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Private Credit & Systemic Risk

ANALYSIS
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INTRODUCTION

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. 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 stress. 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 beyond middle-market corporate lending and begins to tap 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, such as accounting for rapid nonbank credit growth when setting countercyclical buffers and ensuring central banks are prepared to manage liquidity or credit crunches that could emanate 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 world of private credit in greater depth, assess the extent of its interconnectedness in the financial system using well-known reduced-form econometric measures of systemic risk, and conclude with policy implications and recommendations.

Acknowledgement: Samim Ghamami is grateful for research assistance by Yifei Zhu.

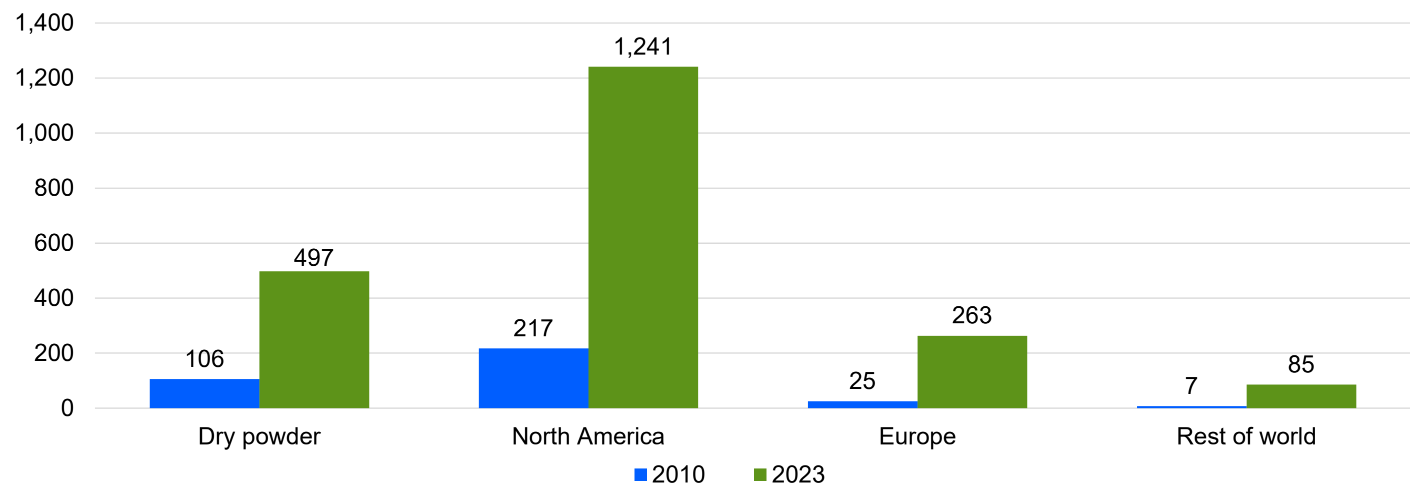
Private Credit & Systemic Risk

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. Global private credit assets, including committed funds that have not yet been invested, so-called dry powder, have surged to more than $2 trillion (see Chart 1). Approximately three-quarters of these assets are in the U.S., putting private credit on par with the high-yield corporate bond and syndicated leveraged loan markets in size.

Chart 1: Private Credit Is Growing Rapidly Across the Globe

Funds managed by private credit outstanding, $ bil



Sources: IMF, Moody's Analytics

As private credit expands into new markets such as asset-backed finance, infrastructure and project finance, and real estate lending of various kinds, its role in the provision of credit will only increase. 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]

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, drawing strong investor interest despite the opacity of the risks involved.

1 International Monetary Fund (2024).

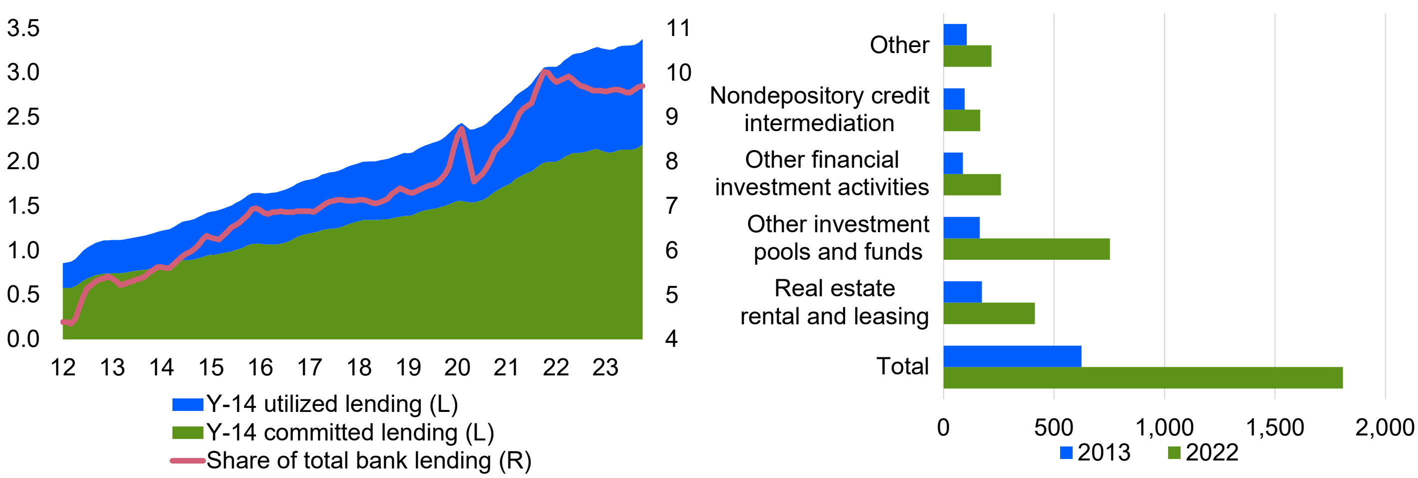
As private credit has increased, regulators have raised reasonable concerns over its rapid growth, increasingly aggressive competition, and a shift toward riskier borrowers and complex deal structures—all of which could erode returns and amplify risks as the market matures.[2]

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 (NBFIs). Banks are increasingly involved in private credit and other NBFIs through partnerships, fund financing, and structured risk transfers that allow them to maintain economic exposure to credit markets while shifting assets off balance sheet (see Chart 2). While such arrangements may offer capital efficiency, they can also obscure the true distribution of risk, prompting regulatory scrutiny over potential capital requirement arbitrage. Recent research documents increasing bank lines of credit to NBFIs, including private credit funds.[3]

Chart 2: Banks Increase Their Lending to Nonbanks

Bank loans to nonbanks, $ tril (L); total share, % (R)

Credit lines and loans to nonbanks by type, $ bil



Sources: Boston Fed, Acharya, Cetorelli and Tuckman (2023), Moody's Analytics

At the same time, private credit channels significant exposures to institutional investors, including pension funds, insurers, and sovereign wealth funds, who are attracted by higher yields but may become exposed to liquidity strains in periods of market stress due to the illiquid and bespoke nature of the asset class. 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 redemption liquidity despite holding illiquid assets. They may rely on tools such as credit lines or net asset value (NAV) lending to manage redemptions, creating emerging links to short-term funding markets. While still modest in scale, these structures introduce potential transmission channels for financial shocks, warranting closer oversight as retail participation expands.

In this paper, we 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 (PCA) and Granger-causality network modeling applied to the stock

2 See, for instance, Federal Reserve (2023). Also, see Cai and Haque (2024) and Degerli and Monin (2024).
3 Acharya, Cetorelli, and Tuckman (2024) and Levin and Malfroy-Camine (2025).

returns and market-implied expected default frequencies of 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.[4] Moreover, we observe a shift in the structure of these linkages: Banks have become less central, while business development companies (BDCs), 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 stress, as evidenced by comparing the COVID-19 pandemic to the Global Financial Crisis (GFC). 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 more equally prominent in the network.

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

In summary, 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. Today's network of interconnections in the financial system is more distributed, with a denser web of connections than it had 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.

(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 segments 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 beyond middle-market corporate lending and begins 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 such as accounting for rapid nonbank credit growth when setting countercyclical buffers and ensuring central banks are prepared to manage liquidity or credit crunches that

4 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 predictive firm-to-firm links through time, allowing us to interpret observed linkages as spillover effects in returns and default risks. 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).

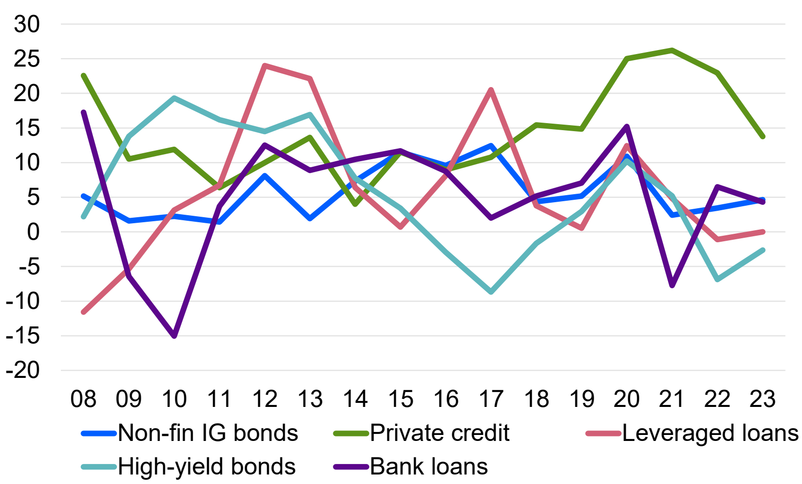
could emanate from stress in private credit markets. These measures can help mitigate systemic risks while ensuring the benefits of this growing source of credit.

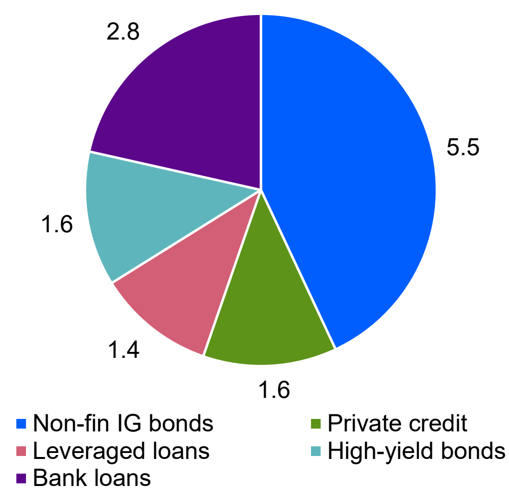
In this paper, we explore the world of private credit in greater depth, describe our analysis and results, and conclude with policy implications and recommendations.

SIZING UP PRIVATE CREDIT

Outstanding U.S. nonfinancial corporate debt has reached record levels, exceeding $13 trillion across investment-grade bonds, high-yield bonds, leveraged loans, and bank and private credit, more than double the total from the early 2000s. 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 surge 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





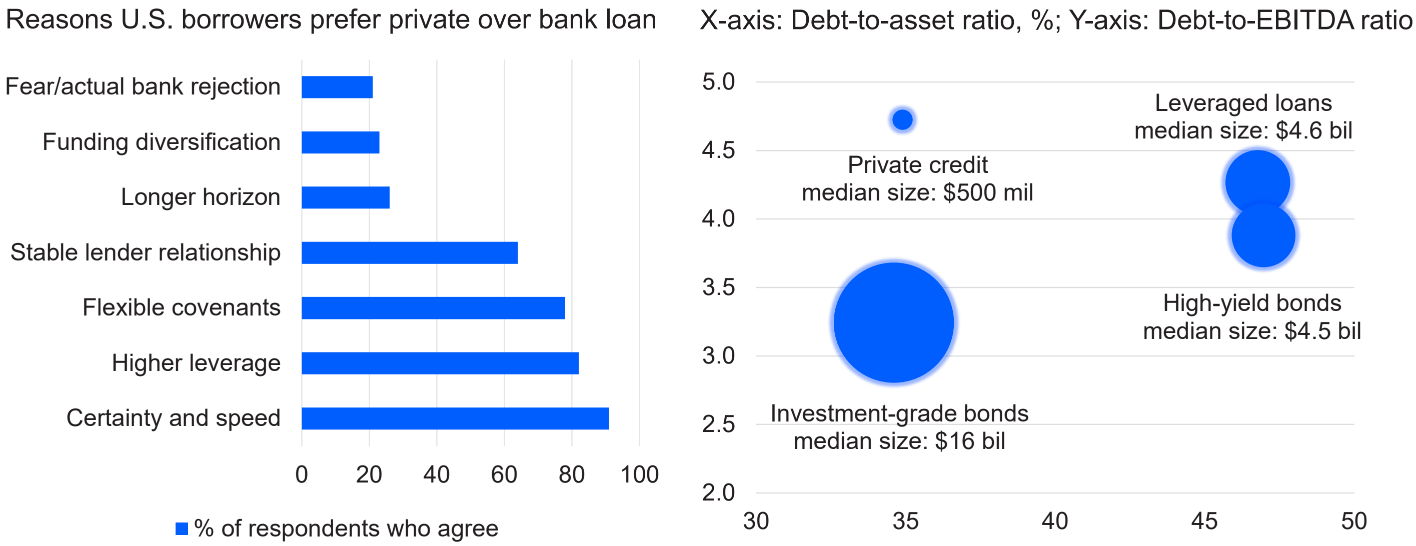
Sources: IMF, Federal Reserve, Moody's Analytics

Approximately half of private credit's $2 trillion in global assets, including assets of BDCs, is in direct loans to middle-market firms that typically generate $50 million to $1 billion in revenues. Their debt needs generally are too small for public bond markets or leveraged loans, and some 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 smaller—around $250 billion—it represents one of the least transparent and fastest-growing areas.[5]

5 Wyman (2024a) and McKinsey (2024).

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

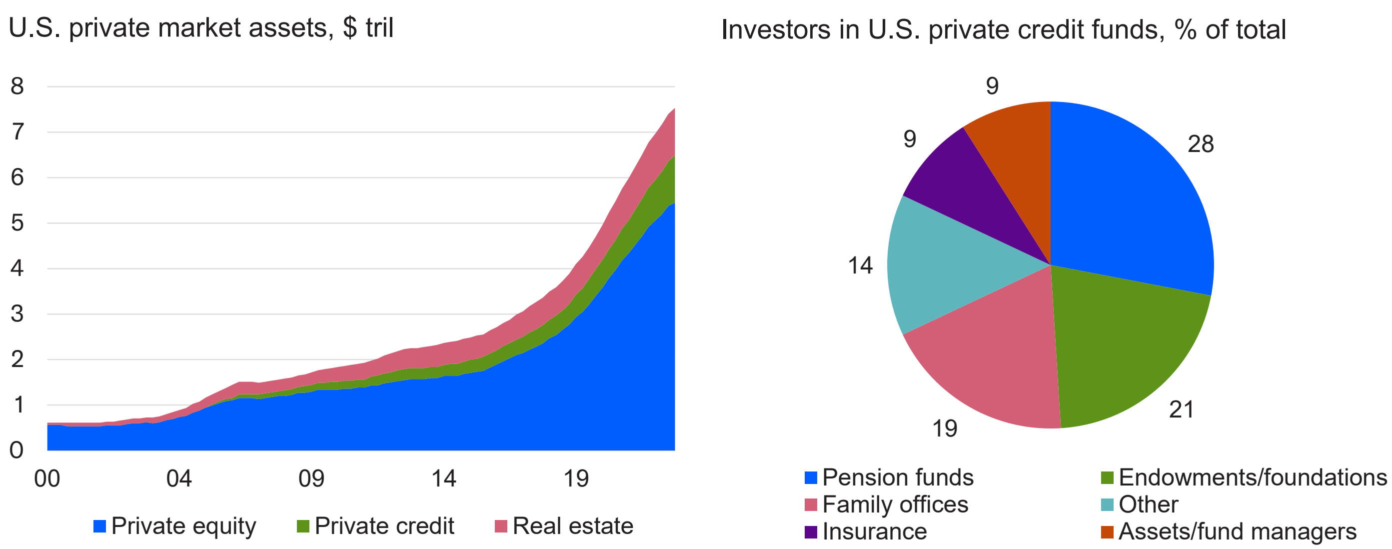


Sources: Univ. of Chicago, IMF, Moody's Analytics

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 5).

Chart 5: What Is Behind the Private Credit Boom?



Sources: Boston Fed, Brookings, IMF, Moody's Analytics

The use of leverage varies considerably across funds, reflecting differing investor mandates, risk tolerances and return targets across the industry. 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 from banks, and to some extent, nonbank lenders—to enhance returns. In some cases, the combined effect of fund-level borrowing and leverage at the portfolio company level results in total leverage profiles that resemble those seen in 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.

In addition to the use of fund-level leverage, private credit managers are increasingly financing their loan portfolios through private collateralized loan obligation, or CLO, structures, with well over $100 billion of private credit CLOs outstanding.[6] Traditionally associated with syndicated corporate loans, CLOs are now being adapted to warehouse and securitize portfolios of middle-market direct loans. 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.

TRANSPARENCY, VALUATION AND LIQUIDITY

Private credit's lack of standardization and limited disclosure complicate efforts to monitor its risks. Unlike public markets, most private credit offers no real-time pricing, relies on bespoke contracts, and has floating-rate exposure, which became more burdensome after interest rates rose beginning in 2022. How burdensome exactly, however, is known only to the fund's insiders.

As the private credit market evolves, some funds have begun to explore semi-liquid structures to accommodate investor demand for redemption options to broaden their investor base.[7] These models introduce a potential duration mismatch, as 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 experiments, 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 leverage limit of a 2:1 debt-to-equity ratio.[8] Most BDCs employ leverage to bring their target rates of return in line with market expectations for equity-like investments. Prices of listed BDC funds tend to follow general equity market movements.

6 International Monetary Fund (2024).

7 Goldman (2024) and Wyman (2024b).

8 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 between them 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 the 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 1940 Act. For more on BDCs, see Horowitz and Gaines (2019).

While still a closed-end fund and holding similarly illiquid and opaque loans, BDCs provide retail and institutional investors with greater fund 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. Mark-to-model assets are vulnerable to swings in market confidence, and when pricing gaps emerge, attention quickly shifts to the balance sheets of those holding similar exposures. In leveraged or liquidity-sensitive institutions, that shift in perception can become self-reinforcing, prompting markdowns or investor redemptions well before the underlying loans default.

GROWING RISKS

The rapid growth of private credit has brought the market to a scale where competition has intensified, drawing in larger participants, including major banks and institutional investors, alongside traditional private credit funds.[9] This increased competition may contribute to a loosening of underwriting standards and a broader shift toward riskier borrowers and more complex loan structures. These developments raise concerns about the potential for higher default rates, especially among smaller, highly leveraged firms that are more susceptible to an economic downturn or higher borrowing costs.

Moreover, features such as payment-in-kind (PIK) 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 all corporate lending toward distressed exchanges, where companies restructure debt to avoid a payment default, potentially resulting in larger ultimate losses for investors (see Chart 6).[10]

Several indicators suggest that riskier segments of corporate credit markets, including private credit, may be vulnerable to broader market corrections (see Chart 7). Aggregate corporate leverage has risen recently, with metrics like debt relative to corporate gross value added trending higher. The historically low credit spreads of the past year recently flared as the global trade war intensified and could spike further should the economy weaken. Meanwhile, interest coverage ratios have declined as many borrowers now face higher interest rates for longer and elevated debt servicing costs. The mounting global trade war also poses fresh uncertainty around corporate earnings, inflation and global demand. In this environment, even modest shocks could prompt a reassessment of risk and return expectations.

While many private credit vehicles are insulated from immediate market repricing because of their closed-end or drawdown structures, they are not immune to broader market dynamics, particularly in a market 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

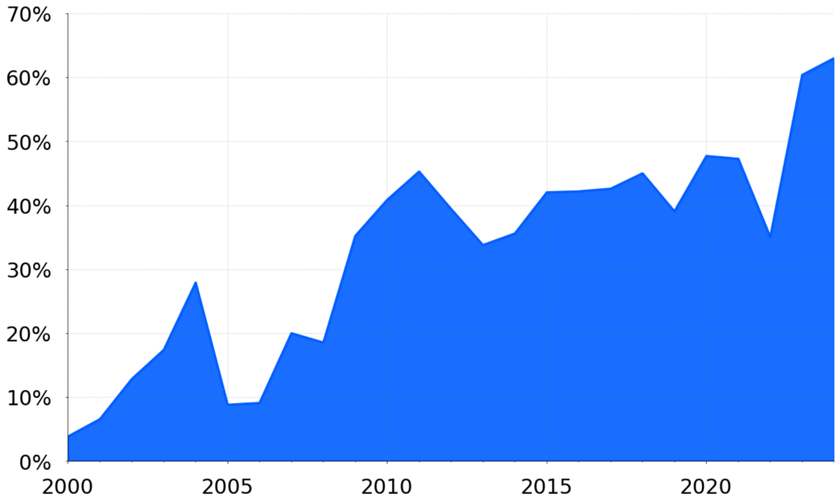
9 Moody's Ratings (2024).
10 Hamilton and Su (2025).

Chart 6: Distressed Exchanges Are on the Rise

Distressed exchanges as a % of all defaults

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

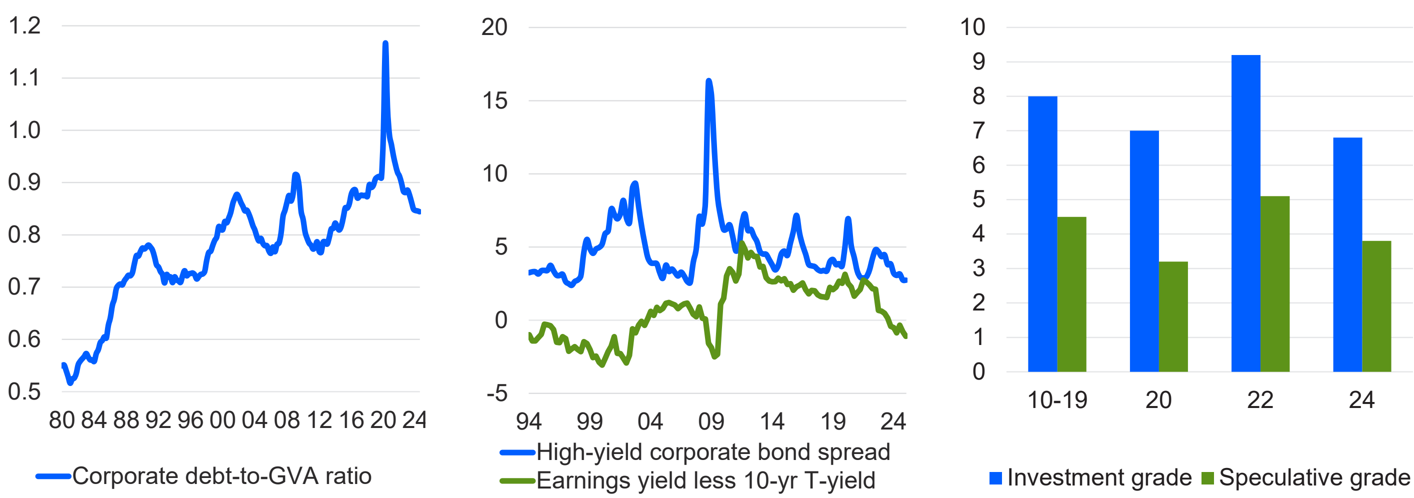
Rather than resulting in defaults such as missed payments or bankruptcies, the expected heightened default risk is more likely to show itself in more distressed restructurings.



Sources: Moody's Ratings, Moody's Analytics

Chart 7: Corporate Leverage and Richly Valued Asset Markets Are a Risk

Nonfinancial corporate debt ratio, # | Nonfinancial corporate debt ratio, % | EBITA/interest expense multiple



Sources: Federal Reserve, BEA, Bloomberg, Apollo, Moody's Analytics

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 latent losses can undermine confidence in the manager's broader portfolio, prompting counterparties to retrench or investors to redeem from more liquid vehicles. This, in turn, can force asset sales and amplify contagion across otherwise unrelated asset classes.

ASSESSING SYSTEMIC RISK

Private credit is becoming increasingly central to the financial system, but its rapid evolution, structural complexity and limited transparency make it difficult to directly observe to what degree and whether it poses any systemic threat to the broader financial system. Instead, we use market-based signals—from the pricing of BDCs and other financial firms—to statistically infer private credit's interconnectedness with the broader financial system and assess potential contagion risks. 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 2004 to 2023, 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 (EDF) from the Moody's public company database and total stock returns from the Center for Research in Securities Prices.[11]

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 the institutions vary in size—banks and insurers are notably larger than BDCs and other NBFIs—all sectors show evidence of 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 the role of interconnectedness in amplifying distress.

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-yr 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

*The BDCs asset universe includes all U.S. private credit funds, and other NBFIs include custodial assets of asset managers.

Source: Moody's Analytics

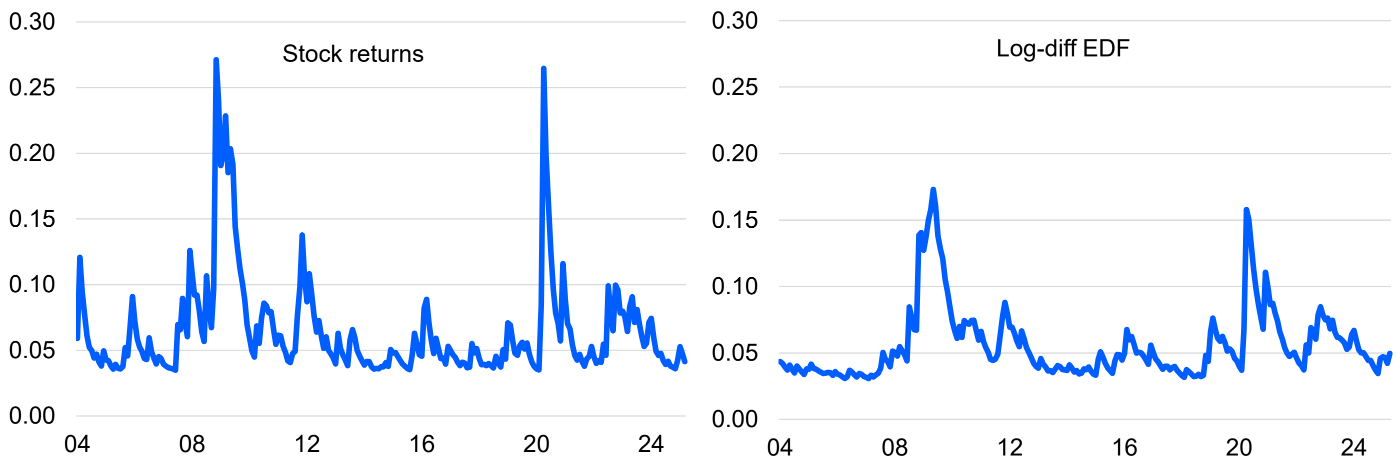
11 Moody's (2020).

VARIANCE OF THE SYSTEM

We first estimate the variance of the system using a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (1,1) model (see Chart 8).[12] We compute these estimates separately for the cross-sectional average of stock returns (left) and the log-differenced EDFs (right).

Chart 8: 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). 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 evolved for different sectors over time (see Chart 9). 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 because of 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.

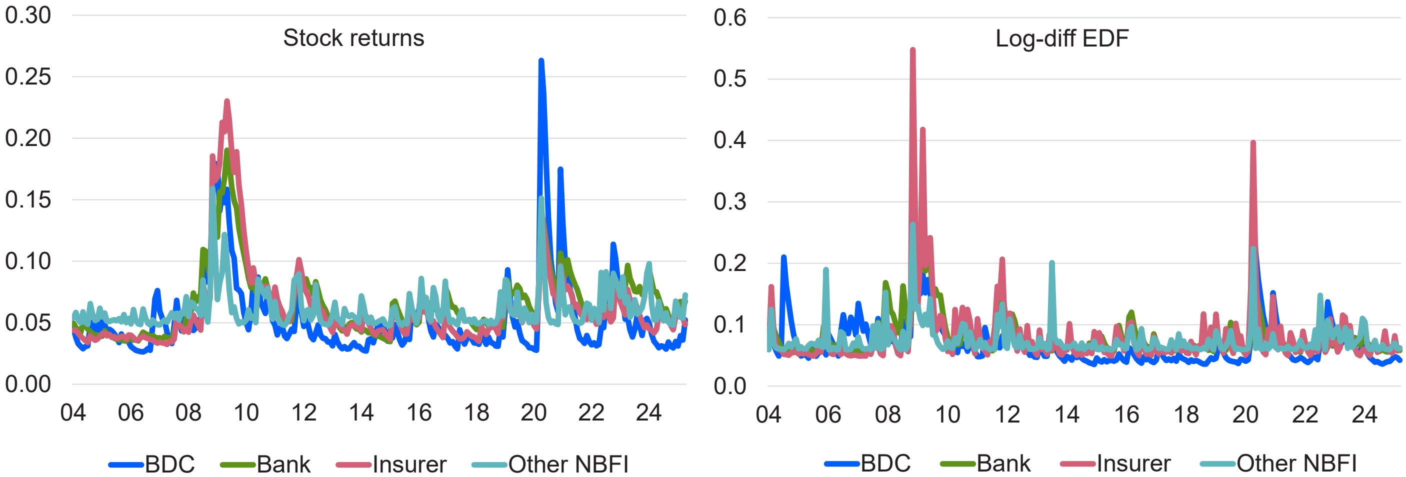
ASSESSING INTERCONNECTEDNESS USING PCA

Next, we 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

12 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 2005 through 2024.

Chart 9: BDC Volatility Shocks More Prominent in COVID-19 Than GFC

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



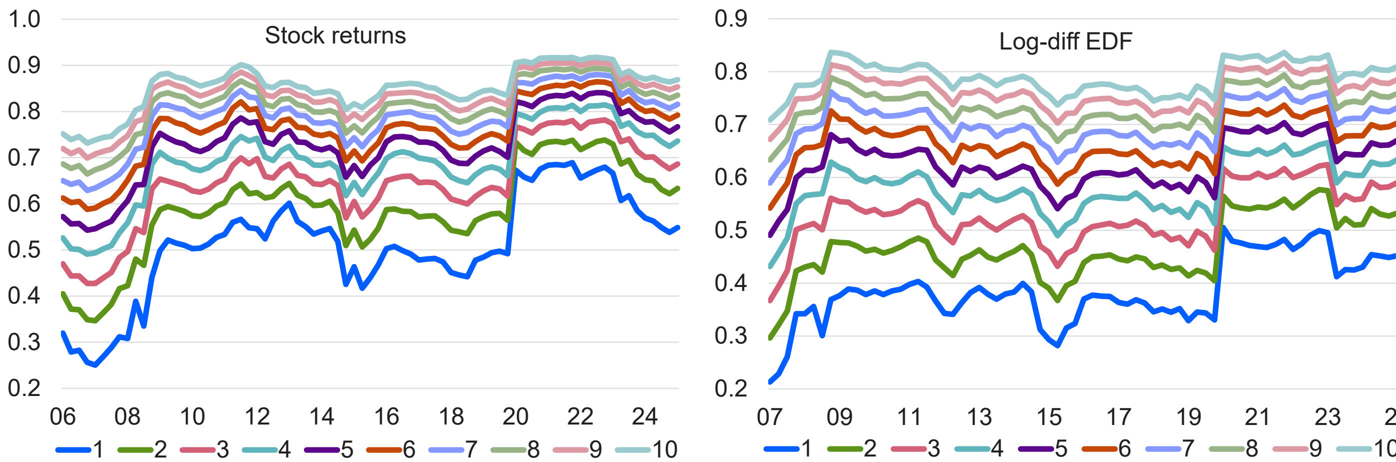
Source: Moody's Analytics

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 return-based PC1 and EDF-based PC1 explain only a modest fraction of the total variance, pointing instead to the importance of idiosyncratic factors (see Chart 10). 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

Chart 10: Leading PCAs More Important Over Time and in Crises

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



Source: Moody's Analytics

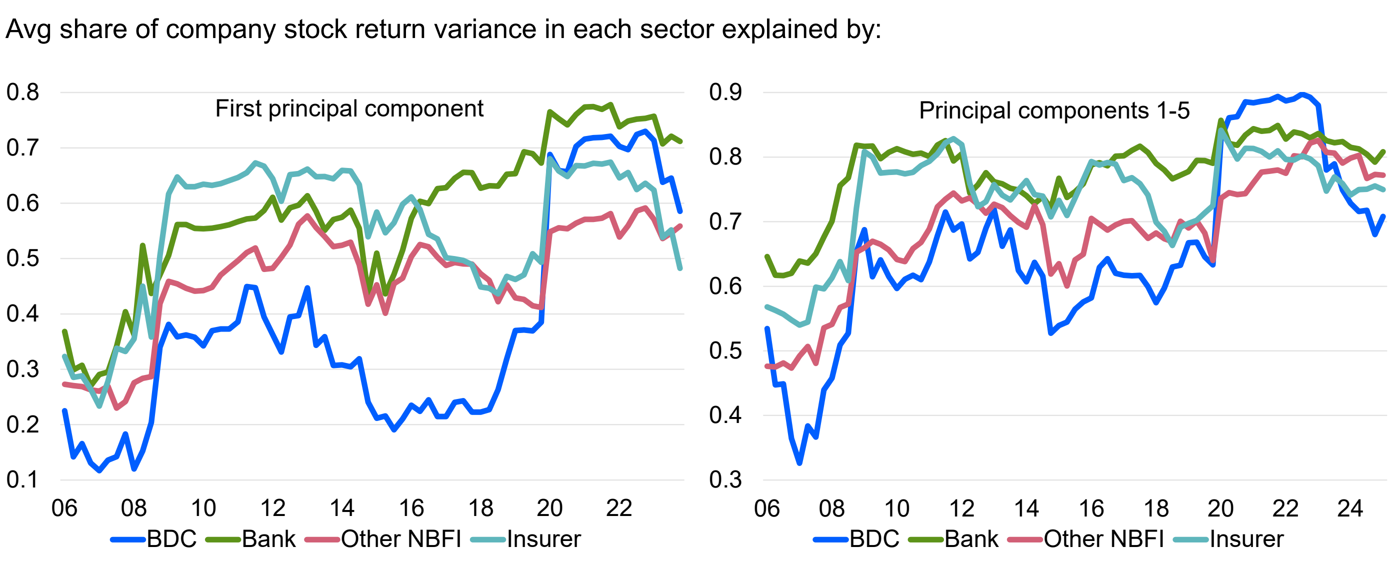
environments, the financial system becomes highly interconnected, and a single systemic factor explains a much larger share of the risk across firms as correlations between different sectors approach unity.

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 11 and 12). 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 remains elevated post-pandemic, suggesting growing BDC sensitivity 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 11: BDCs Increasingly Linked to Principal Components



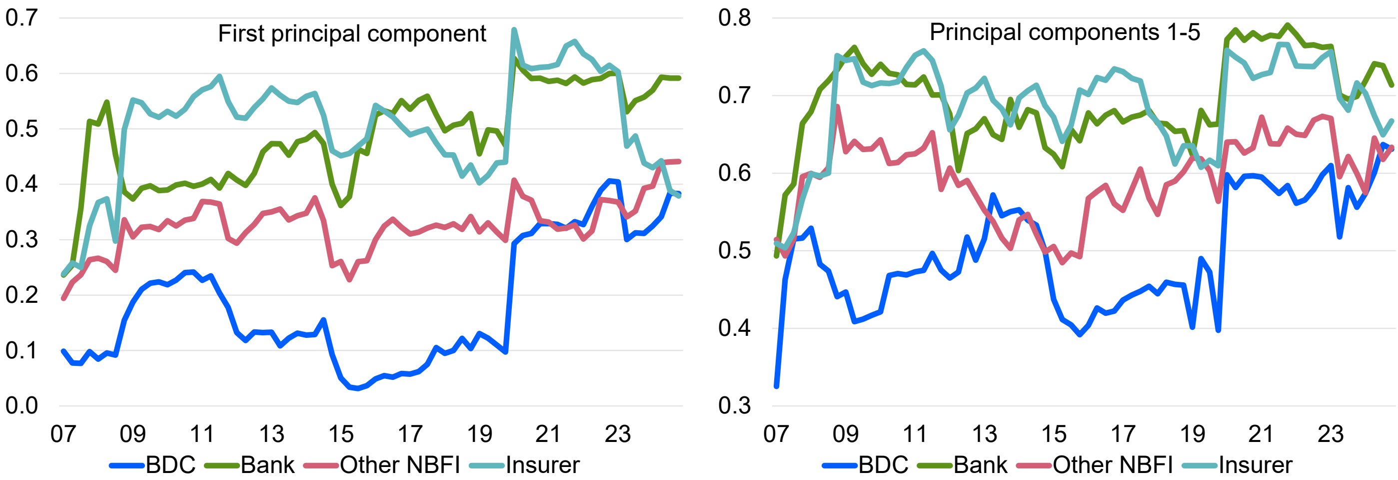
Source: Moody's Analytics

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 such relationships and to look for evidence of spillovers during periods of market stress. We construct a Granger-causality

Chart 12: EDF Variation Explained by System Principal Components

Avg share of company log-differenced EDF variance in each sector explained by:



Source: Moody's Analytics

network to map how risk transmission channels across financial institutions evolve over time, showing that, post-GFC, BDCs have become more important and banks less important in the network during periods of market stress.

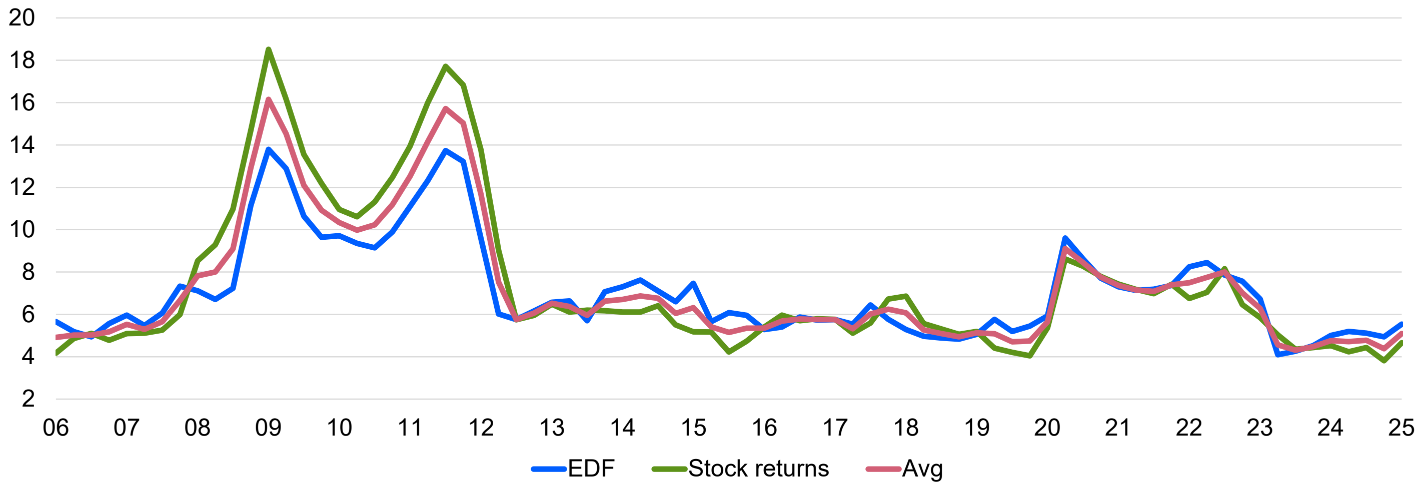
In brief, for three-year rolling windows throughout our sample, we perform pairwise Granger-causality tests on monthly EDF time series and stock return series for all institutions in our sample. For each pair of firms A and B, A is said to Granger cause B if a predictive model of the returns of B on 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 13). In our PCA results, we also see elevated connectivity during periods of stress, but we more generally see 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.

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

Chart 13: Financial Institutions Interconnected in Periods of Stress

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



Source: Moody's Analytics

network had become significantly more interconnected, with connection rates averaging just shy of 10% across all possible group pairings.

Moreover, comparing the GFC period with the post-pandemic period that starts in 2022, Table 2 shows that the BDCs have become more prominent in the network while the banks have become less so. Specifically, BDCs account for relatively more of the total Granger-causality linkages during the COVID-19 shock than they did in the GFC, while the opposite is true for banks. 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 13). 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 (see Chart 14). During the GFC, banks and insurers were the most likely to be both sources and destinations of stress. However, in the COVID-19 shock, we see banks and BDCs slightly more likely to be a source of spillovers (causes) and insurers and other nonbanks somewhat more likely to be the destination of spillovers (effects).

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 15-17). While banks dominated the network during the GFC in a hub-and-spoke pattern, the financial network during the pandemic resembled much more of a web, with banks, insurers, BDCs and other NBFIs taking on more even roles. And in periods of calm, the network becomes less interconnected.

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' connection

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	4.78			
To	Bank	BDC	Other	Insurer
From				
Bank	5.24	6.67	6.67	4.89
BDC	2.22	3.33	2.38	4.44
Other NBFI	3.81	3.57	3.30	4.76
Insurer	6.67	5.56	3.81	5.24

2009M3	Peak financial crisis (stock returns)			
All	18.52			
To	Bank	BDC	Other	Insurer
From				
Bank	**28.57**	**22.78**	**13.33**	**28.89**
BDC	**15.56**	**13.64**	**10.56**	**15.56**
Other NBFI	**15.11**	**11.67**	**10.95**	**12.89**
Insurer	**27.56**	**22.78**	**17.33**	**25.24**

2009M12	Financial crisis recovery (stock returns)			
All	12.19			
To	Bank	BDC	Other	Insurer
From				
Bank	**17.62**	**13.33**	**10.67**	**16.00**
BDC	**8.72**	**9.62**	**9.23**	**9.74**
Other NBFI	**10.22**	**7.18**	**10.00**	**9.78**
Insurer	**15.56**	**15.90**	**14.67**	**15.24**

2019M12	Pre-COVID-19 (stock returns)			
All	4.04			
To	Bank	BDC	Other	Insurer
From				
Bank	4.29	4.00	6.67	4.44
BDC	9.33	4.76	7.56	1.78
Other NBFI	1.78	1.33	6.67	0.89
Insurer	4.00	3.56	2.67	0.95

2020M6	COVID-19 crisis (stock returns)			
All	8.62			
To	Bank	BDC	Other	Insurer
From				
Bank	**10.95**	**8.89**	**10.22**	5.78
BDC	**13.33**	**11.43**	**12.00**	**9.33**
Other NBFI	**8.44**	4.44	5.71	6.22
Insurer	5.78	**11.56**	5.33	**8.57**

2021M3	COVID-19 recovery (stock returns)			
All	7.42			
To	Bank	BDC	Other	Insurer
From				
Bank	6.19	5.33	7.56	7.11
BDC	**8.44**	**17.62**	**8.00**	**9.33**
Other NBFI	6.67	**8.44**	5.71	5.78
Insurer	6.67	7.56	3.11	5.71

2006M12	Pre-financial crisis (EDF)			
All	5.57			
To	Bank	BDC	Other	Insurer
From				
Bank	4.29	5.71	4.29	8.00
BDC	5.71	**9.52**	4.08	4.76
Broker	6.19	8.16	**8.79**	**6.67**
Insurer	2.67	2.86	3.33	6.67

2009M3	Peak financial crisis (EDF)			
All	13.79			
To	Bank	BDC	Other	Insurer
From				
Bank	**22.38**	**15.38**	**9.33**	**24.00**
BDC	6.67	**10.90**	7.18	7.69
Broker	**19.11**	8.21	7.14	**17.78**
Insurer	**16.89**	**12.31**	**12.89**	**19.05**

2009M12	Financial crisis recovery (EDF)			
All	9.64			
To	Bank	BDC	Other	Insurer
From				
Bank	**14.76**	**12.86**	**8.89**	**15.11**
BDC	**10.95**	5.49	7.14	6.19
Broker	**16.00**	5.71	8.10	7.11
Insurer	**10.22**	6.67	**10.22**	7.62

2019M12	Pre-COVID-19 (EDF)			
All	5.82			
To	Bank	BDC	Other	Insurer
From				
Bank	8.10	6.22	7.56	5.78
BDC	6.22	4.29	4.89	3.56
Broker	1.78	6.22	3.33	5.33
Insurer	5.33	6.67	6.22	5.71

2020M6	COVID-19 crisis (EDF)			
All	8.53			
To	Bank	BDC	Other	Insurer
From				
Bank	**15.24**	**14.22**	**13.33**	**12.44**
BDC	**12.00**	6.19	8.00	5.33
Broker	3.56	4.44	**11.43**	7.56
Insurer	6.67	**8.44**	**12.89**	**12.38**

2021M3	COVID-19 recovery (EDF)			
All	7.31			
To	Bank	BDC	Other	Insurer
From				
Bank	**9.52**	8.10	8.00	**10.67**
BDC	**9.05**	5.49	7.14	**11.43**
Broker	4.89	1.90	6.67	5.33
Insurer	**8.44**	4.29	7.56	8.10

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	5.17			
To	Bank	BDC	Broker	Insurer
From				
Bank	4.76	6.19	5.48	6.44
BDC	3.97	6.43	3.23	4.60
Broker	5.00	5.87	6.04	5.71
Insurer	4.67	4.21	3.57	5.95

2009M3	Peak financial crisis (connection rate)			
All	16.15			
To	Bank	BDC	Broker	Insurer
From				
Bank	**25.48**	**19.08**	**11.33**	**26.44**
BDC	**11.11**	**12.27**	**8.87**	**11.62**
Broker	**17.11**	**9.94**	**9.05**	**15.33**
Insurer	**22.22**	**17.54**	**15.11**	**22.14**

2009M12	Financial crisis recovery (connection rate)			
All	10.92			
To	Bank	BDC	Broker	Insurer
From				
Bank	**16.19**	**13.10**	**9.78**	**15.56**
BDC	**9.84**	7.55	**8.19**	**7.97**
Broker	**13.11**	6.45	**9.05**	**8.44**
Insurer	**12.89**	**11.28**	**12.44**	**11.43**

2019M12	Pre-COVID-19 (connection rate)			
All	4.93			
To	Bank	BDC	Broker	Insurer
From				
Bank	6.19	5.11	7.11	5.11
BDC	**7.78**	4.52	6.22	2.67
Broker	1.78	3.78	5.00	3.11
Insurer	4.67	5.11	4.44	3.33

2020M6	COVID-19 crisis (connection rate)			
All	8.57			
To	Bank	BDC	Broker	Insurer
From				
Bank	**13.10**	**11.56**	**11.78**	**9.11**
BDC	**12.67**	**8.81**	**10.00**	7.33
Broker	6.00	4.44	**8.57**	6.89
Insurer	6.22	**10.00**	**9.11**	**10.48**

2021M3	COVID-19 recovery (connection rate)			
All	7.36			
To	Bank	BDC	Broker	Insurer
From				
Bank	**7.86**	6.71	**7.78**	**8.89**
BDC	**8.75**	**11.56**	7.57	**10.38**
Broker	5.78	5.17	6.19	5.56
Insurer	7.56	5.92	5.33	6.90

2006M12	Pre-financial crisis (ratio to all)			
All	100			
To	Bank	BDC	Broker	Insurer
From				
Bank	92	120	106	125
BDC	77	124	62	89
Broker	97	113	117	110
Insurer	90	81	69	115

2009M3	Peak financial crisis (ratio to all)			
All	100			
To	Bank	BDC	Broker	Insurer
From				
Bank	158	118	70	164
BDC	69	76	55	72
Broker	106	62	56	95
Insurer	138	109	94	137

2009M12	Financial crisis recovery (ratio to all)			
All	100			
To	Bank	BDC	Broker	Insurer
From				
Bank	148	120	90	142
BDC	90	69	75	73
Broker	120	59	83	77
Insurer	118	103	114	105

2019M12	Pre-COVID-19 (ratio to all)			
All	100			
To	Bank	BDC	Broker	Insurer
From				
Bank	126	104	144	104
BDC	158	92	126	54
Broker	36	77	101	63
Insurer	95	104	90	68

2020M6	COVID-19 crisis (ratio to all)			
All	100			
To	Bank	BDC	Broker	Insurer
From				
Bank	153	135	137	106
BDC	148	103	117	86
Broker	70	52	100	80
Insurer	73	117	106	122

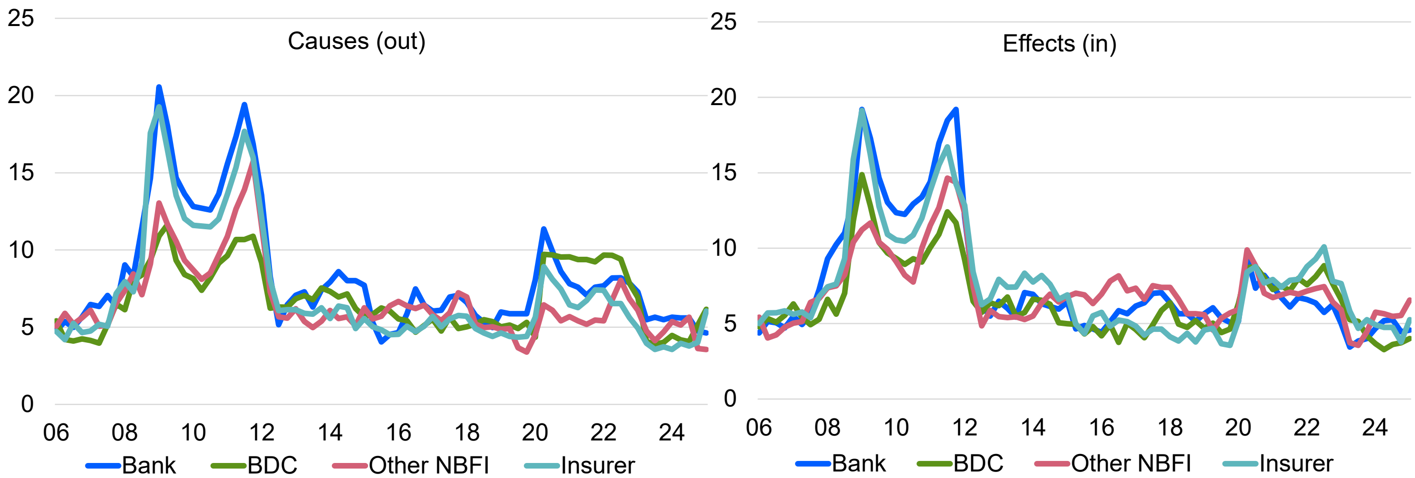
2021M3	COVID-19 recovery (ratio to all)			
All	100			
To	Bank	BDC	Broker	Insurer
From				
Bank	107	91	106	121
BDC	119	157	103	141
Broker	78	70	84	75
Insurer	103	80	72	94

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

Source: Moody's Analytics

Chart 14: BDC and Other NBFI Links Rise in Pandemic Period From GFC

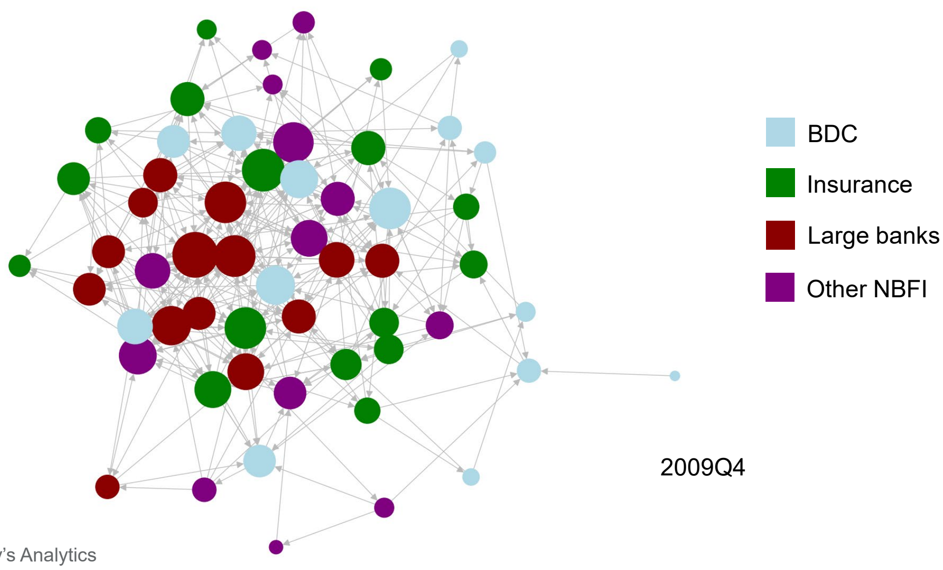
Number of Granger linkages as % of total possible linkages, EDF and returns avg (3-yr rolling windows)



Source: Moody's Analytics

Chart 15: Banks Dominated the System During the GFC

Size of node=degree of forcing connections



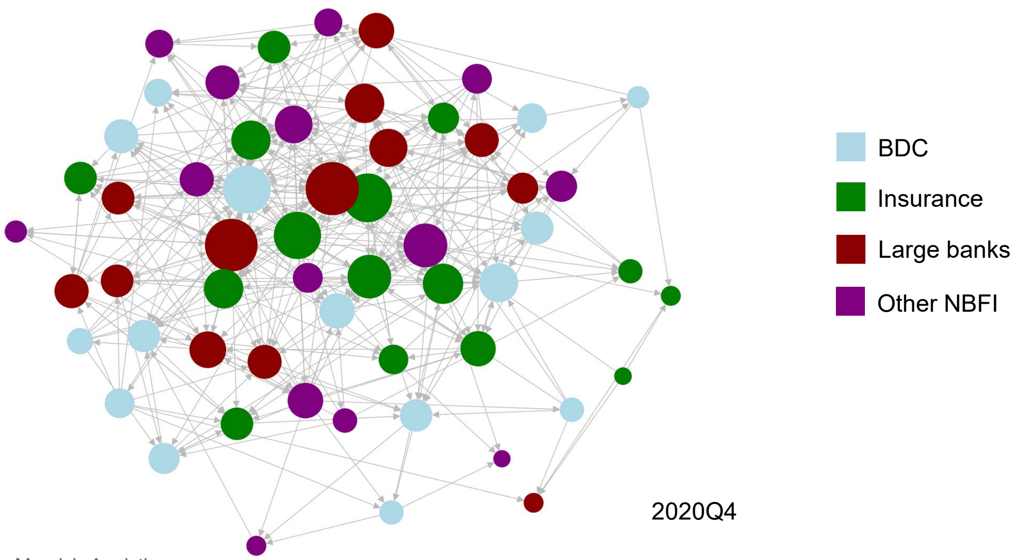
Source: Moody's Analytics

levels within the network (see Table 3). We find that these measures of connectedness during periods of stress are strongly associated with contemporaneous firm-level losses, suggesting that the network structure provides a valuable lens for explaining loss patterns during crises.

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

Chart 16: Network Is More Dispersed but Densely Connected Post-GFC

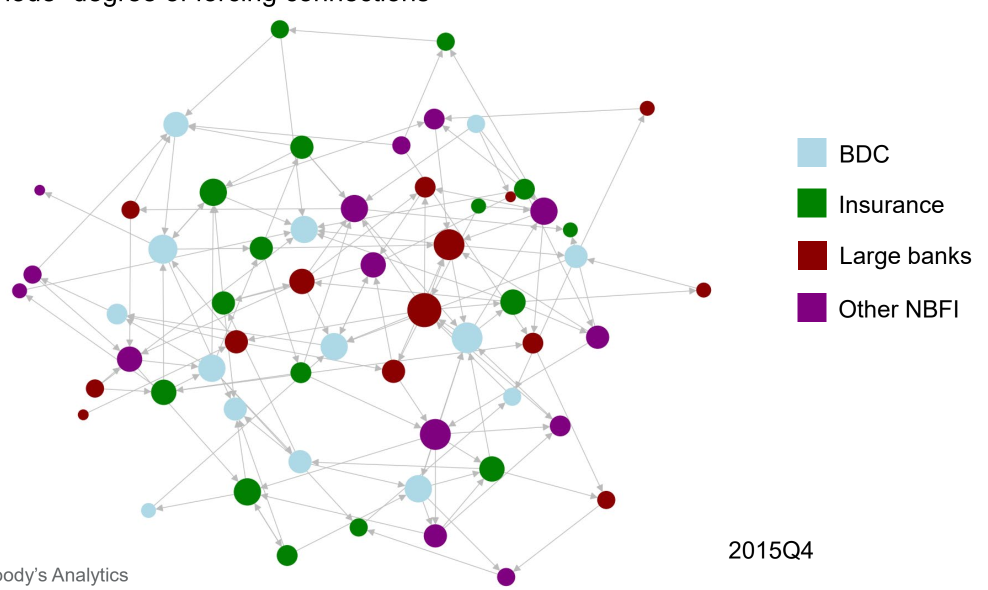
Size of node=degree of forcing connections



Source: Moody's Analytics

Chart 17: Networks Are Less Connected in a Well-Functioning Economy

Size of node=degree of forcing connections



Source: Moody's Analytics

Table 3: Maximum Loss Prediction Estimates

Loss measure	EDF									
Crisis period	GFC					COVID-19				
Window for driver calculation	2007-2009					2018-2020				
Loss observation date	2008M7-2009M6					2020M1-2020M12				
Systemic risk measure	In	Out	In+out	R PCA 1	R PCA 1-5	In	Out	In+out	R PCA 1	R PCA 1-5
Coefficient	1.75	3.01	1.57	45.2	44.4	3.00	0.93	1.58	45.6	49.6
T-statistic	3.20	6.25	5.55	4.35	3.56	4.02	1.11*	3.20	3.68	3.15
R-squared	0.17	0.43	0.38	0.27	0.19	0.22	0.02	0.15	0.19	0.15

Loss measure	Stock return									
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	1.89	2.12	1.29	49.3	67.5	0.88	2.79	1.70	67.1	116.3
T-statistic	3.20	6.25	5.55	4.35	3.56	1.09*	2.78	2.69	4.28	4.30
R-squared	0.22	0.23	0.29	0.30	0.34	0.03	0.09	0.11	0.40	0.35

Notes: The table reports key values from a linear regression of financial institution losses on institution-level Granger connectivity or PCA estimates. Systemic risk measures in each regression are estimated over the indicated 3-yr windows, and losses are recorded over the indicated 1-yr period. For the systemic risk measures, In = proportion of incoming connections in the Granger network, Out = proportion of significant outgoing connections, and In+out = sum of connections. R PCA1 is the R-squared from regressing the firm-level return or EDF on the first principal component and R PCA5 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 insignificant coefficients at the 5% level.

Source: Moody's Analytics

point to increased contagion in the presence of private credit in future crisis episodes.[13] It is well-known that the financial system can become highly fragile under large negative shocks when it is densely interconnected. This should be contrasted with the perhaps more intuitive[14] scenario where a more densely connected financial network may enhance financial stability when the negative shocks are sufficiently small and below a certain threshold.[15]

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 have potential vulnerabilities but, lacking market signals of their own, 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.

13 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 the financial market impact, the GFC was the more significant of the two, and the liquidity crunch created much more market contagion overall. Differences in policy responses may also have shaped the relative impacts across sectors. Nonetheless, controlling for 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 important.

14 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.

15 Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015).

POTENTIAL SOURCE OF CONTAGION

Our analysis shows 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 each other via confidence and market liquidity channels. For example, a surge in defaults on privately held loans might cause an insurer to rebalance away from illiquid assets, putting pressure on publicly traded securities, thus affecting banks and brokers who mark to market. 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' lending to private credit institutions is small in aggregate (approximately $200 billion, equal to no more than 1% of bank assets), 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. Additionally, private equity sponsors often link banks and private credit, as many leveraged deals involve a syndicated loan underwritten by banks 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.

The amplification effect comes into play when these linkages cause 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 related assets' prices, 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, but given the industry's rapid growth, opaqueness, and role in making the financial network more densely interconnected, it 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.[16] The experiences of the GFC and the pandemic bear this out, and private credit will likely be involved in any future crisis.

16 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 the buildup of systemic risk occurred through direct interbank exposures and 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, are 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 fortified with capital and have less direct exposure to each other. 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.[17]

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 risks may now be hidden in private vehicles outside regulators' view.

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

17 Ghamami, Glasserman and Young (2021).

share of credit that migrates outside the regulatory perimeter, the more we are “flying blind” to potential systemic buildups.

The nature of systemic linkages in credit provision, in both corporate markets and increasingly in others too, has changed since the GFC. We have arguably reduced the systemic importance 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 distributed risk. Still, it has also created an intricately connected system where stress could propagate in unforeseen ways. The net effect is that systemic risk has not disappeared; it has evolved, requiring updated tools and vigilant monitoring.

POLICY RECOMMENDATIONS

Given these findings, several policy measures should be considered to mitigate systemic risks arising from private credit markets. Substantial further review and analysis would be required to determine the benefits of 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. However, the steps below would arguably strengthen oversight, improve transparency, and bolster the financial system’s resilience against shocks originating in nonbank credit channels.

- **Expand the regulatory perimeter and oversight:** Financial authorities should consider bringing large private 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 found to be highly interconnected and sufficiently sizable, 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.

- **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. They 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 face losses indirectly) or sectoral leverage limits.

  In addition, central banks should consider how they would respond if a systemic event in private credit markets materialized. While they traditionally serve as lenders of last resort to banks, a crisis in private credit might require liquidity support in other ways, for instance, lending facilities that banks can use to support credit funds.[18]

  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.

In summary, proactive measures on regulation, transparency and macroprudential preparedness can substantially reduce the systemic risk posed by private credit markets as they quickly grow 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.

18 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.

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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, business development companies, 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 only including 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:

$$z_i \equiv \frac{x_i-\mu_i}{\sigma_i} \qquad (1)$$

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

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

The principal components are mean zero and uncorrelated, implying:

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

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:

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

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:

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

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 $x_s = \sum_{i=1}^{N} x_i$. The system variance for the untransformed series x_{st} can be expressed in terms of the correlation of the standardized x_{st} returns:

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

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

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

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 i to the first n principal components:

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

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:

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

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 irst 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:

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

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:

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

Which follows from (2) and $\mathrm{Var}(z_i) = 1$, 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).[19] Note that in-sample, $r_{i,n}^2$ in (9) has the interpretation as the R-squared, or goodness of fit measure, from rregressing x_{it} on the first factors F_{kt} for the $t = 1,\ldots,36$ 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.

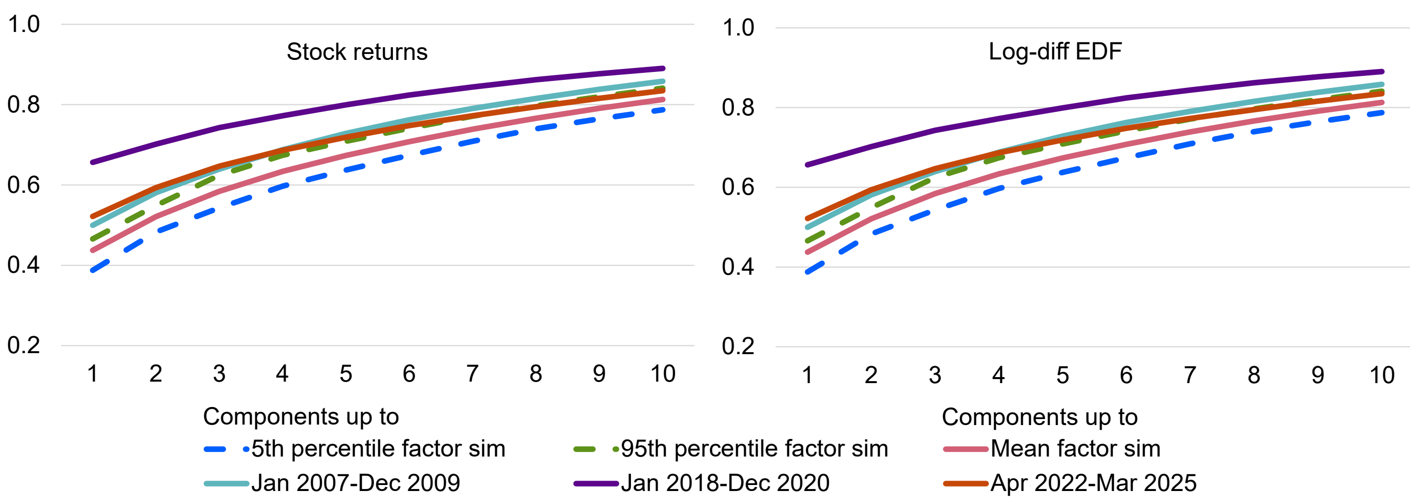
We employ Billio et al.'s bootstrap exercise to establish the thresholds above which principal components provide a significantly different signal from statistical noise. Using the in-sample equivalent of equation (6), we compute $\widehat{h_1}$ on our datasets for each of the overlapping 36-month windows. 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 oof 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).

19 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 (GCNA) 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:

$$x_t^A = a^A x_{t-1}^A + b^{AB} x_{t-1}^B + e_t^A,$$

$$x_t^B = a^B x_{t-1}^j + b^{BA} x_{t-1}^A + e_t^B, \qquad (12)$$

where e_t^A and x_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 (9) 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:

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

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 N firms:

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

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*.

$$\#\text{Out}: (G \rightarrow S) = \frac{1}{N_G} \frac{1}{N-1} \sum_{j \in G} \sum_{i \in S | i \neq j} (j \rightarrow i) \qquad (15)$$

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

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

» **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 N_{G_2} firms in sector G_2.

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

And connections within the N_G firms in an industry *G*:

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

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.

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, bij<0, on the firm's outgoing edges, optionally weighted by the receiving firms' size (total assets).

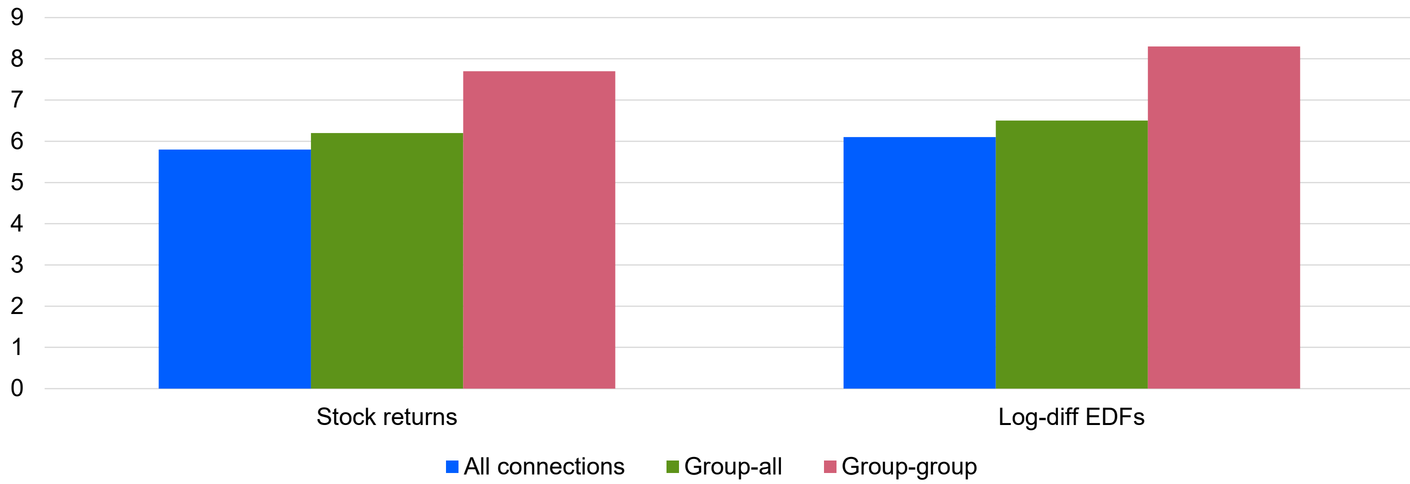
To establish the threshold for statistically significant connections in points 1 and 2 above, we employ Billio et al.'s bootstrap procedure. We perform a Monte Carlo simulation under the null hypothesis of no interdependence among institutions to assess whether observed Granger-causal relationships arise 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.

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 of 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).

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

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