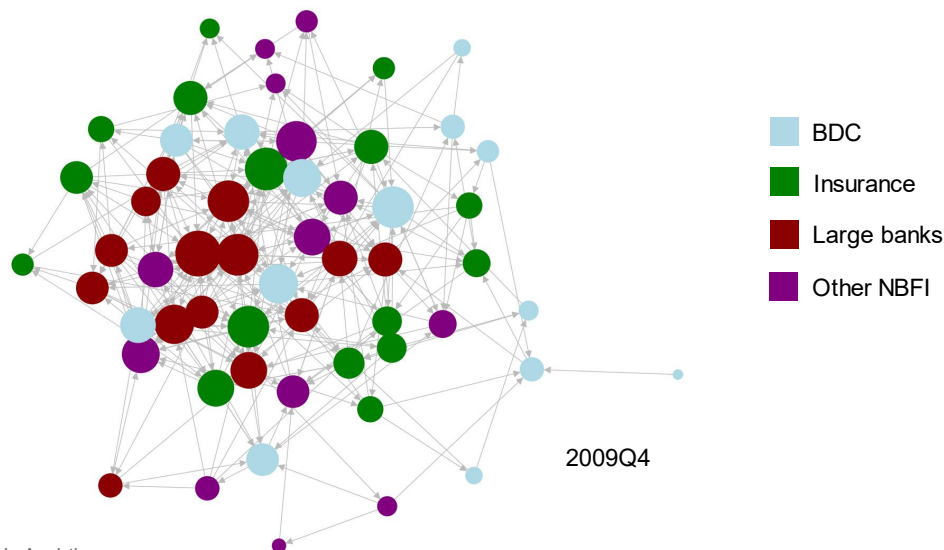


Chart 18: Network Is More Dispersed but Densely Connected Post-GFC

Size of node=degree of forcing connections

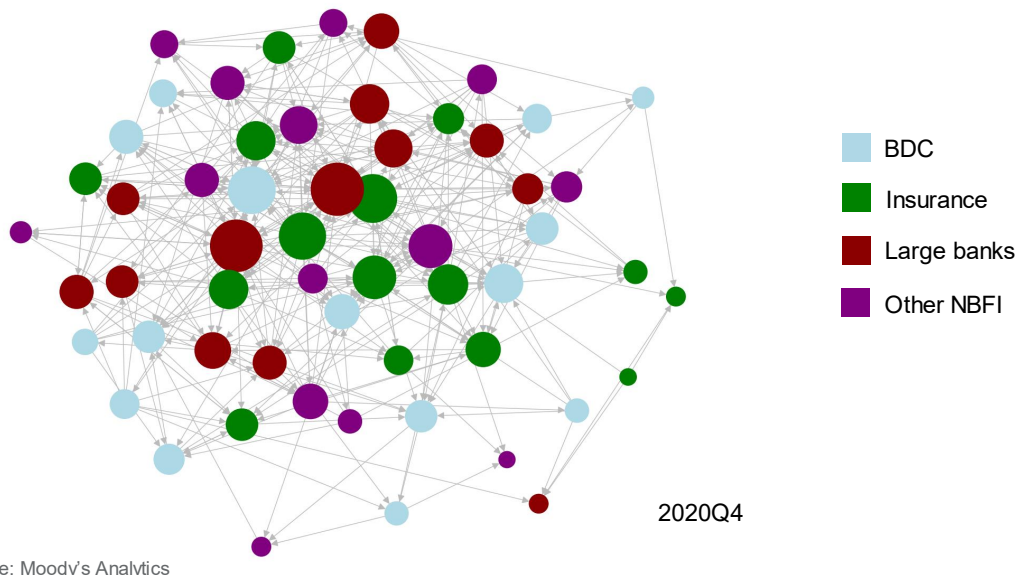
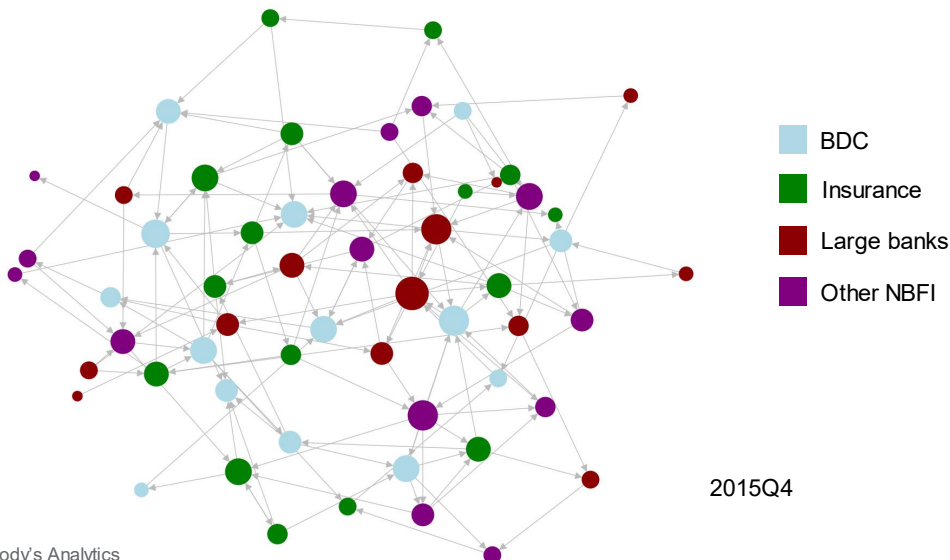


Chart 19: Networks Are Less Connected in a Well-Functioning Economy

Size of node=degree of forcing connections



PREDICTIVE POWER

To close out our analysis, we evaluate the predictive power of PCA and Granger-based measures of connectedness by conducting cross-sectional regressions of realized losses on firms' network connection levels (see Table 3, top panel). We find that these measures of connectedness during periods of systemwide stress are strongly associated with contemporaneous firm-level losses, suggesting that the network structure provides a valuable lens for explaining loss patterns during crises. We also find some evidence that the cross-sectional PCA connectivity across companies before a crisis is predictive of losses during the crisis (see Table 3, bottom panel). We do not find similar predictive power for the Granger connectivity measures, which we attribute to Granger connectivity being statistically meaningful only once a crisis has begun. However, we do see that the PCA connectivity prior to each crisis does also predict the firms in the Granger network that will have the most connectivity during the crisis (see Table 4).

Overall, our PCA and Granger network analyses suggest that the financial system has become more densely interconnected in the presence of private credit, and the impact of private credit and other sectors (particularly the nonbanks) on each other has intensified. In short, our results point to increased contagion in the presence of private credit in future crisis episodes.²² It is well-known that the financial system can become highly fragile under large negative shocks when it is densely interconnected.²³ This should be contrasted with the perhaps more intuitive scenario where a more densely connected financial network may enhance financial stability when the negative shocks are sufficiently small and below a certain threshold.²⁴

²² One caveat of our analysis of network connectivity and contagion under stress is that we have only two significant but highly different market stress periods, the GFC and COVID-19, from which to make our inferences. In terms of financial market impact, the GFC was the more significant of the two, and the liquidity crunch caused much greater market contagion overall. Differences in policy responses may also have shaped the relative impacts across sectors. Nonetheless, controlling for the overall size of the shock by focusing on relative rather than absolute measures of connectedness across sectors and using two related but different measures of performance in stock returns and EDFs, we think our results are strongly suggestive that BDCs have increased in systemic importance, while banks have become less so.

²³ More intuitive in the sense that the losses of a distressed firm are passed to a larger number of counterparties in a highly interconnected, or complete, financial network, reducing the impact of negative shocks.

²⁴ [Acemoglu, Ozdaglar, and Tahbaz-Salehi \(2015\)](#).

Table 3: Maximum Loss Prediction Estimates

Loss measure	In-sample prediction EDF loss ranking									
Crisis period	GFC					COVID-19				
Window for driver calculation	2007-2009					2018-2020				
Loss observation date	2008M7-2009M6					2020M1-2020M12				
Driver variable	In	Out	In+out	R PCA 1	R PCA 1-5	In	Out	In+out	R PCA 1	R PCA 1-5
Coefficient	1.89	2.45	1.55	43.6	38.2	2.88	0.18	1.53	41.2	46.9
T-statistic	3.91*	6.22*	6.55*	4.46*	3.17*	4.11*	0.21	2.9*	3.54*	3.06*
R-squared	0.20	0.40	0.43	0.26	0.15	0.22	0.01	0.13	0.18	0.14

Loss measure	Stock return loss ranking									
Crisis period	GFC					COVID-19				
Window for driver calculation	2007-2009					2018-2020				
Loss observation date	2008M7-2009M6					2020M1-2020M12				
Driver	In	Out	In+out	R PCA 1	R PCA 1-5	In	Out	In+out	R PCA 1	R PCA 1-5
Coefficient	1.92	1.99	1.30	50.7	93.3	0.50	1.47	0.97	63.3	122.0
T-statistic	3.88*	3.72*	4.58*	4.98*	6.12*	0.71	1.74	1.73	3.94*	4.34*
R-squared	0.21	0.20	0.27	0.31	0.40	0.01	0.03	0.05	0.21	0.25

Loss measure	Out-of-sample prediction EDF loss									
Crisis period	GFC					COVID-19				
Window for driver calculation	2005M6-2008M6					2017M3-2020M3				
Loss observation date	2008M7-2009M6					2020M1-2020M12				
Driver variable	In	Out	In+out	R PCA 1	R PCA 1-5	In	Out	In+out	R PCA 1	R PCA 1-5
Coefficient	-1.96	-0.35	-1.02	121.0	118.3	2.33	3.68	2.83	53.8	61.3
T-statistic	-0.35	-0.07	-0.28	2.41*	1.64	1.35	2.11*	2.42*	4.09*	2.39*
R-squared	0.00	0.00	0.00	0.10	0.05	0.03	0.07	0.09	0.22	0.09

Loss measure	Stock return loss									
Crisis period	GFC					COVID-19				
Window for driver calculation	2005M6-2008M6					2017M3-2020M3				
Loss observation date	2008M7-2009M6					2020M1-2020M12				
Driver	In	Out	In+out	R PCA 1	R PCA 1-5	In	Out	In+out	R PCA 1	R PCA 1-5
Coefficient	1.20	0.69	0.77	62.7	40.2	-0.15	-0.42	-0.35	43.0	55.6
T-statistic	1.22	0.70	1.23	4.39*	1.99	-0.19	-0.73	-0.73	5.93*	3.65*
R-squared	0.03	0.01	0.03	0.27	0.07	0.00	0.01	0.01	0.38	0.19

Notes: The table reports key values from a linear regression of financial institution losses on institution-level Granger connectivity or PCA estimates. Exogenous variables in each regression are estimated over the indicated 3-yr windows, and losses are recorded over the indicated 1-yr period. For the exogenous variables, In = proportion of incoming connections in the Granger network, Out = proportion of significant outgoing connections, In+out = proportion of in and out connections. R2 PCA1 is the R-squared from regressing the firm-level return or EDF on the first principal component, and R2 PCA 1-5 is the R-squared from regressing the firm-level return or EDF on the first through fifth principal component. Asterisks on T-statistics indicate statistically significant coefficients at the 5% level.

Source: Moody's Analytics

Table 4: Granger Connectivity Prediction Model Estimates

Dataset	EDF			
Crisis period	GFC			
Window for driver calculation	2005M6-2008M6 (3y)			
Granger connectivity end dates	2008M7-2009M6			
Dependent variable	In Out			
Driver	R PCA 1	R PCA 1-5	R PCA 1	R PCA 1-5
Coefficient	0.17	0.17	0.10	0.07
T-statistic	4.98*	3.08*	2.87*	1.39
R-squared	0.32	0.15	0.14	0.04

Dataset	Stock returns			
Crisis period	GFC			
Window for driver calculation	2005M6-2008M6 (3y)			
Granger connectivity end dates	2008M7-2009M6			
Dependent variable	In Out			
Driver	R PCA 1	R PCA 1-5	R PCA 1	R PCA 1-5
Coefficient	0.12	0.08	0.16	0.2
T-statistic	2.59*	1.25	3.36*	3.12*
R-squared	0.12	0.03	0.18	0.16

Notes: The table reports key values from a linear regression of financial institution losses on institution-level Granger connectivity or PCA estimates. Exogenous variables in each regression are estimated over the indicated 3-yr windows, and losses are recorded over the indicated 1-yr period. For the exogenous variables, In = proportion of incoming connections in the Granger network, Out = proportion of significant outgoing connections, In+out = proportion of in and out connections. R2 PCA1 is the R-squared from regressing the firm-level return or EDF on the first principal component, and R2 PCA 1-5 is the R-squared from regressing the firm-level return or EDF on the first through fifth principal component. Asterisks on T-statistics indicate statistically significant coefficients at the 5% level.

Source: Moody's Analytics

Our empirical results, which depend on having market data available for the firms of interest, could underestimate systemic risk from private credit. BDCs—proxies for the private credit market in our study—represent a small and, in some cases, less risky segment of the private credit market. Also, major institutional investors in private credit, such as pensions, endowments, and wealth management funds, face potential vulnerabilities but, lacking their own market signals, are not amenable to our empirical approach. Enhancing transparency and data reporting would enable more direct measurement of those entities' systemic vulnerabilities, a point we return to in our policy recommendations.

LIMITATIONS OF USING BDCS AS A PROXY

Our use of publicly traded BDCs as proxies for the broader private credit market warrants explicit discussion. BDCs trade on public exchanges, exposing their valuations to market sentiment, liquidity premiums, and retail investor behavior that closed-end private credit funds largely avoid. BDC stock prices may therefore overstate the volatility and correlation of underlying loan values. However, recent events show that even non-traded, semi-liquid private credit vehicles experience stress dynamics—through redemption queues rather than price declines—suggesting that the BDC proxy, while imperfect, captures directionally important phenomena.

Three structural factors may also influence the Granger-causality results. First, BDCs disclose loan-level portfolio detail on a quarterly basis, offering investors a more immediate window into credit conditions than banks, whose reporting is more aggregated. Second, post-2020 government interventions—such as the Bank Term Funding Program, implicit deposit guarantees, and direct support for investment-grade issuers—have suppressed market discipline for banks in ways not available to private credit. Third, BDC shareholders include a larger proportion of retail investors who tend to be more reactive to headlines than the institutional holders of large-cap bank stocks. We therefore interpret our Granger

results as indicating that private credit markets may reveal credit stress earlier than bank equity markets, making them a potentially valuable early-warning indicator for regulators—a conclusion that is arguably more useful for policy than a simple claim of causal primacy.

AN OUT-OF-SAMPLE TEST

The events of early 2026 provide a natural experiment to test the dynamics of interconnectedness documented above. A convergence of factors—record private credit defaults, AI-driven disruption of software borrowers comprising as much as one-fourth of many portfolios, lower interest coverage ratios (median 1.6x), and rising payment-in-kind usage approaching one-tenth of BDC investment income—has triggered a wave of redemption requests across major semi-liquid and evergreen private credit funds.

Importantly, this episode allows us to assess the distribution of stress across industry groups rather than the magnitude of aggregate losses, since BDCs were the only group to experience material and statistically significant drawdowns during 2025-2026, while other groups did not.

Fund-level data reveal the scale of the stress: Blackstone's BCRED received redemption requests of 7.9% of shares; Apollo's ADS BDC, 11.2%; Morgan Stanley's North Haven Private Income Fund, 10.9%; Carlyle's CTAC, 15.7%; Ares, 11.6%; and Blue Owl funds, as high as 21.9%. All invoked contractual 5% quarterly caps, fulfilling only 43% to 50% of requests. The episode prompted JPMorgan to mark down software-related loan collateral preemptively, further reducing its fund borrowing base.

These developments are consistent with the variation in firm-level connectivity identified in our PCA analysis. In particular, measures of PCA-based connectivity computed during the COVID-19 crisis are predictive of which firms ultimately experienced the largest losses in 2025-2026 (see Table 5). As in Billio et al. (2012), who show that network measures computed during periods of heightened volatility can foreshadow the distribution of losses in subsequent crises, the out-of-sample evidence here speaks to where stress materializes, conditional on a shock, rather than to the aggregate severity of the shock itself.

Table 5: Prediction of 2025-2026 BDC Stock Return Losses From Prior Connectivity

Loss measure		Loss measure									
Loss window		2025M3-2026M3									
Window for driver calculation		2020-2022					2023M3-2026M3				
Driver		In	Out	Int+Out	R PCA1	R PCA 1-5	In	Out	Int+Out	R PCA1	R PCA 1-5
Coefficient		0.93	-0.08	0.62	23.18	102.7	-0.33	-1.63	-1.29	21.46	38.1
T-statistic		1.09	-0.08	0.86	1.13	2.85*	-0.22	-1.38	-1.30	1.59	1.63
R-squared		0.02	0.00	0.01	0.02	0.12	0.00	0.03	0.03	0.04	0.04

Notes: The table reports key values from a linear regression of financial institution losses on institution-level Granger connectivity or PCA estimates. Exogenous variables in each regression are estimated over the indicated 3-yr windows, and losses are recorded over the indicated 1-yr period. For the exogenous variables, In = proportion of incoming connections in the Granger network, Out = proportion of significant outgoing connections, In+out = proportion of in and out connections. R2 PCA1 is the R-squared from regressing the firm-level return or EDF on the first principal component, and R2 PCA 1-5 is the R-squared from regressing the firm-level return or EDF on the first through fifth principal component. Asterisks on T-statistics indicate statistically significant coefficients at the 5% level.

Source: Moody's Analytics

POTENTIAL SOURCE OF CONTAGION

Our analysis suggests that private credit funds will likely be more central in the financial system in future stress periods. In contrast, large banks may become relatively less central in propagating shocks. In other words, the locus of contagion has shifted toward nonbank lenders, including private credit. This aligns with intuition, as post-GFC, banks are better capitalized and less interconnected via interbank exposures. In contrast, private credit funds have grown in number and size, creating new interconnections through club deals, co-investments, and common LP investors.

Even without direct exposure, institutions can influence one another through confidence and market liquidity channels. Our network analysis captures this dynamic: Cross-sector Granger linkages (for example, between insurers and banks) approximately doubled during pandemic stress, indicating that the fortunes of these entities became intertwined.

Interconnectedness also comes from more concrete financial ties. Overlap in investors is one channel—the same institutional investors, say an insurance company or a sovereign wealth fund, might hold stakes in private credit funds, CLOs, and public corporate bonds. If losses occur in one investment, that investor may be forced to liquidate assets elsewhere, propagating stress.

Bank funding is another channel—while banks' committed lending to private credit institutions is small in aggregate (approximately \$300 billion), certain banks may have outsize exposures through fund credit lines or warehousing loans to be syndicated to private funds. These banks could face strain or cut other lending if private credit funds stumble. Systemically important U.S. banks further have additional exposure through their CLO books, which overall amounts to nearly \$150 billion, with two-thirds held by the four largest U.S. banks.²⁵ While some of this represents conventional syndicated lending, there is significant overlap with the middle market, and bank books are opaque due to accounting aggregation practices. Additionally, private equity sponsors often link banks and private credit, as many leveraged deals involve a syndicated bank loan and a privately placed tranche. If the company falters, both bank loans and private credit investors are affected. Such intertwined structures mean distress can spread through multiple pathways, not unlike how mortgage and nonbanking linkages fueled contagion in the GFC.

Amplification occurs when these linkages create a feedback loop. For instance, a few loan defaults in private credit funds might raise concerns about fund valuations given their illiquidity, prompting investor redemption requests in semi-liquid credit funds. Funds then draw on bank credit lines to meet liquidity or sell any liquid holdings. Some larger BDCs hold traded loans or bonds as well. Those actions can further tighten credit conditions for other borrowers or pressure the prices of related assets, creating a vicious cycle. Because transparency is limited, opacity heightens the uncertainty and fear, potentially leading investors to assume the worst and retrench more sharply.

Private credit funds do not yet appear to be systemically important entities compared with other large systemically important financial institutions. However, their rapid growth, opacity, and role in making the financial network more densely interconnected mean they could disproportionately amplify a future crisis. The interconnected financial system has a dual nature: It spreads risk under normal circumstances, arguably making the system more resilient to small negative shocks, but it also means that once thresholds are breached, the system can experience contagion.²⁶ The experiences of the GFC and the pandemic bear this out, and it appears increasingly likely that private credit will be part of any future crisis.

²⁵ FDIC – Risk Review 2026

²⁶ Acemoglu et al. (2015).

EVOLVING LINKAGES

Significant changes have occurred in systemic linkages in the financial system since before the GFC. Prior to the GFC, banks and other highly regulated entities dominated credit intermediation, and systemic risk arose from direct interbank exposures and from off-balance-sheet vehicles such as asset-backed conduits and structured investment vehicles sponsored by banks and broker-dealers. When those links snapped, the contagion was ferocious.

In response, global policymakers implemented numerous reforms to reduce leverage and rein in riskier activities, which pushed nonfinancial lending and credit risk to nonbank financial institutions. Today, a more diverse set of players, including private credit funds, BDCs, CLOs, and credit hedge funds, is engaged in providing credit alongside banks and public markets.

The systemic linkage map has consequently evolved. Rather than a hub-and-spoke centered on large banks and broker-dealers as was the case in the GFC, the network is more distributed. Our findings show that BDCs and other nonbanks have become more central to network connectivity over time, while banks' centrality has somewhat diminished. Nonbanks have also become relatively more connected to one another in the post-GFC period, and, hence, the "too interconnected to fail" problem now encompasses nonbanks to a greater degree.

This does not mean that banks are irrelevant—far from it, as banks remain the largest nodes by balance sheet. But they are now well-capitalized and have less direct exposure to one another. The risk has migrated into longer chains and more opaque corners that retain some linkages back to the banking system.

The new linkages introduce new modes of systemic stress. Whereas the GFC contagion was driven by solvency fears and frozen interbank lending, a future crisis might involve a liquidity freeze in the nonbank part of the financial system. For example, private credit funds could halt withdrawals, CLOs may hit trigger points, etc., affecting banks via their CLO holdings or lines of credit, and impinging more broadly on credit availability in the economy.

The opacity of these linkages—who holds what risk and who is exposed to whom—can lead to slower recognition of problems and delayed intervention. When policymakers realize the extent of the interconnections, the damage will already be done. Policymakers may not be able to identify or may underestimate the severity of complex network effects as long as private credit remains opaque. It is well-known that some private credit funds operate under weaker collateral requirements or lower-quality collateral than regulated institutions. Suboptimal levels of collateral can increase contagion and risks to financial stability. This could be due to illiquid collateral fire sales, low levels of collateral, or, at the other extreme, the buildup of excessive collateral in the financial system, leading to inefficient allocation of firms' assets.²⁷

Comparing pre- and post-GFC systemic linkages, we can summarize as follows: (1) More players are involved now—the network includes banks, broker-dealers and insurers, but also BDCs, private equity firms, funds, etc., making oversight more complex. (2) Risk has become more dispersed across entities, which may reduce the chance of a single point of failure but could also allow many smaller failures to interact. (3) The financial system is now more distributed but also more densely networked, like a web, rather than a tiered structure, which can also be brittle. (4) Pre-GFC, risks were hidden in bank-backed off-balance-sheet vehicles, whereas the risks are now hidden in private vehicles outside regulators' view.

²⁷ Ghamami, Glasserman, and Young (2021).

The common theme is that the lack of transparency allows risks to accumulate. And data gaps remain a serious issue in the current landscape, as there is limited information on loan covenants, true portfolio valuations, and the overlap of fund investors. This echoes the concerns that regulators have raised about nonbank financial intermediation. The greater the share of credit that migrates outside the regulatory perimeter, the more we are “flying blind” to potential systemic buildups.

POLICY RECOMMENDATIONS

Given these findings, several policy measures should be considered to mitigate systemic risks arising from private credit markets. These measures would strengthen oversight, improve transparency, and bolster the financial system’s resilience against shocks originating in nonbank credit channels. Substantial further review and analysis would be required to assess the benefits of such measures from a safety and soundness perspective, relative to the potential costs of constraining the healthy growth of the industry and the provision of credit to the economy.

- » **Expand the regulatory perimeter and oversight:** Financial authorities should consider bringing large private credit credit intermediaries under a supervisory framework commensurate with their systemic footprint. This does not necessarily mean bank-like regulation but rather targeted monitoring of risk factors such as degree of interconnectedness, leverage, credit concentration, and counterparty exposure in private credit funds. Regular stress-testing or scenario analysis of major private credit portfolios and their interactions with banks, insurers and pension funds should be conducted. If certain institutions or funds are ultimately found to be highly interconnected and systemically significant in size, regulators might designate them for enhanced supervision.

The goal is to detect the buildup of systemic risk early—for example, if multiple funds are lending to the same vulnerable industry or hidden leverage is rising via total return swaps or other means, the supervisors would have the data to act or at least alert market participants. Additionally, bank regulators should monitor banks’ indirect exposures via inter alia structured risk transfer, credit lines and derivatives to private credit funds and incorporate those into bank stress tests. And state insurance regulators, who generally have oversight responsibility in the U.S., should enact and maintain robust regulations concerning vertical integration, valuation methodologies, potential conflicts of interest, and concentration limits regarding affiliated fund managers.

- » **Enhance transparency and data reporting:** Data gaps must be closed so that regulators and market participants can see the private credit landscape more clearly. This could involve expanding reporting requirements: Large private credit funds could be required to report standardized metrics on portfolio composition, credit quality, performance and financing structures. Similarly, more granular data on corporate borrowers (like leverage and interest coverage of firms receiving private loans) should be collected, potentially through coordination with central credit registries or supervisory data from banks that arrange these deals.

Transparency reduces opacity-driven fear—if investors and regulators know where the risks lie, they are less likely to all run for the exits blindly. Even with a lag, improving public disclosures can also help in the appropriate pricing of risk; for instance, consistent reporting of default rates and recovery rates in private credit would allow better comparison with public markets. Regulators should also harmonize data-sharing internationally and across regulatory bodies, given the global nature of investment flows, an effort emphasized by the International

Monetary Fund and Financial Stability Board. In short, better data and transparency will enable more informed decision-making and reduce the likelihood that problems fester unrecognized.

- » **Address hidden leverage and liquidity mismatches:** Policymakers should scrutinize the multiple layers of leverage in the private credit ecosystem. While many private credit funds themselves use limited leverage, their investors might use subscription credit facilities or leveraged fund-of-funds, and the borrowing companies may also be highly leveraged, meaning that systemwide leverage may be higher than it appears. Regulators might set guidelines or limits on fund-level leverage and encourage robust risk management practices that take full account of the multiple levels of leverage.

Likewise, liquidity mismatches—where funds offer more frequent redemptions but hold illiquid loans—should be addressed. Securities regulators should ensure private credit funds, especially those targeting retail investors, have appropriate liquidity gates and redemption terms, as the FSB and International Organization of Securities Commissions recommend, to prevent run dynamics. In the U.S., regulators should exercise extreme caution in expanding retail access through weakening the “accredited investor” standard or other means. The Department of Labor’s recently proposed rule on inclusion of investment alternatives in the \$10 trillion 401(k) market requires particular attention. Regulators should also conduct periodic liquidity stress tests on these more liquid funds. Ensuring that fund structures align with asset liquidity will help contain any one fund’s distress and forced asset sales, which depress market prices and spill over onto other institutions.

- » **Integrate private credit into macroprudential policy frameworks:** Central banks and financial stability authorities should incorporate private credit trends into their systemic risk monitoring. For example, if private credit is fueling a corporate credit bubble (rapid debt growth among weaker firms), macroprudential tools could be adjusted, such as countercyclical capital buffers for banks (since banks may indirectly face losses) or sectoral leverage limits.

In addition, central banks should consider how they would respond if a systemic event in private credit markets were to materialize. While they traditionally serve as lenders of last resort to banks, a crisis in private credit might lead to calls for liquidity support in other ways, for instance, lending facilities that banks can use to support credit funds.²⁸ Regulators should conduct an exhaustive ex ante, as opposed to ex post, analysis of the costs and benefits of different approaches to such a meltdown.

Cooperation among agencies will be critical. Bank regulators, securities regulators for private equity funds, and central banks should share information and coordinate actions under a unified financial stability mandate. The Federal Reserve’s Financial Stability Report has already started highlighting private credit risks; building on that, scenario analyses that include a private credit shock should be part of systemic risk exercises. Ultimately, treating private credit as an integral component of the credit cycle in policymaking ensures that the broader financial system can absorb a private credit downturn without severe disruption to credit provision.

²⁸ See, for instance, [Duffie and Keane \(2023\)](#), [Buiter, Cecchetti, Dominguez, and Serrano \(2023\)](#), and the references therein for more on central bank lending facilities and market-function purchase programs.

In summary, proactive measures in regulation, transparency and macroprudential preparedness can substantially reduce the systemic risk posed by private credit markets as they grow rapidly and become increasingly intertwined with the regulated financial system and public markets. The objective is not to stifle the beneficial innovation that private credit provides but to shine a light on its risks and linkages so that a rapidly growing part of corporate finance, and potentially other sectors, does not become a blind spot. By extending oversight to match the evolving landscape, improving data to match the complexity, and readying the policy toolkit, we can enjoy the efficiency gains of these markets without compromising financial stability.

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Appendix: PCA and Granger-Causality Network Methodology

In this appendix, we describe the data utilized in our study, detail the principal component analysis and Granger-causality network methodologies for measuring systemic risk, and present additional results to demonstrate the robustness of our analysis. The PCA and Granger-causality network methodologies follow the approach Billio et al. (2012) developed for stock returns and are extended to expected default frequencies by Hughes and Malone (2015).

DATA

We utilize two datasets of market signals on large banks, insurance companies, BDCs, and other large nonbank financial institutions domiciled in the United States. The first source comprises monthly-frequency five-year EDFs from the Moody's public company EDF database. The second comprises monthly-frequency total stock return data from the Center for Research in Securities Prices database. In addition, we employ data on total assets in the EDF database to help identify the largest firms in each industry group, corroborated by public sources, and to present size-weighted results where relevant.

Our main results reflect the performance metrics of 60 firms from 2004 through 2024, which have been covered by both datasets since at least 2007. We chose this threshold since BDC coverage in both sources grew from only eight in 2005 to 14 in 2007. The list of firms is more stable for the other industries, but a few firms dropped from the sample in the 2020s. We also repeated the analysis with the full 100 firms covered by both sources, allowing the firms included to vary over time, and report proportions or averages rather than aggregates to retain comparability with the smaller sample. The results are qualitatively similar.

We apply data transformations for the PCA and Granger network analyses to ensure stationarity and comparability across firms. All EDF series are log-differenced for the analysis. This transformation helps stabilize variance over time and mitigates the possibility of spurious EDFs. The stock returns are expressed as monthly percentage total returns.

PRINCIPAL COMPONENT ANALYSIS

We apply principal component analysis to 36-month rolling windows of the firm-level return and EDF data. The PCA decompositions yield orthogonal, uncorrelated factors ordered by the share of the total variance they explain at each time point in the window. In our PCA, both the return and EDF windows are standardized to zero mean and unit variance to ensure comparability across firms with different levels of volatility. Missing data are handled using an unbalanced panel approach for each window by including only firms with available data for the entire 36 months. All PCAs are based on the correlation matrix, ensuring that components reflect patterns of co-movement rather than absolute scale. We retain up to 10 principal components for each window. R-squares for each firm are computed by regressing their standardized returns (or log-differenced EDFs) on the selected components, and we produce industry aggregates by averaging R-squared values across firms or industry groups.

Formalizing the PCA approach, let x_i be the random monthly stock return, or log-differenced EDF, of institution $i = 1, \dots, N$. Further, let $E(x_i) = \mu_i$ and $Var(x_i) = \sigma_i^2$, unobserved population means and variances, and define the standardized return of institution i :

Assuming covariance matrix of Z has rank N , the principal components of Z_k are random factors, F_k , that are a linear combination of Z_k :

$$F_k = \sum_{i=1}^N L_{ik} Z_i \quad (2)$$

The principal components are mean zero and uncorrelated, implying:

$$Cov(F_k, F_l) = E(F_k F_l) = \begin{cases} \lambda_k & \text{if } k = l \\ 0 & \text{if } k \neq l \end{cases} \quad (3)$$

where λ_k is the k -th eigenvalue, and interpretable as the variance of F_k . If x has rank N , the order- N PCA decomposition allows us to express the z 's, and x 's, as an exact linear combination of the F_k 's:

$$z_i = \sum_{k=1}^N L_{ik} F_k \quad (4)$$

where L_{ik} is the coefficient loading for factor F_k for an institution i and this follows from the fact that the matrix of loadings is orthonormal. Note that compared with (2) we are summing over k not i .

To measure aggregate trends in systemic risk, we can focus on the variation across time windows in the factors themselves, and express the cumulative variance explained by the first n factors as a percentage of the total factor variance:

$$h_n = \frac{\sum_{k=1}^n \lambda_k}{\sum_{k=1}^N \lambda_k} \quad (5)$$

Because the factors are orthogonal, the cumulative variance is the simple sum of the factor variances. PCA factors are ordered from highest to lowest variance. Thus, the cumulative R-squared indicates how much of the total variation is explained by the first n factors in a regression of individual returns on those factors. A larger R-squared for low n suggests higher levels of interconnection between firms.

The system return can be thought of as the sum of individual firm returns. The system variance for the untransformed series x_{St} can be expressed in terms of the correlation of the standardized returns:

$$\sigma_S^2 = \sum_{i=1}^N \sum_{j=1}^N \sigma_i \sigma_j E(z_{it} z_{jt}) \quad (6)$$

And then decomposed into loadings and eigenvalues, which follows from substituting (2) and (3) into (6):

$$\sigma_S^2 = \sum_{i=1}^N \sum_{j=1}^N \sum_{k=1}^N \sigma_i \sigma_j L_{ik} L_{jk} \lambda_k \quad (7)$$

Following Billio et al., the contribution of the risk of firm i to the total risk of the system can be measured as an elasticity of response of the system variance to the variance of firm i holding all other terms in (7) constant. That elasticity can be shown to be proportional to a weighted average of the square of the factor loadings times eigenvalues of the single institution to the first principal components:

$$PCAS_{i,n} = \frac{\partial \ln \sigma_i^2}{\partial \ln \sigma_S^2} = \frac{\sigma_i^2}{\sigma_S^2} \frac{\partial \sigma_S^2}{\partial \sigma_i^2} = \frac{\sigma_i^2}{\sigma_S^2} \sum_{k=1}^n L_{ik}^2 \lambda_k \quad (8)$$

Billio et al. define PCAS only for n such that all factors 1 through n have variance that exceeds a threshold criteria. Note that PCAS can be formulated equivalently as:

$$PCAS_{i,n} = \frac{\sigma_i^2}{\sigma_S^2} r_{i,n}^2 \quad (9)$$

where, $r_{i,n}^2$ is the proportion of firm i 's total variance that is explained from projecting the normalized return or EDF on the first n factors and term $\frac{\sigma_i^2}{\sigma_S^2}$ is the firm's ratio to the system variance. This follows from expressing (4) as a function of the first n components and an uncorrelated residual, representing the higher-order components:

$$z_i = \sum_{k=1}^n L_i F_k + \varepsilon_i \quad (10)$$

The term $\sum_{k=1}^n L_i F_k$ is the projection of z_i onto the first n factors, and hence the projection variance ratio can be written:

$$r_{i,n}^2 = \frac{\text{Var}(\sum_{k=1}^n L_{ik} F_k)}{\text{Var}(z_i)} = \frac{\sum_{k=1}^n L_{ik}^2 \text{Var}(F_k)}{1} = \sum_{k=1}^n L_{ik}^2 \lambda_k \quad (11)$$

Which follows from (2) and $\text{Var}(z_i) = 1$ establishing the equivalence of (8) and (9).

Given we do not observe the underlying distributional parameters directly, that is, the μ_i, σ_i, L_{ik} and λ_k terms, we estimate them on 36-month rolling windows. Even in-sample, the mathematical properties of the PCA continue to hold, including sample equivalents of (5) and (9).²⁹ Note that in-sample, $r_{i,n}^2$ in (9) has the interpretation as the R-squared, or goodness of fit measure, from regressing x_{it} on the first factors F_{kt} for the $t = 1, \dots, 36$ observations in each rolling window. In our empirical work, we found these R-squared values to have more robust time-series behavior than PCAS itself because the latter was more sensitive to unpredictable shifts in $\frac{\sigma_i^2}{\sigma_S^2}$ over time, and thus we reported our results by firm grouping for the R-squared part of PCAS.

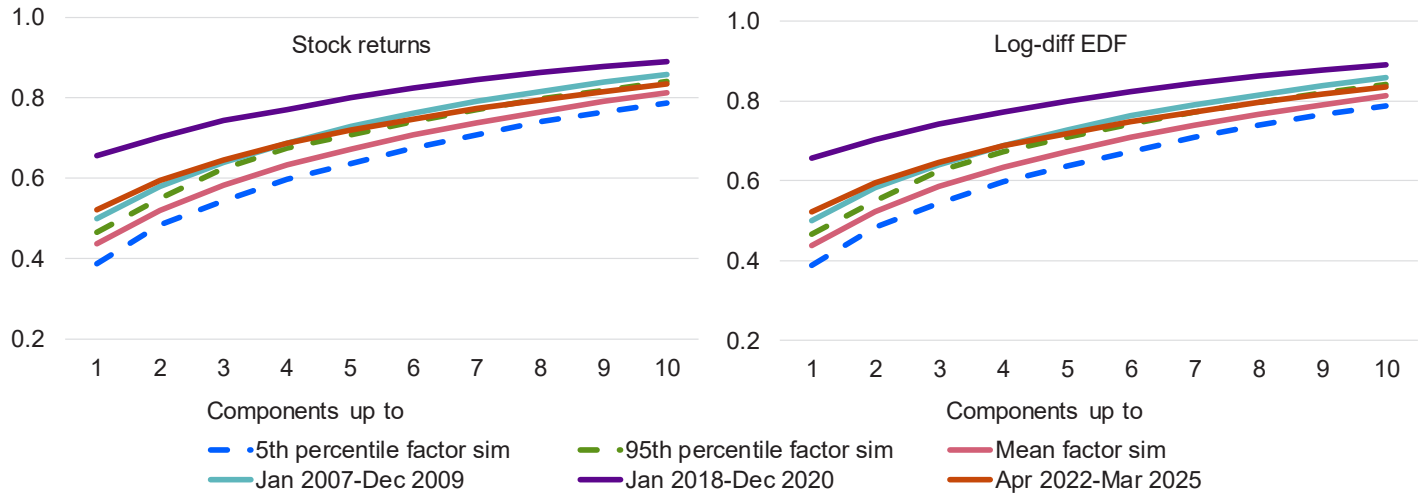
We employ Billio et al.'s bootstrap exercise to establish the thresholds above which principal components provide a significantly different signal from statistical noise. Using the in-sample equivalent of equation (6), we compute $\widehat{h}_1$ on our datasets for each of the overlapping 36-month windows. We define a threshold H as the average of the lowest quintile of $\widehat{h}_1$ values over all windows. Excluding higher-risk windows, we compute the average covariance matrix from the remaining windows and simulate 100 multivariate normal datasets, repeated 1,000 times. We refer to this as the low-signal simulation.

From these simulations, we derive the empirical distribution of the estimate of h_n for each n , $\widehat{h}_n$, along with 95%, 99% and 99.5% confidence intervals, giving us criteria for detecting the number of factors that are statistically different from the low-signal simulation. We test for the significance of factors at key periods by checking whether the observed R_n^2 in that period exceeds the simulated confidence bounds. The leading factors from the GFC and COVID-19 periods exhibit statistically significant deviations for both the EDF and stock return datasets (see Chart A1).

²⁹ Jolliffe (2002).

Chart A1: PCA Thresholds Identify Meaningful R-Squared Values

Share of total variation explained by ranked principal component groupings, actual vs. simulated 3-yr windows



Source: Moody's Analytics

GRANGER-CAUSALITY NETWORK ANALYSIS

We employ Granger-causality network analysis to model dynamic, directional interdependencies among financial institutions. Each institution is a node, and directed edges represent predictive relationships: If the past values of one institution help forecast another's current values, a link is drawn. This transforms time-series data into a time-evolving network, allowing us to use network theory tools to identify influential nodes, trace paths of potential influence, and monitor shifts in the system's structure over time. Unlike PCA, which provides a static, symmetric view of co-movement, GCNA captures dynamic, asymmetric linkages, revealing transmission channels of risk, leading and lagging institutions, and evolving predictive connections that better reflect real-world spillovers.

The Granger-causality test, which is central to the detection of connections in the network, assesses in a linear statistical model whether lagged values of one time series contain information that improves the forecast of another time series beyond what is already explained by its own lags. Formally, for two time series x_t^A and x_t^B on firms A and B , A Granger-causes B if including past values of x_t^A in a vector autoregression model significantly improves the prediction of x_t^B compared with a vector autoregression model that includes only past values of x_t^B .

Formally, let x_t^A and x_t^B be two stationary, zero-mean time series. We can represent their predictive linear interrelationships with the following dynamic model:

$$\begin{aligned} x_t^A &= a^A x_{t-1}^A + b^{AB} x_{t-1}^B + e_t^A, \\ x_t^B &= a^B x_{t-1}^B + b^{BA} x_{t-1}^A + e_t^B, \end{aligned} \quad (12)$$

where e_t^A and e_t^B are two uncorrelated white noise processes and a^A, a^B, b^{AB}, b^{BA} are model coefficients. Then, B Granger-causes A when b^{AB} is statistically different from zero, as indicated by a standard F-test comparing the model estimates with and without the x_t^B term. Similarly, A Granger-causes B when b^{BA} is different from zero. The system model in (12) is an order 1 vector autoregression, but we also consider order-2 vector autoregression in our analysis by including both first and second lags of both variables in each equation.

We will use the notation $(j \rightarrow i)$ to represent an indicator function for connections

$$(j \rightarrow i) = \begin{cases} 1 & \text{if } j \text{ Granger causes } i, \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

On our two datasets, we run the pairwise Granger-causality tests for all firms to define the significant directed network edges on rolling three-year windows. With a static sample of 60 firms, this results in 3,540 directed pairwise tests (60×59) per window. For each window, a Granger-causality network is constructed by including a directed edge from firm A to firm B if the F-test rejects the null hypothesis of no Granger causality at a 5% significance level. The networks evolve over time as the windows roll forward, capturing changes in firm-to-firm connections.

To better isolate firm-level dynamics and minimize the influence of common market-wide shocks, we first residualize each firm's time series with respect to the contemporaneous cross-sectional average. For stock returns, this entails regressing each firm's returns over the 36-month window on the equal-weighted average returns across all firms and retaining the residuals, about equivalent to computing an excess return. The same approach is applied to log-differenced EDFs on the industry average log-differenced EDF. The resulting residual series then serve as inputs to the Granger-causality tests. This preprocessing step ensures that the detected causal relationships are more likely to reflect firm-specific linkages than general market movements. Following Billio et al., we ran a separate version of the analysis.

From the sequence of Granger-causality networks, we compute several simple metrics to characterize systemic interconnectedness and industry-specific dynamics over time:

1. **Degree centrality.** This measures how overall connectedness evolves over time. In the network defined at each window, this is the count of pairwise connections divided by the number of possible connections among firms:

$$DGC \equiv \frac{1}{N(N-1)} \sum_{j=1}^N \sum_{i \neq j} (j \rightarrow i). \quad (14)$$

2. **Sector-level connectivity.** For each industry group (banks, insurers, BDCs and other NBFIs), we calculate:

- » **Sector out-degree:** The proportion of connections from the N_G firms in industry G to any other firm in the system S .
- » **Sector in-degree:** The proportion of connections from any firm in the system S to the N_G firms in industry G .

$$\#In: (S \rightarrow G) = \frac{1}{N_G} \frac{1}{N-1} \sum_{i \in G} \sum_{j \in S | i \neq j} (j \rightarrow i) \quad (16)$$

- » **Sector-level adjacency matrix:** A matrix summarizing the density of connections from one industry group to another. Each entry in the matrix represents the proportion of significant causal links from the N_{G_1} firms in sector G_1 to the firms in sector G_2 .

$$\#Out - in: (G_1 \rightarrow G_2) = \frac{1}{N_{G_1}} \frac{1}{N_{G_2}} \sum_{j \in G_1} \sum_{i \in G_2} (j \rightarrow i) \quad (17)$$

And connections within the firms in an industry G :

$$\#Out - in: (G \rightarrow G) = \frac{1}{N_G} \frac{1}{N_G-1} \sum_{j \in G} \sum_{i \in G | i \neq j} (j \rightarrow i) \quad (18)$$

3. Graphical network visualization. For select periods, we provide visual depictions of the Granger-causality networks. We apply the Kamada-Kawai force-directed layout algorithm to visualize the Granger-causality network. This method positions nodes in two-dimensional space by minimizing a spring energy function, such that nodes with stronger or more numerous connections are drawn closer together. It visually represents the network's structure and the most and least central nodes. We also size the depicted nodes by the number of incoming and outgoing connections.

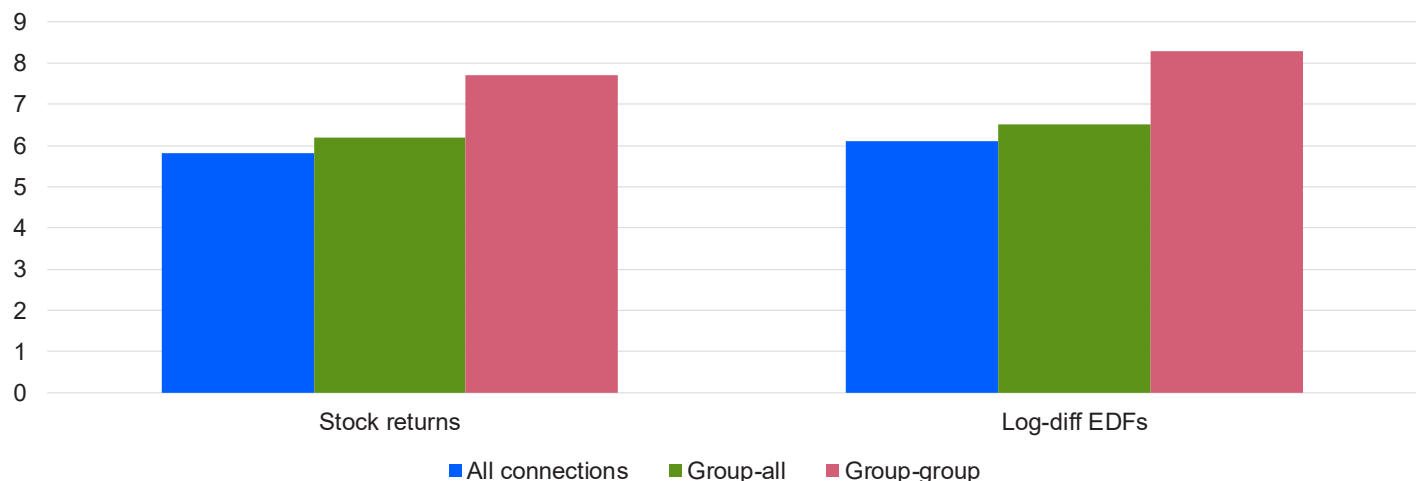
4. Forcing and damping measures. For each firm, we compute:

- » Forcing strength: The sum of positive coefficients from significant Granger links, that is, $b^{ij} > 0$, on the firm's outgoing edges, optionally weighted by the receiving firms' size (total assets).
- » Damping strength: The sum of negative coefficients from significant Granger links, that is, $b^{ij} < 0$, on the firm's outgoing edges, optionally weighted by the receiving firms' size (total assets).

To establish the threshold for statistically significant connections in points 1 and 2 above, we employ Billio et al.'s bootstrap procedure. We perform a Monte Carlo simulation under the null hypothesis of no interdependence among institutions to assess whether observed Granger-causal relationships arise by pure chance. We simulate 60 independent time series, matching the number of firms in our sample, then test for pairwise Granger causality at the 5% significance level across all 9,900 possible directed pairs. This procedure is repeated 500 times, producing a distribution of the number of significant connections under the null. As expected, the mean of this distribution is close to 5%, reflecting the nominal significance level of the test. Sampling variation around this mean results in a confidence band; for instance, Billio et al. report a 90% confidence interval between 4.9% and 5.5%. Observing an empirical share of connections above this upper bound suggests that the network structure is unlikely to be driven by chance alone. We also run the same exercise on smaller samples of 15 firms connected to 15 other firms to establish the significance threshold for cross-group connectivity (see Chart A2). We indicate these thresholds on the connection charts and tables in the main text.

Chart A2: Granger Thresholds Identify Meaningful Connection Levels

Bootstrap estimates of minimum thresholds for statistically significant connection rates at 95% confidence level



Source: Moody's Analytics

PREDICTIVE LOSS MEASURES

To assess whether exposure to common risk factors helps explain firm-level vulnerability, we test the predictive value of the firm-level PCA R-squared statistics and Granger network connection counts. Specifically, for PCA, we examine whether firms with higher R-squared values on the leading PCA components—reflecting greater co-movement with broader market dynamics—tend to experience larger losses during stress periods. For the Granger networks, we test whether firms that are more connected in the Granger network, based on their in- or out-connection counts measures, are more likely to experience large losses during stress periods. In each case, we do this by regressing firm-level losses during crisis episodes on the corresponding firm-level PCA or Granger measures. For example, we compute PCA R-squared using data from 2007-2009 and use them as drivers in a regression model to explain each firm's total losses in 2009. Although our initial design included both in-sample and out-of-sample testing, we report only in-sample estimates because we found that pre-event connection estimates had borderline significance, consistent with the notion that network effects shift dramatically in periods of stress, as demonstrated in the model of Acemoglu et al. (2015).

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