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Building an integrated surveillance framework for highly leveraged NBFIs – lessons from the HKMA

Kevin Cheng, Zijun Liu, Silvia Pezzini and Liang Yu[+]

Abstract

This paper proposes a new approach to monitoring systemic risks arising from highly leveraged non-bank financial institutions (NBFIs) such as hedge funds and family offices. These types of entities usually employ a high degree of leverage, with the potential to create and amplify market stress through their concentrated portfolios and interconnectedness. At the same time, they are diverse in nature, nimble and subject to little disclosure. As such, much-needed efforts to address NBFI risks from a system-wide perspective are often impeded by data gaps. In light of the ongoing policy discussions on the NBFI sector, and recent progress in collecting more granular supervisory data, the paper highlights that multiple data sources can be integrated in new ways to extract valuable information and signals for timely NBFI monitoring. In particular, granular data from trade repositories and from regulated entities such as banks can be used to narrow data gaps. Based on the HKMA's experience, the paper explains the analytical underpinnings of building a surveillance framework to monitor highly leveraged NBFIs and suggests practical strategies that might be adopted by regulators and supervisors.

JEL classification: G01, G23, G28.

Keywords: data gap, non-bank Financial Institutions, systemic risk.

[+] This paper has been prepared by Kevin Cheng (formerly HKMA, currently ASEAN+3 Macroeconomic Research Office), Zijun Liu (HKMA), Silvia Pezzini (HKMA), and Liang Yu (BIS).

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1. Introduction

Since the Great Financial Crisis (GFC), non-bank financial institutions (NBFIs) have considerably expanded their footprint in the global financial system. While NBFIs provide diversification benefits to the financial system, they have also become a major source of financial instability and have attracted increasing policy attention (Carstens (2021); Aramonte et al (2022)). Of particular concern to policymakers are "highly leveraged NBFIs" which, through their leverage, concentration of exposures, liquidity mismatches and interconnectedness, can magnify and propagate shocks through the financial system, as seen during the collapse of LTCM (BIS (1999); Edwards (1999)) and Archegos (ESMA (2022a); FSB (2022a)).

This paper focuses on highly leveraged NBFIs such as hedge funds and family offices. These firms are often not subject to prudential regulation and have little entity-level disclosure. They are diverse in nature, engaging in complex or opaque derivatives transactions, and their trading strategies can change rapidly to explore market opportunities. Direct and indirect market linkages as well as their high leverage can amplify liquidity stresses. Their failure may lead to credit losses, market dislocation, or even spark fears of contagion in the financial system with potential systemic consequences. In addition, the sector has been growing fast and the increasingly active role of these highly leveraged NBFIs in markets magnifies their importance from a financial stability perspective. While enhanced market surveillance by regulatory authorities is much needed to identify rising risks and vulnerabilities posed by highly leveraged NBFIs, the question is how to do it given the existence of important data gaps.[1]

In this paper, we draw on the recent experience of the Hong Kong Monetary Authority (HKMA). The HKMA adopted its NBFI surveillance framework in Q3 2021 as part of its regular financial stability surveillance toolkit. At the time of writing, the framework had served over time to flag a number of hedge funds and family offices, which were later reported in negative news or became involved in legal proceedings, suggesting the framework could unmask certain hidden vulnerabilities and risks before they manifested themselves.

HKMA's experience provides salient lessons. First, despite limited disclosure by highly leveraged NBFIs, central banks and regulatory authorities can narrow the data gap by exploiting granular data sets that have become available in recent years, thereby unveiling a clearer landscape of the NBFI sector. These granular data sets (e.g. trade repository data and granular transaction-based banking data) report information on NBFIs as counterparties, which make it possible to reconstruct NBFIs' positions with some confidence. Second, a practical structure is provided for combining banking data with market data, textual big data and macro data in an integrated way to assess the impact and vulnerability dimensions for individual NBFIs and identify NBFIs that warrant further close monitoring.

The rest of the paper is structured as follows. Section 2 describes the surveillance framework for highly leveraged NBFIs as implemented by the HKMA, and explains the analytical underpinnings of the approach. Some findings from implementing the

1 A key theme emerging from work carried out by the FSB (2022b) is the existence of important data gaps in authorities' NBFI risk monitoring.

framework and evaluating its performance are also illustrated. Section 3 draws lessons from the HKMA experience that might be useful for other central banks and regulators. Section 4 concludes.

2. HKMA's experience in building an NBFI surveillance framework

2.1 The backdrop

Highly leveraged NBFIs such as hedge funds have experienced notable growth in Hong Kong SAR, according to the Securities and Futures Commission (SFC)'s latest Asset and Wealth Management Activities Survey.[2] Assets under management (AUM) by hedge funds in Hong Kong SAR expanded to US$ 197 billion in 2021 from US$ 132 billion in 2017, an increase of nearly 50%. Until the new approach described in this paper became available, surveillance and risk monitoring of highly leveraged NBFIs – such as hedge funds and family offices – had to rely on ad hoc surveillance methods, such as market news and supervisory enquiries, that provided only limited insights or partial snapshots at a particular time.

The collapse of Archegos in March 2021, although it had little exposure in Hong Kong SAR, served as a wake-up call for central banks and supervisors globally, including the HKMA. In the aftermath, the HKMA decided to integrate a host of diverse data sets into a structured framework, so that risk exposures to a large number of NBFIs could be identified, together with their risk characteristics. The HKMA was encouraged in this venture by the considerable improvement in supervisory data driven by the G20 Data Gaps Initiative[3] (see Box 1) and technological advances in financial supervision (suptech).[4]

[2] SFC (2022).

[3] FSB and IMF (2022).

[4] FSB (2020).

Box 1

The HKMA's efforts to enhance supervisory data

In 2014, the HKMA started developing a new framework for trade repository (TR) data analysis to assess the market's financial stability and potential risks. TR data are trade-level data on OTC derivatives, which G20 jurisdictions started to collect using trade repositories after the GFC. The Hong Kong Trade Repository (HKTR) data cover all OTC derivative transactions in five asset classes – equities (EQ), interest rate (IR), foreign exchange (FX), credit (CD) and commodities (CM) – that are either booked or conducted in Hong Kong. For each transaction, a comprehensive set of data fields is reported by regulated financial institutions, including counterparty, notional value and the underlying assets. The data are updated daily.

Since 2018, to cope with the granularity and large size of HKTR and granular banking data, the HKMA has enhanced its use of big data analytics and data science techniques to gain deeper insights into trends, patterns, and causal relationships in a number of areas. Among the techniques used are (i) natural language processing (NLP) to analyse unstructured data, such as news articles, social media posts, and policy documents, providing valuable insights into public sentiment, economic trends and market intelligence; (ii) network analysis to understand interconnectedness between various elements of the financial system; and (iii) data visualisation to optimise the use of graphical representations to display and analyse complex data sets.

In 2019, the Granular Data Reporting (GDR) initiative was launched to collect structured transaction-level data on banks' activities. Granular loan data cover a range of information including loan amount, tenor, pricing, counterparty and collateral (Wu and Liu (2020)). The data are updated monthly.

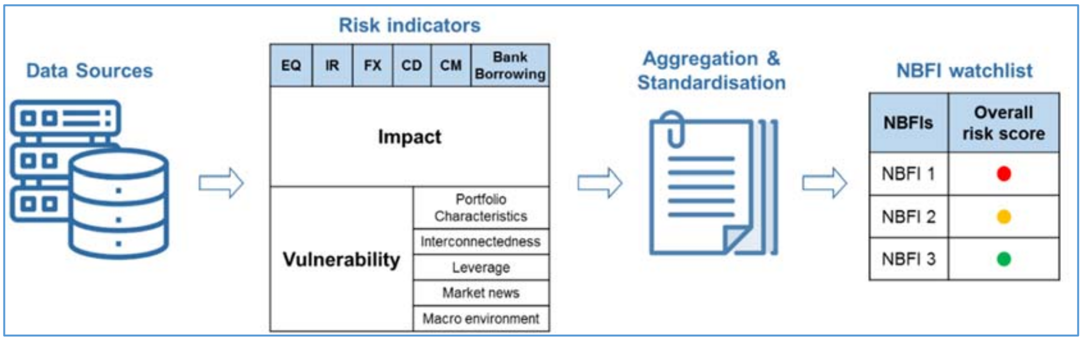
2.2 Key features

The purpose of the HKMA's NBFI surveillance framework is to sift through all the available information on NBFIs and organise it for the purpose of giving an initial assessment of the systemic risk posed by individual NBFIs, so that a smaller set of NBFIs can be identified for further monitoring. The framework produces a ranking based on various risk indicators. Such an approach adopted is similar in spirit to the Basel Committee's assessment methodology for Global Systemically Important Banks (G-SIBs), which assesses systemic risks using easily computable and easily explainable indicators. Alternatives such as model-based approaches (see Drehmann and Tarashev (2011)) may be more rigorous but also more complex to develop and to explain, and thus less suitable for the huge amount of information and large number of NBFIs to be considered in this case.

The scope of this project is NBFIs that use significant leverage to maximise returns, mainly including hedge funds and family offices. NBFIs such as broker-dealers and insurance companies are excluded here as they are subject to prudential regulation with relevant data being available for surveillance efforts. Money market funds, index funds and large asset managers are also excluded. Although some of these entities may also use derivatives, the purpose tends to be to hedge risks or reduce costs rather than to acquire leverage for return maximisation.

Key steps in producing NBFI watchlist

Graph 1



Graph 1 illustrates the key features of the HKMA's framework. First, various data sets feed into the calculation of various risk indicators (see Table 1). These indicators are calculated for both the impact and vulnerability dimensions, across five derivative asset classes as well as bank borrowing. Second, the risk indicators are aggregated and standardised to compute an overall risk score for each NBFI, using a risk-weighted approach that reflects the underlying risk of different asset classes. Finally, a watchlist of NBFIs is produced by ranking them according to their overall risk scores. See Section 2.3 and Appendix for further details.

2.3 Risk indicators

To guide the development of a surveillance framework from a financial stability perspective, the key question is under what conditions would highly leveraged NBFIs such as hedge funds or family offices potentially pose a systemic risk. While many studies provide useful insights on prominent failures of hedge funds (Dixon et al (2012); Chan et al (2007)), few have developed quantitative risk indicators to address the question. Factors which could contribute to the systemic impact of a highly leveraged NBFI include its absolute size, the riskiness of its portfolio, and the potential contagion to the rest of the financial system (King and Maier (2009)).

The HKMA framework incorporates a range of risk indicators as listed in Table 1. Under impact, the framework takes the size of the NBFI's positions, which is often considered as the most important factor when assessing systemic risk (IOSCO (2011)). Under vulnerability, the framework takes a range of indicators arising from the NBFI's portfolio characteristics, the NBFI's interconnectedness and leverage, as well as market news and macro environment, as described below.

Further details of the calculation of risk indicators can be found in the Appendix.

List of risk indicators

Table 1

Dimensions/Categories		Risk Indicators	
Impact		1	*Size of gross positions in bank borrowing and OTC derivatives*
Vulnerability	**Portfolio characteristics**	2	*Portfolio Volatility*
		3	*Stock concentration*
		4	*Sector concentration*
		5	*Small-cap stocks*
		6	*Substantial interest stocks*
		7	*Illiquid stocks*
	Interconnectedness	8	*Number of counterparties*
		9	*Prime broker concentration*
		10	*Crowded trade*
	Leverage	11	*Leverage*
		12	*Fast-growing position*
	Market news	13	*Market news*
	Macro environment	14	*Market volatility*

Impact: Size of gross positions

The direct credit or trading exposures of banks and prime brokers to highly leveraged NBFIs are the most obvious channel through which NBFIs could affect the stability of the financial system. The collapse of a hedge fund leads to forced liquidations of positions, write-downs and losses. A disorderly unwinding, which is often the case without government intervention, could generate heavy losses to counterparties with large positions. A large hedge fund could even be too big to fail abruptly, as seen in the demise of LTCM in late 1998, in which the US Federal Reserve eventually intervened by facilitating a bailout by LTCM's major creditors (BIS (1999); Edwards, (1999)).

The total leveraged position of an NBFI is more relevant than its net asset value or assets under management (AUM) in obtaining a full picture of its systemic impact. For example, in early 1998, LTCM had borrowed over USD 120 billion against only USD 5 billion in equity, and the notional amount of its total OTC derivatives positions was estimated to be over USD 1 trillion (BCBS (1999)). In the HKMA framework, this size indicator measures the gross positions taken by the NBFI using bank loans and OTC derivatives. Trade repositories and banking data at a granular level are used to reconstruct NBFI positions. A separate regulatory exercise has shown these estimates to be reasonably reliable. The set of gross positions could be further enriched in the future as more information becomes available on other instruments through which NBFIs can acquire leverage.

Vulnerability – Portfolio characteristics: concentration, liquidity risk and market risk in an NBFI's portfolio

It is established in the literature that portfolio risk is positively correlated with the volatility of underlying assets, stock concentration and the share of small-cap stocks (Zaimovic et al (2021)). In particular, if the NBFI holds a derivative position in a stock that is large compared with its market capitalisation, and if the position is sizeable, its unwinding can generate large potential losses (King and Maier (2009)). Hedge funds and family offices may also invest in illiquid assets, such as private equity, real estate, or distressed debt, which in times of market stress can be difficult to sell quickly without incurring significant losses, potentially leading to fire sales and exacerbating market volatility (Aragon and Strahan (2012)).

These portfolio-based dynamics were well demonstrated in the failure of LTCM, which had built up large positions in relatively small and illiquid markets. It subsequently became a major concern that a disorderly unwinding of LTCM's positions could trigger severe liquidity shortages in these markets. In the case of Archegos, the firm had highly concentrated positions in a number of stocks. When the price of one stock in its portfolio fell unexpectedly for external reasons, Archegos faced margin calls that eventually forced it to unwind its whole portfolio at fire sale prices. At that point, other stocks in its portfolio experienced severe selling pressure, thereby propagating losses to a broader set of institutions.

In the HKMA framework, a number of indicators capture such portfolio dynamics by quantifying, for each NBFI portfolio of derivative positions, the share in high-volatility assets and, for positions in equity derivatives, the concentration of the top five underlying holdings, concentrations at the sector level, and the share of small-cap stocks, substantial interest stocks, and illiquid stocks respectively.

Vulnerability – Interconnectedness: number of counterparties, prime broker concentration and crowded trades

We also consider the degree of interconnectedness of an NBFI to amplify its systemic vulnerability in relation to the banking sector. We capture interconnectedness using three indicators: the number of counterparties, prime broker concentration and crowded trades.

When an NBFI with many counterparties fails, its contagion effect will depend on the size of the shock, the loss-absorbing capacity of its counterparties and the degree of information available to manage the risks. As revealed in the Archegos incident, the family office was able to build very large positions partly because its many counterparties were unaware of Archegos' total positions and therefore were unable to manage risks effectively (Bouveret and Haferkorn (2022)). Similarly, LTCM borrowed from many different counterparties using little collateral, and its counterparties were unaware of LTCM's borrowing from other counterparties. The number of counterparties is a simple indicator that can capture such potential risks.

Furthermore, as shown in the literature on network analysis of systemic risk, the potential contagion risk from a network node depends on not only the number of counterparties, but also the size of exposures the node has relative to other connected nodes (Acemoglu et al (2015)). Therefore, an indicator on prime broker concentration is introduced to reflect the risk that an NBFI may have a large concentrated position with any of its individual prime broker counterparties, such that its failure could greatly affect the prime broker.

In addition, many studies have highlighted the potential for hedge funds to engage in crowded trades (defined as the situation in which several entities build similar positions on the same stock) and herd behaviour, which could have a destabilising effect on markets (Kyle and Xiong (2001); King and Maier (2009)). The crowded trade indicator can be used to capture the risk of indirect contagion from similar positions held by NBFIs.

Vulnerability – Leverage: gross positions to net assets, and fast-growing positions

Leverage is commonly understood as an important indicator of hedge fund risk. NBFIs with elevated leverage have a higher risk of financial distress as they are more vulnerable to sudden changes in asset prices, which would force them to deleverage, amplifying asset price drops. A sequence of negative events leading to market stress can start with losses on leveraged positions (Liang and Park (2010)). In particular, the combination of leverage and the fact that it is not transparent to credit providers and market regulators highlights its potential role in amplifying shocks (FSB (2022a)). As information on NBFIs' leverage is usually unavailable on a comprehensive and accurate basis, we introduce two proxy indicators: a leverage indicator measured by total gross positions to net asset value (as suggested by IMF (2018)), complemented by another indicator reflecting fast-growing positions. The intuition is that fast growth in an NBFI's positions is likely to reflect a build-up of leverage.[5] The granular data set collected consistently over time makes it possible to measure this variable, which would not be available otherwise. While neither of the two indicators captures a precise measure of NBFI leverage, together they capture some signal of likely use of leverage by the NBFI.

Vulnerability – Market news

A market news or sentiment score indicator is also included in the risk assessment to factor in negative news about specific NBFIs as reported in the financial press. This indicator is based on textual analysis using news databases with a wide coverage, such as the Global Database of Events, Language, and Tone.

Vulnerability – Macro environment

Hedge fund returns are negatively correlated with overall market volatility, and with the VIX index in particular (Dash and Moran (2005)). There are two elements to this: NBFIs' positions tend to be more vulnerable to shocks when markets are volatile; and risky positions become more visible when they are tested by adverse conditions such

5 We are mindful of the limitations of this approach to quantifying leverage by an NBFI. For example, the growth in positions may reflect fund inflows, representing a possible false positive. A fast build-up of leverage could also be followed by a reduction, which would potentially result in a false negative. However, the increased monitoring frequency of this proxy indicator can help spot a genuine build-up in leverage in the absence of better alternatives.

as volatile markets, echoing Warren Buffett's saying that "you only find out who is swimming naked when the tide goes out". The macro environment indicator measures the degree of overall financial market uncertainty or stress based on stock market volatility indices. The indicator is market-wide and not specific to individual NBFIs.

2.4 Aggregation of risk indicators

To reach an overall risk assessment of each NBFI, the risk indicators (except for the Macro Environment indicator, which we treat as a multiplier factor) are assigned into Low-Medium-High risk buckets based on thresholds derived mainly from data distributions, and then aggregated to derive impact and vulnerability scores respectively (see Appendix 2 for details). Finally, based on the combination of the impact and vulnerability scores being in the High, Medium or Low bucket, an overall risk category is assigned according to Table 2. For example, an NBFI's overall risk assessment is red if both its impact and vulnerability scores are in the High bucket. Generally speaking, NBFIs with amber risk require close monitoring and NBFIs with red risk are considered for possible follow-up actions. This approach is similar to the practice in many central banks to use risk rating matrices to determine the intensity of supervision required.[6]

Impact – Vulnerability matrix

Table 2

		Impact		
		High	Medium	Low
Vulnerability	High			
	Medium			
	Low			

2.5 Findings

The HKMA regularly uses the NBFI surveillance framework to consolidate information on over 1,000 NBFIs and produce a watchlist of 10 NBFIs for closer monitoring. Table 3 illustrates an anonymised version of the NBFI watchlist based on data as of December 2022. The results show that some NBFIs had medium-high impact scores and medium vulnerability scores, and are worthy of closer monitoring.

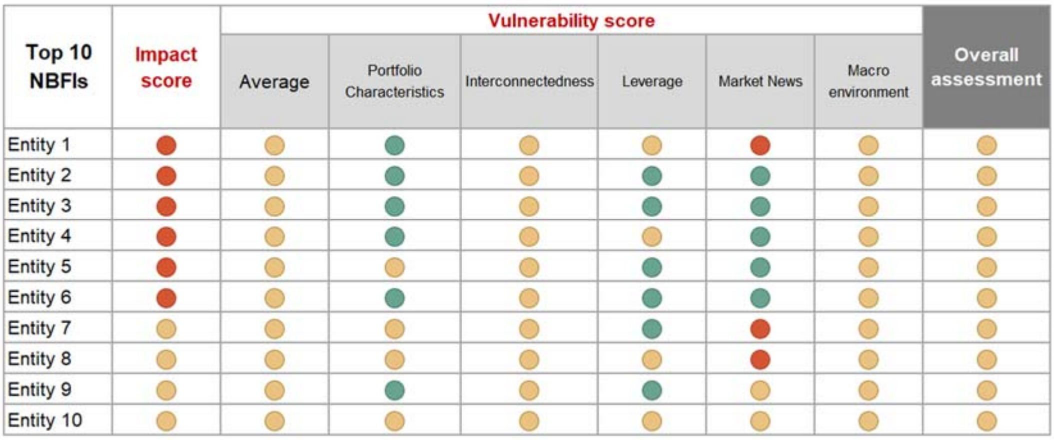
What follows are observations on the NBFIs in the sample of over 1,000 NBFIs at the cut-off date of 16th December 2022. NBFIs with large positions tend to be more diversified and to have less concentration in their top five underlyings (see Graph 2), have a lower percentage of their portfolios in highly volatile stocks or in small cap stocks (see the red entities on Graph 3), and generally have a relatively low share of their portfolio in crowded trades (see Graph 4 and 5). Nevertheless, some medium-

6 Financial Action Task Force (2014).

sized NBFIs are found to score relatively high on certain risk indicators. For example, some NBFIs on the watchlist put a significant share of their equity derivative portfolio in the top five underlying stocks, and some others have equity derivative positions that appear large relative to the market capitalisation of the underlying stocks.

NBFI watchlist

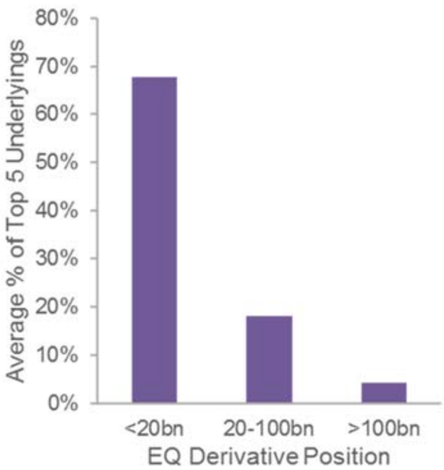
Table 3



Note: Data as of 16 December 2022.

Percentage of top five underlyings by NBFI EQ derivative position size

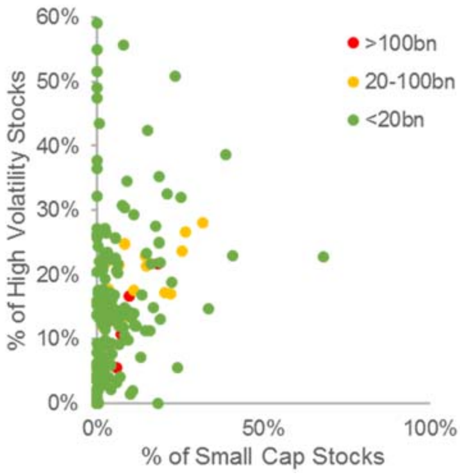
Graph 2



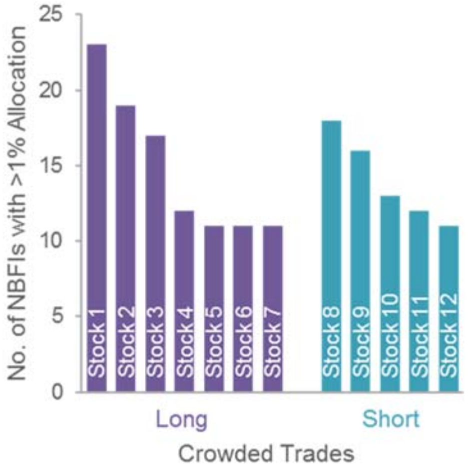
Note: Top five underlyings exclude equity indices.

Percentage of high-volatility stocks vs. percentage of small-cap stocks

Graph 3

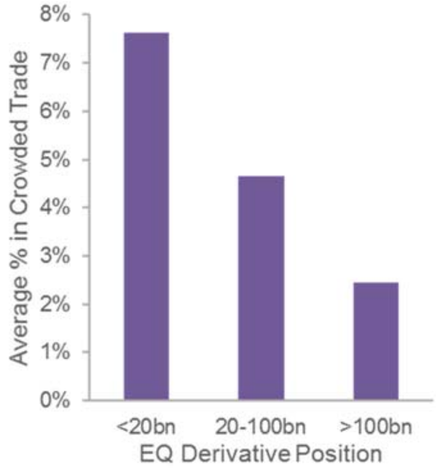


Number of NBFIs with more than 1% of portfolio allocated to stocks Graph 4



Note: Stock indices are excluded from crowded trades.

Percentage of portfolio in crowded trades by NBFI position size Graph 5

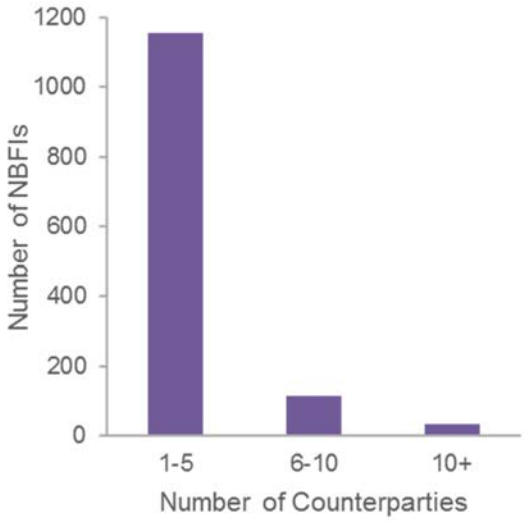


Although most NBFIs have no more than five counterparties (see Graph 6), Graph 7 reflects a more comprehensive picture of the interconnectedness between NBFIs (blue) and the largest 12 prime brokers (purple) in equity derivatives, taking into account the size of the NBFIs' positions relative to their prime brokers' portfolios. Some NBFIs have positions that account for more than 10% of their prime brokers' total position with all NBFIs (coloured in red). This means that, if these NBFIs default, their counterparties may suffer large losses.

The framework also considers the impact of market events, such as general stock market shocks. When volatility increases sharply in markets key to HKTR exposures, NBFIs' vulnerability scores rise, reflecting the fact that NBFIs' portfolios tend to become more subject to price swings and potentially more vulnerable to further shocks. For example, in Q4 2022, the more volatile macro-environment drove up the vulnerability scores of some of the NBFIs from Low to Medium, as demonstrated in Graphs 8 and 9.

Number of NBFIs by number of counterparties

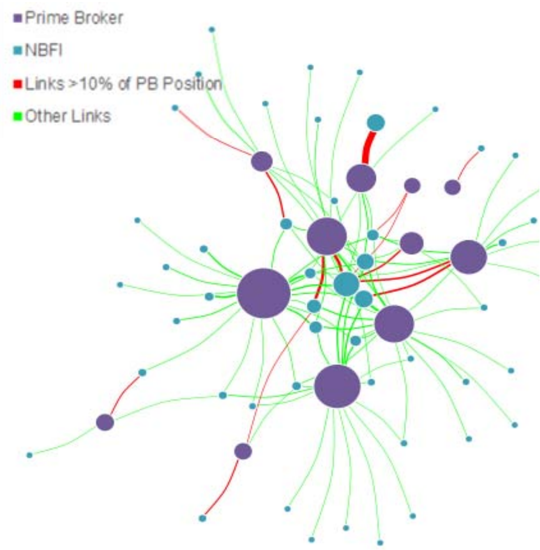
Graph 6



Note: All positions include HKTR derivatives (equity and other asset classes) and bank loans.

Network diagram of NBFIs' positions with top 12 prime brokers

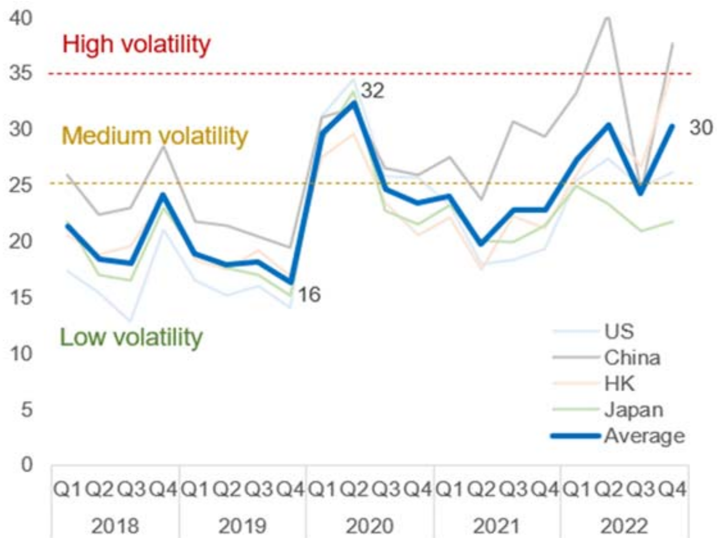
Graph 7



Note: Only equity derivative positions are included. Node size is proportional to the total position of the NBFI or prime broker, and link width is proportional to the size of positions between NBFIs and prime brokers. Links with size below HK$ 5bn (US$ 600m) are excluded.

Macro volatility in four markets key to HKTR OTC derivative exposures

Graph 8

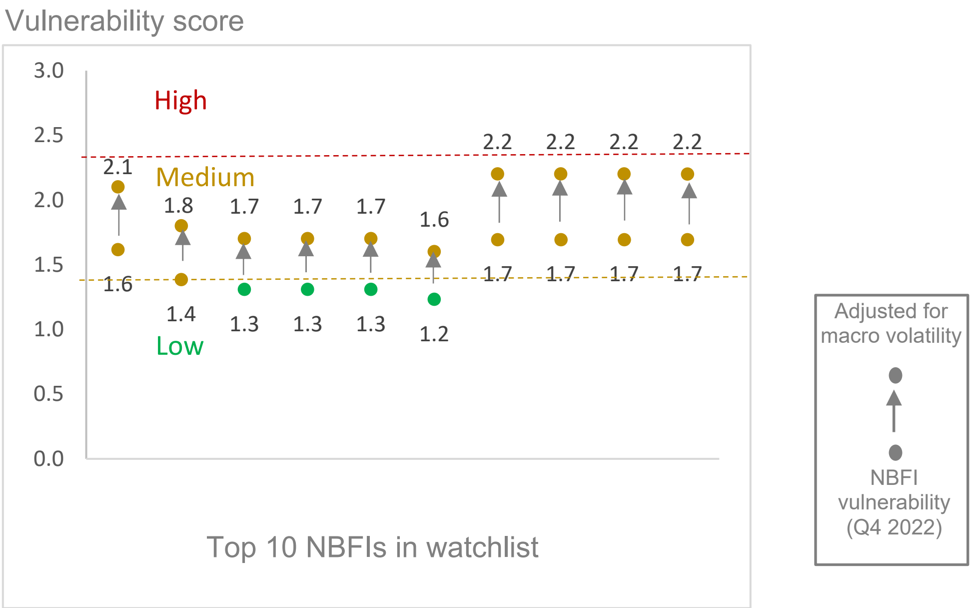


Note: US volatility is measured by the CBOE VIX, China volatility by the CBOE China ETF VIX and S&P China 500 1-Month Realised Volatility Index (from Q1 2022), HK volatility by the HSI VIX, and Japan volatility by the Nikkei VIX.

Source: Bloomberg

NBFI vulnerability scores in 2022Q4 after applying the macro environment volatility multiplier

Graph 9



2.6 Performance evaluation

The performance of HKMA's framework is evaluated here in two ways.

The first way is to assess whether the framework can unmask hidden risks ex ante before they manifest themselves in the public domain. This is carried out by checking if the top 10 NBFIs on the watchlist are revealed objectively afterwards as being more vulnerable or risky. If so, it suggests that the framework is able to sound an early warning by flagging vulnerable NBFIs for closer monitoring.

Indeed, since the HKMA adopted the proposed framework in Q3 2021 as part of its financial stability surveillance toolkit, the resultant watchlists have, over time, been able to identify several NBFIs that were later reported in negative news, such as being involved in legal proceedings.

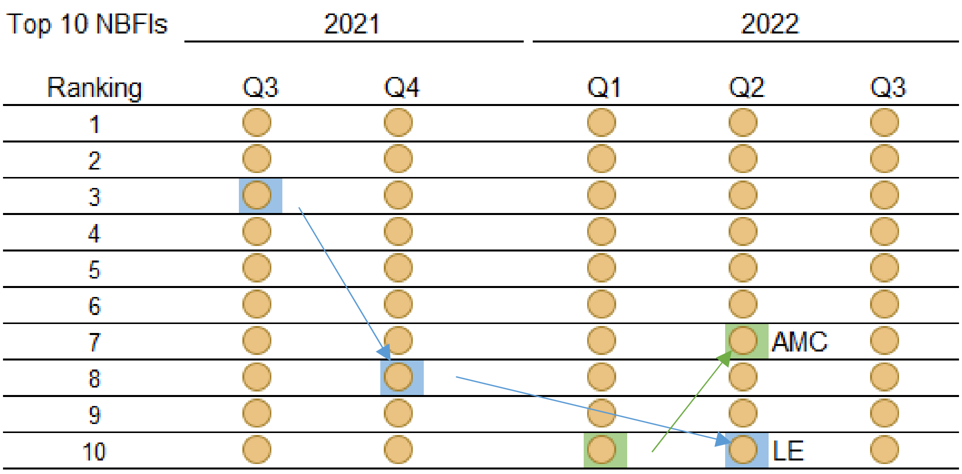
Table 4 presents an evolution of the NBFI watchlists produced by the HKMA between Q3 2021 and Q3 2022. One of the NBFIs, represented by the blue shadow, is the same NBFI that has been followed over time. It first appeared on the NBFI watchlist in Q3 and Q4 2021, and was later reported in the news in Q2 2022 for its involvement in regulatory legal proceedings.[7] Another NBFI, shadowed in green in Table 4, was initially flagged on the Q1 2022 watchlist. Later, during Q2 2022, it was reported in the news that some prime brokers were taking pre-emptive risk management action against the NBFI due to concerns about its trading behaviour.

[7] The specific NBFI dropped in ranking after the initial alert due to a reduction of its exposures, which lowered its impact score. Such pattern was visible during its monitoring.

This exercise shows that the framework can provide early warning signals to facilitate timely surveillance of NBFIs.

Assessing the NBFI watchlist using negative news

Table 4



Note: Each dot represents an NBFI. Its place in the table indicates the overall assessment score of the top 10 NBFIs on each quarterly watchlist. Two individual NBFIs are shaded in blue and green for assessment purposes.

Legend: Negative news: legal event (LE); actions by market counterparties (AMC).

A second way to check the validity of the NBFI framework is by feeding through the framework the OTC derivative positions of Archegos just before its collapse in March 2021. Archegos had a negligible Hong Kong nexus, such that the HKTR had only limited data on the size of Archegos' positions. Hence the global derivative positions of Archegos revealed after its default were used. The exercise shows that Archegos would have ranked as number one on the Hong Kong NBFI watchlist with both a red impact score and a red vulnerability score if its trading activities had taken place in Hong Kong. This result suggests that, if comprehensive data are made available, the framework can identify risks and give an early warning.

3. Key takeaways

The HKMA experience carries important lessons in pursuing a practical solution to monitor the potential systemic risks arising from highly leveraged NBFIs.

First, despite limited disclosures by highly leveraged NBFIs, central banks and regulatory authorities can improve monitoring of the sector by combining new and increasingly available granular data sets.

While data on the NBFIs' portfolios are not directly available, they can be sourced and reconstructed with some degree of confidence through reporting by regulated financial intermediaries to trade repositories (TRs) and via banking data reporting exercises. Box 2 provides a summary of data sources that can be used in the NBFI surveillance framework and their increasing availability to regulatory authorities around the world.

The complete data set should include granular information on each NBFI's derivative and borrowing positions, such as position size, long/short direction, underlying stock name and counterparty name (ideally using standardised identifiers to facilitate aggregation), and leverage. For OTC derivatives, data analytical capabilities in identifying, rescaling, aggregating, and validating the data are also essential. In particular, when analysing data from OTC derivative trade repositories, the potentially large data volume and complexities involved (van Lelyveld (2017)) may call for significant statistical resources to ensure that the risk indicators can be accurately and promptly updated.

Box 2

Useful data sources for NBFI surveillance framework

Template-based regulatory data: Most jurisdictions collect data from banks regarding their top counterparties, including NBFIs, for example as part of the regulatory regime on large exposures.[8] However, these regulatory returns typically capture NBFI exposures only above a certain threshold and do not have granular information about NBFI portfolios.

Transaction-level data on bank loans: In recent years, many central banks and regulatory authorities have started to collect granular transaction-level data on bank loans. Examples include the European Central Bank's AnaCredit project,[9] the China Banking and Insurance Regulatory Commission's On-site Examination and Analysis System Technology (EAST) system, the Hong Kong Monetary Authority's Granular Data Reporting (GDR) initiative, and the Bank of Thailand's Regulatory Data Transformation (RDT) project.[10]

Trade repository data on OTC and Exchange-Traded derivatives: According to the Financial Stability Board, most major jurisdictions have implemented trade reporting requirements for OTC derivatives (FSB, 2021). While the initial commitment by the G20 Leaders in 2009 included a commitment to report only OTC derivatives to TRs, some jurisdictions, such as the European Union, also collect data on exchange-traded derivatives.

Trade repository data on securities financing transactions: The FSB recommended in 2015 that authorities should collect trade-level data for repo markets, and should consider doing the same for securities lending markets (FSB, 2015). Some jurisdictions have implemented or started to implement the recommendation, such as the European Union,[11] the United States[12] and Japan.[13]

Commercial databases: Financial market-related information, such as stock market capitalisation and volatility, can be obtained from data providers such as Bloomberg and Capital IQ. There are also commercial databases on hedge fund size and performance, such as Preqin and EurekaHedge.

Second, an indicator-based approach for NBFI monitoring can effectively utilise this granular data. While recognising the promising benefits that this approach brings, we should also be mindful of potential limitations.

8 BCBS (2014).

9 See European Central Bank, https://www.ecb.europa.eu/stats/money_credit_banking/anacredit/html/index.en.html

10 See Bank of Thailand Annual Report 2020.

11 ESMA (2022b).

12 SEC (2021).

13 BOJ (2020).

An indicator-based approach serves as an alternative to the traditional ways of evaluating the risk-taking or potential failure of individual hedge funds, for example, by measuring hedge funds' volatility and returns (Agarwal et al (2017)), or by assessing fund-level variables such as fund performance, size and age (Liang and Park (2010)).

While diverse sources including public and supervisory data can be combined to produce an integrated framework for NBFI monitoring, challenges remain as to how to extract meaningful indicators from such large amounts of scattered data, and when seeking to do so, central banks and regulatory authorities should be mindful of potential limitations. For example, the HKMA data still do not cover all aspects of NBFI positions such as those using cash markets and exchange-traded derivatives. The measurement of certain indicators such as an NBFI's leverage are based on proxies and remain incomplete. While the framework measures financial interconnections between NBFIs and the banking sector, interconnections may also exist within the NBFI ecosystem that are more difficult to capture. The framework focuses on the first-order effects and does not include second-order market effects such as the correlation of exposures within or among different asset classes, constrained by existing calculation capacities. As the consolidation of multiple indicators may be imperfect, it is important to understand the underlying logic to be able to identify what drives changes in the underlying scores.

Furthermore, while most major jurisdictions have introduced trade reporting requirements, an individual regulatory body may not have access to trades conducted in markets outside its jurisdiction and is therefore not able to detect a full picture on the global positions of NBFIs that have market footprints across multiple jurisdictions. Aggregation of information across multiple jurisdictions at the global level could be challenging, partly due to legal and regulatory restrictions regarding data-sharing. One possible interim solution is to share red flags on potentially risky entities based on the analyses of individual jurisdictions while discussions on data sharing between jurisdictions remain ongoing.

Despite these limitations, it is still possible for such a framework to serve its purpose in providing useful indications of vulnerable NBFIs for closer monitoring and potential follow-up actions. The framework and the underlying thought process are not static and can be continuously improved via an iterative process or tailored to meet specific supervisory needs.

4. Concluding thoughts

NBFIs with large leveraged positions can pose serious risks to the financial markets. Drawing lessons from the HKMA experience, this paper shows how data from diverse sources including granular supervisory data can be integrated and transformed into useful early warning indicators for market surveillance and NBFI monitoring.

In the current environment of heightened market volatility and tight financial conditions, hedge funds with opportunistic strategies have been particularly active in building market positions to bet on certain market events. In doing so, however, they may trigger and amplify market dislocations, leading to potential systemic risks. As a first line of defence, robust surveillance and timely identification of highly leveraged NBFIs that may pose systemic risks are vital.

As policymakers around the world look into NBFI vulnerabilities and consider policy tools to enhance the financial sector resilience, this paper sheds light on a new way to narrow data gaps and identify systemically important NBFIs. We note that regulators in several other jurisdictions have also been making efforts in a similar direction,[14] and we hope this paper can contribute to further discussions at a regional and global level.

[14] In the US, the Hedge Fund Working Group (HFWG) under the US Financial Stability Oversight Council (FSOC) has made progress in developing its risk monitoring, drawing on qualitative and quantitative information about hedge fund activities in financial markets. FSOC has recently proposed to use the framework to help the process for designation of NBFIs as systemic. In Europe, ESMA and ESRB used supervisory data from the European Market Infrastructure Regulation (EMIR) to show how EMIR data could monitor risk by tracking Archegos positions with EU counterparties. At the international level, the FSB and IOSCO are also doing more work to ensure that data from trade repositories can be used to detect risk build-up ex ante.

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Appendix 1: Calculation of the risk indicators

Impact indicator

The NBFIs' positions are calculated using the aggregation of two measures: gross derivatives positions and bank borrowing positions (indicator 1 in Table 1)

$$(1)\ Size = Gross\ derivative\ positions + borrowing\ positions.$$

For derivatives, size is measured using gross notional positions in over-the-counter (OTC) derivatives. Alternative measures of the size of derivative positions which had been considered include mark-to-market values and net notional positions (netting long and short positions in the same underlying instrument). Mark-to-market values are based on current market prices and therefore may not reflect the potential risk in NBFIs' positions. As for net notional positions, while they may be a more accurate reflection of risk in some cases, market risk may not be fully eliminated after netting long and short positions, such as due to differences in the maturity or type of derivative transactions. Hence, we consider it more prudent to use gross notional positions of OTC derivatives than alternative measures. [15]

In order to gain a more comprehensive picture of NBFIs' systemic impact, their derivative positions across all asset classes are considered. Different derivative asset classes tend to have different underlying risks. For example, equity, credit, and commodity derivatives are typically considered to be riskier than interest rate and FX derivatives over a long-time horizon. Therefore, gross derivative positions in different asset classes are combined using risk weights derived from the BCBS-IOSCO standardised approach for initial margin.[16] As the initial margin reflects the size of the potential loss on the positions at the start of the contract, its calibration by asset class can serve as a proxy of the underlying riskiness of the derivative positions in different asset classes. The gross derivative position in the size indicator is the risk-weighted sum of gross positions from all asset classes, calculated as follows:

$$Gross\ derivative\ positions = \sum_s w_s P_s$$

where s denotes the asset class (equity, FX, IR, CD or CM), P_s is the size of the NBFI's position in asset class s, and w_s is the risk weight used for asset class s, with $w_{equity} = 1$, $w_{FX} = 0.4$, $w_{IR} = 0.27$, $w_{CD} = 0.67$, and $w_{CM} = 1$.

Vulnerability indicators

Portfolio characteristics (indicators 2-7 in Table 1):

The analysis of portfolio characteristics aims to measure concentration, liquidity risk and market risk in individual NBFIs' portfolios and is operationalised via six indicators:

[15] Though not used as a formal indicator, the magnitude and direction of net positions for OTC derivatives in each asset class are monitored as a supplementary measure to ensure that NBFIs building up risky positions in these individual asset classes can also be detected.

[16] BCBS and IOSCO (2013).

portfolio volatility, stock concentration, sector concentration, small-cap stocks, substantial interest stocks and illiquid stocks.

A volatility indicator is calculated for NBFI positions in each asset class of OTC derivatives using the formulas below.

$$Volatility(EQ) = \frac{Positions\ in\ high\text{−}volatility\ stocks}{Total\ EQ\ positions},$$

where high-volatility stocks are defined as stocks with 60-day volatility in the top quartile of the whole sample across all leveraged NBFIs.

$$Volatility(FX) = \frac{FX\ positions\ in\ volatile\ currency\ pairs}{Total\ FX\ positions},$$

where volatile currency pairs are defined as currency pairs with option-implied volatility in the top quartile of the whole sample across all leveraged NBFIs.

$$Volatility(IR) = \frac{IR\ positions\ with\ duration > 5Y}{Total\ IR\ positions}.$$

The share of positions with a duration longer than five years is used to capture the duration risk in the NBFI's interest rate portfolio.

$$Volatility(CD) = \frac{CD\ positions\ rated\ BB\ or\ below}{Total\ CD\ positions}.$$

The share of positions that have reference entities rated BB or below is used to measure the riskiness of the NBFI's credit portfolio.

$$Volatility(CM) = \frac{Positions\ in\ volatile\ commodities}{Total\ CM\ positions},$$

where volatile commodities are defined as commodities that have realised volatility above a certain threshold.

The NBFI Portfolio Volatility indicator is then calculated across all asset classes, weighted by the size of the NBFI's risk-weighted positions in each asset class as follows.

$$(2)\ \ PortfolioVolatility = \sum_{s=1}^{5} k_s \cdot \frac{w_s P_s}{\sum_{s=1}^{5} w_s P_s}$$

where k_s denotes the $Volatility$ risk indicator for asset class s.

Other indicators of portfolio characteristics are computed only for equity derivatives as below.

$$(3)\ \ StockConcentration = \frac{Positions\ in\ top\ 5\ stocks}{Total\ EQ\ positions},$$

where the stocks under analysis are limited to individual equities. Positions in stock indices are not included in the top five stocks because they do not represent concentration.

$$(4)\ \ SectorConcentration = \frac{Positions\ in\ largest\ individual\ sector}{Total\ EQ\ positions},$$

where sectors can be defined based on the industrial sector of the underlying stocks, such as technology.

(5) $SmallCapStocks = \frac{Positions\ in\ small{-}cap\ stocks}{Total\ EQ\ positions}$,

where small-cap stocks are defined either based on industry classifications or defined as the lower quartile of the one-year average market capitalisation of all stocks in the sample. The classification of small-cap stocks in Hong Kong is based on the Hang Seng Composite SmallCap Index.

(6) $SubstantialInterestStocks = \frac{Positions\ in\ substantial\ interest\ stocks}{Total\ EQ\ positions}$,

where a stock is defined a substantial interest stock in relation to an NBFI if the NBFI's position in that stock is 5% or more of the stock's one-year average market capitalisation. The 5% threshold for the share of substantial interest stocks indicator is based on the approach of the Securities and Futures Ordinance (SFO) Part XV – Disclosure of Interests.[17]

(7) $IlliquidStocks = \frac{Positions\ in\ illiquid\ stocks}{Total\ EQ\ positions}$,

where illiquid stocks can be defined as stocks with average daily trading volume (normalised by the market cap) below a certain threshold.

Interconnectedness (indicators 8-10 in Table 1):

(8) $NumberOfCpty =$ *Number of counterparties of the NBFI in OTC derivatives (in all asset classes) and bank borrowing.*

(9) $PBConcentration = \frac{\sum_{j=1}^{N} \frac{P_{ij}}{P_j}}{N}$,

where P_{ij} is the gross position of bank borrowing and OTC derivatives between NBFI i and prime broker j, P_j is the total gross position of prime broker j with all NBFIs, and N is the number of prime brokers in the sample. This indicator measures the risk that several prime brokers have concentrated exposures to a particular NBFI.

(10) $CrowdedTrade = \frac{Positions\ in\ crowded\ trade\ stocks}{Total\ EQ\ positions}$.

This indicator aims to capture the risk that NBFIs with positions in the same stock (crowded trade) may be vulnerable to a common shock. An equity derivatives position is defined as a crowded trade if at least 5% of NBFIs in the sample have exposure to the stock, and if each NBFI invests at least 1% of its equity derivatives portfolio in that stock. The crowded trade indicator is only computed for equity derivatives and is not extended to other asset classes.

[17] It states that substantial shareholders - individuals and corporations who are interested in 5% or more of any class of voting shares in a listed corporation, must disclose to both the Hong Kong Exchange and the listed corporation their interests, and short positions, in voting shares of the listed corporation.

Leverage (indicators 11-12 in Table 1):

Derivatives do not have a standard definition of leverage. Thus, an approach outlined in the International Monetary Fund (2018) is adopted to compute a fund's leverage from derivatives as the ratio of gross derivative positions divided by the fund's net asset value (NAV); we use AUM if data on NAV are not available. The proxy indicator on fast-growing positions is defined as the three-month growth rate in the NBFI's outstanding derivative positions (including all asset classes) and bank borrowings. Specifically:

$$(11) \quad Leverage = \frac{Gross\ derivative\ positions + Borrowings}{NAV}.$$

$$(12) \quad FastGrowingPosition = \frac{Current\ total\ positions}{Total\ positions\ three\ months\ ago} - 1,$$

where total positions include gross derivative positions and bank borrowing.

Market news (indicator 13 in Table 1):

We source the tone (usually ranging from –10 to +10, with 0 indicating neutral) of market news about specific NBFIs as well as the volume of articles related to each NBFI to calculate a daily volume-weighted tone. The main data source is the Global Database of Events, Language, and Tone (GDELT).[18] As a measure of the sentiment score on the NBFI, the daily positive and negative results over the previous year are ranked, and the score with the most negative sentiment for the NBFI is selected.

$$(13) \quad MarketNews = Sentiment\ score\ from\ textual\ analysis$$

Macro-environment (indicator 14 in Table 1):

$$(14) \quad MacroEnvironment = Stock\ market\ volatility\ index.$$

If the NBFIs are active in more than one market, the average of volatility indices across all markets is used. For example, given that most equity derivatives in Hong Kong are referenced to stocks listed in Hong Kong, Mainland China, the US and Japan, the macro-environment indicator is calculated using the average of the volatility indices in the four relevant stock markets (HSI Volatility Index, CBOE China ETF Volatility Index, CBOE VIX and Nikkei Stock Average Volatility Index). A single volatility index for a specific stock market may be used if most equity derivatives in that market are referenced to local stocks.

The Macro-environment indicator is market-wide and not specific to individual NBFIs. The indicator is combined with other indicators of Vulnerability (which are combined additively) as a multiplier. The multiplier takes a value of 1, 1.3, or 1.5 to reflect the Macro volatility situation. The multiplier is constant for all NBFIs within the same time period, but changes over time, indicating when the market environment becomes more or less volatile.

[18] Global Database of Events, Language, and Tone: https://www.gdeltproject.org/.

Appendix 2: Steps to derive the risk scores

After the risk indicators are calculated, the indicators are combined to produce an overall risk assessment for individual NBFIs following the steps below.

First, each of the first 13 risk indicators is converted into one of the three standardised risk scores – low (1), medium (2) or high (3) – according to predefined thresholds. The approach to setting the thresholds depends on the availability and distribution of data for each risk indicator. For example, if enough historical data on NBFIs' positions is available and the distribution of data is close to normal distribution, the thresholds can be set based on sample standard deviations; otherwise, a more ad hoc approach may be needed.

In some cases, thresholds can be set based on external studies and empirical analysis as to what constitutes high or low levels of risk. For example, information on the leverage of hedge funds that have experienced notable failures, such as Archegos, can be used as a reference to set the threshold for high-risk bucket. In other cases, thresholds for risk indicators are calibrated using expert judgment based on the distribution of the data, e.g. setting fixed percentiles such as top 25 percentile as the high-risk threshold. [19]

Second, overall scores for impact and vulnerability are calculated for each NBFI. The impact score is simply the standardised score for the size indicator mapped into low, medium or high. The vulnerability score is first calculated as the simple average of the standardised risk scores across indicators 2 to 13 in Table 1. This approach is consistent with similar studies in the literature, such as Dattels et al (2010) and Aikman et al (2018). The average of these risk scores is then multiplied by the macro-environment indicator, reflecting the fact that market volatility could amplify an NBFI's vulnerabilities in all dimensions. The resulting number is then itself standardised and categorised as Low, Medium or High vulnerability score based on pre-set thresholds. An overall risk assessment is then given according to the colour matrix shown in Table 2, which assigns the overall risk assessment based on the combination of the impact and vulnerability scores being in the High, Medium or Low bucket. For example, an NBFI's overall risk assessment is red if both its impact and vulnerability scores are in the High-risk bucket.

[19] For the sake of preserving confidentiality of the surveillance process, the thresholds for individual risk indicators are not shown here.

Appendix 3. Prominent failures of highly leveraged NBFIs

During recent decades, each episode of volatility in financial markets has intensified policymakers' discussions on the systemic implications of financial institutions outside the existing regulatory perimeter, in particular the risks posed by highly leveraged NBFIs.

Regulators first became attentive to highly leveraged NBFIs in the wake of the 1997 Asian financial crisis and during global market turbulence that accompanied the collapse of the hedge fund Long-Term Capital Management (LTCM) in September 1998. LTCM's case was not unique, nor it was the last one, as demonstrated by the Archegos debacle in 2021 and its ripple effect across markets.

To some extent, the collapse of Archegos was linked to both its own fraudulent behaviour and the failure of many investment banks to manage risk. Nevertheless, the problems were not fundamentally different from the collapse of LTCM. Both LTCM and Archegos were NBFIs that had built up excessive leverage, enabled by a failure of market discipline while their counterparties had failed to appreciate the magnitude of the risks until the vulnerability became evident. In the case of LTCM, the Fed foresaw the potential for market contagion and intervened before the crisis worsened, whereas the Archegos incident developed into margin calls and fire sales that set off a chain of distress in financial market. However, the banking sector was in general more resilient compared to two decades ago, which helped to contain the potentially material impact on the financial system.

Long-Term Capital Management

LTCM was a highly leveraged hedge fund, and its meltdown in 1998 has become a classic case study of a crisis event in financial markets.

The hedge fund was engaged primarily in "relative value trades". More specifically, it bought high-yielding, less liquid bonds, such as Danish mortgage-backed securities, bonds issued by emerging markets and junk corporate bonds, and sold low-yielding, more liquid bonds such as US government bonds, in a bet that the yield spread between high and low-risk bonds would narrow. In pursuing its strategy and seeking high rates of return, LTCM amassed substantial leverage through an extensive use of interest rate swaps. In so doing, LTCM built up very large positions, some of which were in relatively small and illiquid markets.

As the Asian financial crisis continued and Russia defaulted on its local sovereign debt in 1998, the yield spread sharply widened, which was the opposite of the outcome expected by LTCM. When its investments turned sour, LTCM had difficulties in paying creditors and derivatives counterparties. The concern was that if its numerous counterparties all exited from their positions at the same time, widespread fire sales would be created on top of the already turbulent market, which might have triggered severe liquidity shortages and sharp falls in asset prices.

To avoid such adverse market consequences and preserve financial market stability, the US Federal Reserve eventually intervened by facilitating a bailout by LTCM's major creditors.

Sources: "A Review of Financial Market Events in Autumn 1998", Committee on the Global Financial System, BIS, Oct 1999; Edwards, F (1999) "Hedge Funds and the Collapse of Long-Term Capital Management", *Journal of Economic Perspectives*, Vol 13, no 2, pp 189-210.

Archegos Capital Management

Archegos was a highly leveraged family office that collapsed in 2021.

It held large positions concentrated in a number of US stocks such as Viacom and Discovery and a few Chinese stocks like Baidu and Tencent Music. Some of the positions were held via total return swaps, a type of derivative that allowed it to take big leveraged stakes without disclosing these positions in public.

Its bets started to incur losses after Viacom's stock offering fell apart. Archegos failed to pay additional margins to its derivatives counterparties, prompting a massive fire sale of stocks as some of its counterparties rushed to exit from the fund's positions. Since Archegos' market footprint was substantial in those stocks, the simultaneous exits led to sharp falls in asset prices in those market segments.

The failure of Archegos resulted in more than USD 10 billion in losses across several large banks, including Credit Suisse and Nomura, which were affected the most.

Sources: News reports; "Leverage and derivatives - the case of Archegos", European Securities and Markets Authority, May 2022.

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