CAPITAL MARKETS

Reframing Financial Markets as Complex Systems

Tools for Systemic Risk Analysis, Portfolio Management, and System-Level Investing

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EXECUTIVE SUMMARY

Industries worldwide are evolving rapidly amid new technologies and policy shifts, while markets are more interconnected than ever. Information travels almost instantaneously across global networks, meaning a shock in one market can ripple quickly through others. The investment industry must continually adapt to changing economic and market environments, yet traditional financial models—built on assumptions of equilibrium and rational actors—often struggle to capture the unpredictable, networked, and nonlinear behaviors observed in financial markets.

This report reconsiders how we understand financial markets, framing them as complex systems and offering alternative approaches to traditional financial models. By applying methods from complex systems sciences, it equips financial professionals with new tools for systemic risk analysis, portfolio management, and system-level investing. Techniques such as agent-based modeling and network theory can be used to understand and capture complex market phenomena such as emergent behavior, nonlinearity, feedback loops, and structural resilience.

For portfolio managers and risk analysts, adopting a systems perspective means moving beyond normal distributions and equilibrium-based models to capture investment complexity and better inform scenario planning, portfolio optimization, and risk management. For regulators, it means leveraging new models to strengthen systemic risk oversight and macroprudential policies.

The report comprises two primary sections. The first section introduces core ideas from complex systems sciences that challenge the assumptions of traditional financial analysis and evolve our understanding of systemic risk. The second section demonstrates how complex systems methods—specifically, ABM and network theory—can be applied to systemic risk oversight and investment decision making.

Ultimately, this report provides a clear and approachable foundation for those new to complex systems, agent-based models, and network theory. By taking seriously the view that financial markets are complex systems, investment professionals and regulators can access new tool kits for anticipating financial stability risks, improving portfolio resilience, and analyzing system-level behavior in capital markets and the broader economy. Yet, beyond new tools, it seeks to spark a shift in thinking—challenging conventional paradigms of market behavior and fostering the mindset needed to thrive in a world defined by complexity, uncertainty, and accelerating change.

Key Takeaways

- *Financial markets are complex adaptive systems.* Financial markets and economies are not static but dynamic, evolving, and highly interconnected. Dense webs of interconnection mean that changes in one area of a system can have nonlinear, dramatic effects in other areas of the system or change the behavior of the system as a whole.
- *Complex systems represent a new paradigm for financial modeling.* Traditional equilibrium and normal-distribution models struggle to explain the "stylized facts" or statistical features of global markets. Such characteristics as heavy-tailed distributions, nonlinearity, and volatility clustering indicate the need for a complex systems lens, which is better suited to analyze how systems with many different agents (e.g., market participants) interact, adapt, and influence each other over time, generating the statistical characteristics observed in real markets. This systems lens can be used to explain and anticipate real-world phenomena, such as bubbles, crashes, and sudden shifts in investor sentiment.
- *Portfolio management can benefit from a dynamic, systems-based approach.* Financial markets often depart from the assumptions of classical finance models, such as the widely-used capital asset pricing model (CAPM), which assumes rational agents and equilibrium. Insights from behavioral economics and complexity economics suggest that market behavior is more accurately captured by incorporating the subrational decision making of market participants (e.g., herding behavior), networked and feedback effects, and regime shifts into models. Complex systems offer a systematic way of understanding how these behaviors drive price changes and volatilities across markets.
- *Systemic risk analysis demands a complex systems lens.* Nonlinearity, feedback loops, and dense interconnections within financial systems mean that small disturbances can cascade into systemic events or be dampened unexpectedly. Rather than examine assets in isolation, systems-focused risk analysts trace how shocks permeate across overlapping webs of relationships.
- *Agent-based modeling and network theory are practical tools for building resilience into portfolios and markets.* Methods that simulate heterogeneous investor behavior and map contagion paths enable scenario tests that reveal hidden vulnerabilities and emerging market regimes. For these reasons, some central banks have started to use network theory and agent-based models to enhance stress tests, while others use scenario analyses to tackle emerging climate-related financial risk.

INTRODUCTION

We live in a vastly interconnected world where information, capital, goods, and services can transit rapidly through networks of people, institutions, markets, and economies. These interdependencies affect economic activity at all scales—from local market behavior to global macroeconomic events. To effectively assess risk and forecast systemwide impacts, analytical models must be able to account for these multiscale and complex webs of interactions.

Although the theoretical foundations of complexity economics (see Arthur 2015) and system-focused approaches to the economy can be traced back to the 1950s and 1960s (see Appendix A), it is only within the past few decades that globalization, interconnection, and the mass availability of big data have prompted what some scholars refer to as a "complexity turn" (see Castellani 2014; Urry 2005). Indeed, the embrace of complex systems has become implicit in the modern economy. For example, the development of artificial neural networks (ANNs) that underpin the deep learning architectures of large language models (LLMs) stems from progress in the complexity sciences. In the future, complex systems approaches will continue to grow as they are increasingly deployed in modeling, monitoring, and responding to pressing global challenges, including emerging pandemics, rising global inequality, and climate change (Hébert-Dufresne, Allard, Garland, Hobson, and Zaman 2024).

Complex systems sciences can be described generally as a multidisciplinary framework for understanding highly dynamic, interconnected, and evolving systems. Whether studying an ant colony, a human brain, or an economy, complex systems approaches assume system components interact to produce macro-level outcomes that are more than the sum of individual actions. This perspective shifts the focus from isolated parts of the system to the collective behavior arising from system dynamics.

For financial markets, two general approaches for applying complex systems have emerged. **Econobiology**, or "evolutionary economics," uses lessons from evolutionary biology to understand complex economic and market behavior. **Econophysics** is inspired by complexity frameworks and statistical modeling in physics and applied to economic and market behavior (Rickles 2011).

Both approaches, however, overlap to a significant extent in their theoretical assumptions and analytic methodologies. For example, both hold that market-level phenomena (e.g., volatility, crashes, contagion, innovation) result from myriad interactions among heterogeneous agents (e.g., investors, firms, governments, regulators), often yielding unexpected (i.e., heavy-tailed) or nonlinear outcomes. Additionally, both approaches consider the characteristics of financial markets to be well suited for systems-based analyses. As such, this report introduces key features of complex systems commonly described within both approaches (see **Exhibit 1**) and identifies modeling techniques used across the complexity sciences.

Exhibit 1. Key Features of Complex Systems

- **Emergence:** Higher-order features or patterns arise from lower-level interactions. For example, market volatility or liquidity crises emerge from the interactions of many traders and institutions and cannot be traced to a single actor. Asset bubbles and crashes are emergent phenomena of the entire market system.
- **Heterogeneous adaptive agents:** Market participants differ in their goals and strategies, but they are mutually interdependent and adapt to each other's behavior and environmental conditions. Investors, fund managers, and regulators react to each other's activities, often in feedback loops.
- **Nonlinearity and feedback loops:** Financial systems do not operate linearly. Small events can trigger outsized effects due to feedback patterns. For instance, a minor sell-off can snowball into a crash if it triggers margin calls[1] and panic selling.[2] Feedback loops (reinforcing or dampening) are common, as seen when banks restricting credit to preserve balance sheet liquidity further depresses the economy, causing more losses in a vicious cycle.
- **Interconnected networks:** Financial entities are linked through webs of relationships (counterparty links, asset correlations, cross-shareholdings, etc.). A network view looks at how connections between agents transmit and in some cases amplify risk. For example, the network of exposures between banks can propagate losses during market stress, and index inclusion can generate excess price co-movement between underlying stocks (Claessens and Yafeh 2011).[3] Likewise, exchange-traded fund (ETF) ownership and arbitrage can generate co-movement in equity returns beyond fundamentals (Da and Shive 2018; Israeli, Lee, and Sridharan 2017).
- **Self-organization:** Structure or order can emerge from the bottom up. We see this in markets through such phenomena as industry clusters, the emergence of new financial ecosystems (e.g., decentralized finance), or the spontaneous formation of trading conventions. System organization often grows organically—for instance, decentralized finance platforms have evolved as a self-organizing network of users and protocols (Alonso 2024).

[1] When buying stock on margin (i.e., brokerage firm lends cash to the investor), investors must have a margin account, using assets in the account as collateral at a designated margin level (FINRA 2023). Margin calls occur when a brokerage house demands money to bring the equity in an investor's account back up to the margin level (Clarke, de Silva, and Thorley 2013).

[2] Panic selling refers to a sharp sell-off of a stock or investment based on fear or overreaction to potential decreases in price.

[3] The so-called index effect—where a stock price increases following inclusion in an index—may be diminishing and is likely to be context specific (Greenwood and Sammon 2025; Chen, Singal, and Whitelaw 2016).

- **Resilience (and fragility):** Complex systems may exhibit **resilience** (the capacity to absorb shocks and reorganize), but they can also harbor hidden fragility. Resilience analysis goes beyond simple diversification: It examines structural vulnerabilities and how a system's interconnected relationships and constraints might amplify or mitigate shocks. For example, two banks might both appear well capitalized (individually robust), but if they are highly interdependent via common exposures, the system may still be fragile (see Pang and Shrimali 2024).

In the investment industry, some firms are starting to embrace complexity. Institutional investors with long investment horizons are working to foster system-level investing, which recognizes the interconnectivity and mutual dependence between investments and healthy financial, environmental, and social systems (Burkart, Ziegler, and Aiken 2024; Burckart and Lydenberg 2021). Building a systems-level portfolio acknowledges that marketwide return drivers explain a large share of long-term portfolio outcomes. Those drivers, in turn, rely on collective efforts to self-organize in ways that mitigate risk and boost the resilience of interdependent financial, environmental, and social systems (Lukomnik and Burckart 2024).

Stakeholders in wealth management have also advocated for systemic investment frameworks. Within wealth management, the focus is on identifying leverage points within the system, where targeted investments can create outsized effects, and synergistic investments that create value through fostering enabling conditions (i.e., conditions that promote certain behaviors over others) and coordinated amplification of returns across asset classes (Tews, Jay, Andersen, and Paetzold 2025).

With respect to regulators, the Federal Reserve Bank of New York (2007, p. 5) acknowledged that "the notion of systemic risk in the financial system bears a strong resemblance to the dynamics of many complex adaptive systems in the physical world." Market instability is increasingly seen as a product of networked interactions; in practice, this has meant augmenting stress tests and oversight frameworks with models of network contagion, feedback loops, tipping points, and resilience (Battiston, Farmer, Flache, Garlaschelli, Haldane, Heesterbeek, Hommes, Jaeger, May, and Scheffer 2016). The Financial Policy Committee at the Bank of England also acknowledged the need to understand contagion and amplified effects in densely connected financial networks (see Bank of England 2024). In order to meet these goals, the Bank of England identified current and future applications of agent-based modeling in central bank research and policy (Borsos, Carro, Glielmo, Hinterschweiger, Kaszowska-Mojsa, and Uluc 2025).

Looking ahead, we expect complex systems approaches to play an increasing role in tackling new challenges, such as climate-related financial risk, fintech and decentralized finance ecosystems, and cybersecurity risks. These domains all involve **networks** of interactions, **adaptive agents**, and potential tipping points and regime changes, making them well suited for complexity-informed analysis.

Even so, analyses based in complex systems have yet to see widespread adoption across the investment industry. Academics in economics and finance have advocated incorporating complex systems–based approaches into standard financial analysis and investment practices. For example, J. Doyne Farmer (director of complexity economics at Oxford) and W. Brian Arthur (at the Santa Fe Institute) emphasize that traditional financial models often miss critical dynamics, such as **nonlinearity** and emergent phenomena (see Farmer 2024; Arthur 2015). They argue for analytical tools, such as network analysis and agent-based modeling—adopted from physics, biology, and other disciplines—to be applied to investment and financial regulation (Battiston et al. 2016).

With this goal in mind, this report introduces key concepts in complex systems analysis. The first half of the report focuses on how a systems analysis can transform our understanding of financial markets and systemic risk. The second half introduces modeling techniques commonly used to analyze complex systems that are well suited for investment and risk management assessments. Importantly, adopting a complex systems view moves us forward by challenging core assumptions in traditional financial analysis and offering alternative tool kits that can be applied to understand, forecast, and strengthen capital markets.

FINANCIAL MARKETS AS COMPLEX SYSTEMS

Neoclassical economics has been the standard of practice for over a century (Neck 2022). It assumes agents are rational and that their aggregated behavior drives markets toward equilibrium. In this view, markets function efficiently to balance supply and demand, where deviations (e.g., mispricings and bubbles) are anomalies. However, many notable economists—Thorstein Veblen, Joseph Stiglitz, Joan Robinson, and Friedrich Hayek, among others—have pointed out that these assumptions often fail to match the observed behaviors of individuals and markets.[4] Investors do not always act rationally in the real world; they exhibit biases, possess incomplete information, and are influenced by each other. Likewise, markets often exhibit persistent deviations from equilibrium (trends, cycles, crises) that are not mean-reverting.

These nontrivial statistical features of market behavior observed across financial instruments, assets, and time periods are often referred to as **stylized facts**.[5] Cont (2001) conducted a noteworthy metareview of empirical studies of asset returns, identifying eleven distinct stylized facts across decades of research. A subsequent study by Ratliff-Crain, Van Oort, Koehler, and Tivnan (2025) found 8 of the 11 stylized facts persist in modern US stock markets despite significant regulatory shifts and technological progress (see **Exhibit 2**).

The identification of stylized facts indicates the need for alternative narratives of market behavior that explain why these empirical regularities emerge in financial data.

Part of the answer lies in the tendencies of human behavior to exhibit patterns that fail to conform to assumptions of rational equilibrium models. Herbert A. Simon (1955) proposed that individuals aim for satisfactory solutions rather than optimal ones, given cognitive and information limitations—a term that became known as **bounded rationality**.[6] In finance, this means investors might follow norms or rules of thumb (see Simonian 2025), and their decisions can be inconsistent or biased, as demonstrated by Kahneman and Tversky's (1979) work on prospect theory, which describes how individuals weigh potential losses and gains differently under varied conditions. If agents are not strictly rational, how should we expect markets to behave?

[4] See Veblen (1898), Robinson (1969), Stiglitz (1987), Dixit and Stiglitz (1977), Hayek (1945), and von Hayek (1937). Additionally, Kenneth Arrow, known for his contributions that facilitated the dominance of general equilibrium theory in economics, later participated in discussions of complexity economics and acknowledged the discrepancies between equilibrium as an ideal and the realities of market behavior (Arthur 2019).

[5] More precisely, stylized facts refer to "stable patterns that emerge from multiple empirical data sources after abstracting from the minutia of the evidence" (Oldham 2019, p. 2) that "any putative theory of markets ought to explain" (Buchanan 2012).

[6] Simon (1962) also directly contributed to the study of complex systems in his article "The Architecture of Complexity."

Exhibit 2. Stylized Facts in US Stock Markets

Stylized Fact	Description
Absent linear autocorrelation	A linear relationship is not found between a present return and past returns (except for very short, intraday horizons).
Heavy tails	Return distributions exhibit more extreme outcomes than predicted by a normal distribution, often displaying power-law or Pareto-like tails.
Aggregational Gaussianity	Return distributions differ at different timescales such that distributions are nonnormal at short time intervals and more Gaussian (normal) as returns are aggregated over longer time horizons.
Intermittency	At any timescale, returns display a high degree of variability. "This is quantified by the presence of irregular bursts in time series of a wide variety of volatility estimators" (Cont 2001, p. 224).
Volatility clustering	Large changes in asset prices (up or down) tend to be followed by more large changes, and small changes are followed by more small changes, creating periods of high or low volatility.
Conditional heavy tails	"Even after correcting returns for volatility clustering (e.g., via GARCH-type models), the residual time series still exhibit heavy tails" (Cont 2001, p. 224).
Slow decay of autocorrelation in absolute returns	Although asset returns may exhibit little autocorrelation, the magnitude of returns (absolute or squared) shows a slowly decaying positive autocorrelation, roughly following a power law, signaling long-range dependence and persistent volatility clustering.
Volume/volatility correlation	Trading volume is correlated with measures of volatility.

Source: Ratliff-Crain et al. (2025).

One way to answer this question is by analogy to ecosystems (see Thinking Ahead Institute 2017). In ecology, an ecosystem consists of diverse entities (e.g., species) interacting within an environment, leading to changes in species population, competition, and adaptation. Crucially, an ecosystem does not always settle into static equilibrium—it can cycle or suddenly shift if conditions change (think of predator–prey cycles or invasive species overgrowth, which can force native plants and animals to alter their behaviors). In an analogous way, financial markets can be thought of as an ecosystem of agents and strategies (see Farmer 2024). Investors, traders, institutions, and regulators continuously adjust their behavior in response to the collective outcomes of past actions (Lo and Zhang 2024). In this sense, markets, like ecosystems, are constantly evolving.

Investors exploit market inefficiencies as they emerge by adopting new strategies, whether switching from momentum to value, for example, or by tactical asset allocations. But these adjustments of individual portfolios produce subsequent higher-level activity at the market level (e.g., market volatility) that can create mispricing opportunities to exploit, generate new risks, or stimulate demand for other investment strategies. This back-and-forth influence between activities of market participants and emergent market behavior can lead to the deviations from normal distributions observed in stylized facts that cannot be adequately captured in traditional financial models. New techniques are needed to account for changes in market prices and to create accurate forecasts (Farmer and Geanakoplos 2009; Barbrook-Johnson, Mercure, Sharp, Peñasco, Hepburn, Anadon, Farmer, and Lenton 2024). A state of equilibrium, therefore, cannot be assumed when adopting a complex systems view of markets. It may occur under certain conditions, but it is one possible state among many.[7]

Market Insights for Investors and Investment Professionals

If we view capital markets as complex ecology-like systems, we gain unique insights into investment strategies that would otherwise be missed. Specifically, viewing capital markets as complex systems offers new insight into investor behavior and market anomalies. By reframing market and investor behaviors through a complex systems lens, investment professionals can more easily identify and describe events in the market that fail to adhere to assumptions of equilibrium or efficient price movements. Next, we discuss key issues investors are likely to encounter when analyzing markets through a lens of complex systems.

Herding Behavior

If we treat investors as agents who observe and adapt to market conditions and the behaviors of other investors, it is unsurprising that herding occurs in the market. Herding is defined as a group of investors trading in the same direction over a period of time (Nofsinger and Sias 1999). More specifically, it describes large groups of agents (i.e., investors) acting in unison without central control. Investor herding behavior can occur for a variety of reasons (see Hirshleifer and Hong Teoh 2003). Some investors may deliberately follow other investors in purchasing securities by, for example, tracking momentum.[8] Other investors may inadvertently herd following the release of new information or react to the same changes in fundamental factors (Spyrou 2013). Regardless of the dominant strategy, if enough investors start buying into a rising market, their collective action can increase security prices and further validate the trend. This positive feedback loop can lead to self-reinforcing price movements and eventual bubbles.

[7] Complexity researchers have used agent-based models to identify which analytical regime, traditional equilibrium or complexity, is best suited under varying market conditions. They found that in an environment where investors adapt slowly to new observations of market behavior, the market converges to a rational expectations regime where traditional equilibrium models prevail; however, as traders rapidly adapt to new market observations—as is often observed in real investment scenarios—greater trading heterogeneity emerges and the market self-organizes into a complex regime (LeBaron, Arthur, and Palmer 1999). Since this landmark research, findings have upheld the general conclusions of a regime shift from a homogeneous rational expectation equilibrium to a complex heterogeneous regime, though updated models indicate this shift occurs at faster learning rates than initially proposed (Ehrentreich 2004).

[8] Momentum strategies focus on buying or selling based on past returns of the stock, focusing on buying recent winners and selling recent losers. This form of herd behavior would not be rational under the efficient market hypothesis, which assumes market prices reflect all available information (Bikhchandani and Sharma 2000, p. 282).

The feedback loop generated by herding can only be indirectly captured by traditional analyses, such as general equilibrium models, where investors maximize individual utility. Stated differently, if we assess every investor in isolation (or as the aggregated sum of isolated investors), it is impossible to fully anticipate the impacts of their interactions. As observed in a report from Thinking Ahead Institute (2017, p. 2), "Investors are inclined to assess the likely impact of their actions in isolation and therefore potentially miss the additional impact from other investors acting in a similar manner." However, techniques used to study complex systems are oriented around simulating multiple heterogeneous agents that interact and self-organize into groups, generating emergent, higher-level effects (often in the form of stylized facts).

Using agent-based models (ABMs) (discussed later in this report), the impact of herding behavior can be analyzed.[9] ABMs have been used to simulate how herding in household borrowing can lead to market boom and bust cycles, recreating observed housing price volatilities before, during, and after a housing market crash (Glavatskiy, Prokopenko, Carro, Ormerod, and Harre 2021; Geanakoplos, Axtell, Farmer, Howitt, Conlee, Goldstein, Hendrey, Palmer, and Yang 2012). Likewise, heavy-tailed stock price distributions consistent with market data were successfully recreated by simulating randomized communication channels between investors; these communication channels led to the formation of clusters of agents that followed each other's investment behaviors, which resulted in power-law distributions of asset prices (Cont and Bouchaud 2000). In essence, systems modeling allows analysts to see how boundedly rational investor decision making, including herding behaviors, leads to the emergence of key features of the stock market, including the previously listed stylized facts (Shapira, Berman, and Ben-Jacob 2014). By capturing realistic statistical features of the market, these models may assist with anticipating and scenario-planning future impacts of herding in the market.

Network Effects in Asset Pricing

Network effects in asset pricing refer to situations in which the value or performance of an asset is influenced not just by fundamentals but also by the interconnectedness of markets. Modern markets have strong network characteristics due to correlations between assets, companies, sectors, and investors (see Pacelli 2025). For instance, consider how index funds and ETFs connect assets: When money flows into or out of a market-capitalization-weighted index fund, all stocks in the index experience buy or sell pressure simultaneously according to their weight in the index. Linked by index membership, the underlying portfolio assets are thus transacted together algorithmically irrespective of fundamental value. The rise of index-based products has therefore strengthened the links between previously uncorrelated assets, as evidenced by stocks with high passive ownership/index membership—yet from different sectors and diverse underlying

[9] A classic example is using ABMs to explain and predict the coordinated flying patterns of a murmuration or large flock of starlings.

business models—collectively displaying rising betas (Brightman and Harvey 2025). When enough trades occur algorithmically, the market becomes less elastic, generating heavy-tailed return distribution swings, increased idiosyncratic volatility, and elevated sensitivity to marketwide shocks (Boothe and Subedi 2024; Höfler, Schlag, and Schmeling 2025).

Along with the rise in index investing, markets have seen an increased overlap in asset holdings between investors.[10] A commonly referenced outcome of portfolio overlap is the potential to transmit financial distress. If two institutions share a common asset, the immediate liquidation of the asset by one institution will impact the asset price and portfolio of the other institution (Braverman and Minca 2018). As more investors are linked to a common asset, dependencies arise not just between assets within a single portfolio but also between different investors (e.g., banks, mutual funds, and pension funds) and their portfolios.

Another example of interconnectedness comes from a study by Chen, Wu, Li, Bao, and Koedijk (2024), which suggests that information diffusion on social media platforms is highly associated with the co-movement of excess stock returns. This finding indicates that mapping the topology of information diffusion across distributed investor networks may be relevant for portfolio construction and risk management.

In short, understanding the effects of highly networked interactions is crucial if financial markets are treated as complex systems. Such techniques as network analysis and agent-based modeling have been used to capture asset and investor interconnections, often in the context of risk analysis (see Konstantinov and Fabozzi 2025; Bookstaber, Paddrick, and Tivnan 2018). Examples of both techniques can be found later in this report.

Regime Shifts and Adaptation

Approaching financial markets as a system allows analysts to anticipate and observe regime shifts in financial markets. Inspired by "phase transitions" in physics, regime shifts appear as changes in the qualitative behavior of the whole system due to an often very small change in some parameter (Harré and Bossomaier 2009). "In other words, as new technologies, policies, or geopolitical factors emerge, long-established statistical relationships and market behaviours can shift (i.e., inducing abrupt structural changes in time-series data, invalidating prior assumptions of stable trends)" (Hepburn, Ives, Loni, Mealy, Barbrook-Johnson, Farmer, Stern, and Stiglitz 2025, p. 3). Understanding regime changes is crucial for both anticipating market behavior and determining the resiliency of financial markets.

[10] See Gualdi, Cimini, Primicerio, Di Clemente, and Challet (2016) for an analysis of US institutional holdings from 1999 to 2013; Kim (2021) for evidence of overlap from the South Korean equity fund market; and Koide, Hogen, and Sudo (2022) for a review of portfolio overlaps between Japanese financial institutions and global investment funds.

As part of the system, investors learn and adapt to changing conditions. For example, after the 2008 Global Financial Crisis (GFC), many investors became more risk averse, focusing on downside protection. This adaptive shift influenced market behavior in subsequent years (e.g., a sustained preference for lower-volatility stocks; see Torga, Roma, Roma, Ferreira 2023). But as memories of the crisis faded and new opportunities (such as tech startups) arose, risk tolerance grew again. Market regimes, therefore, emerge not just as the backdrop for investors to consider but also as the consequence of investor behavior and risk tolerance. It is this ongoing dynamic and feedback between market conditions and investor actions that leads to market regime shifts, whether from high fear to high risk appetite or from bear to bull markets. Understanding and anticipating these transitions can improve investment strategy implementation and inform timing.

Regulatory bodies also evolve, leading to the rise and fall of regulatory trends and frameworks. Lukomnik and Hawley (2021), for example, discussed the advent of a stewardship code in the United Kingdom or the SEC Form N-PX proxy disclosure requirements in the United States as regulatory regime shifts. Other regime changes include broad adoption of transition finance policies (see Mak and Vinelli 2024; Hall, Foxon, and Bolton 2017) or the surge of organizations, coalitions, and initiatives promoting net-zero investment goals.[11] Indeed, climate mitigation policy regime shifts indicate broader concern about potential tipping points and abrupt transitions into new environmental and economic regimes (Hepburn et al. 2025).

Taking a complex systems approach encourages us to go beyond considering investors or assets in isolation and directs attention to interaction patterns. These patterns include which strategies reinforce or counteract each other, how diverse micro-level behaviors emerge as macro-level outcomes, where critical thresholds may lie, and what new regimes will replace old ones.

How Can Complex Systems Be Used in Portfolio Management?

A complex systems approach is not itself an investment strategy; rather, it is a way of conceptualizing and investigating market phenomena. Even so, adopting a complex systems lens can change the way asset owners and managers approach investing by allowing them to incorporate key aspects of complex systems, such as interconnection and adaptability, which are particularly relevant to dynamic portfolio construction and multifactor approaches.

[11] A list of organizations associated with net-zero investment frameworks is available at https://rpc.cfainstitute.org/topics/net-zero-investing/who-is-developing-the-net-zero-investment-frameworks.

Traditional single-factor and smart beta strategies[12] have evolved into more complicated factor timing and multifactor portfolios, requiring techniques that capture ongoing changes in factor dependencies (Jacobs, Levy, and Lee 2025). For example, within a multifactor portfolio, factors may interact or be highly positively or negatively correlated or uncorrelated at different times, demanding attention to regime-switching signals and agile reallocation and rebalancing in response to changing market conditions, economic outlook, or investment goals (Backhaus, Isiksaul, and Bausch 2022; Shu and Mulvey 2025). Investment products have also evolved, signaled by the rise of multifactor index funds, which dynamically allocate capital among multiple traditional factors (e.g., momentum, value, minimum volatility; see Doyle and Hayman 2024; Amenc, Goltz, and Sivasubramanian 2016; Amenc, Ducoulombier, Esakia, Goltz, and Sivasubramanian 2017). Due to its emphasis on interconnected networks and nonlinear dynamics that produce systemwide effects, complex systems analysis may aid in measuring and forecasting risk–return and asset interactions within these dynamic, multifactor strategies.

We also see the relevance for new complexity-driven methodologies as some of the largest institutional investors move away from fixed-weight strategic asset allocation (SAA) and toward a total portfolio approach (TPA) (Thinking Ahead Institute 2019). TPA promotes an integrated view of the portfolio as a dynamic balance sheet where every investment decision is evaluated in terms of its marginal impact on total fund risk, liquidity, return, and flexibility (Elkamhi and Lee 2025). Managers consider dynamic factors/exposures (beyond traditional Fama–French factors) across interdependent and overlapping asset classes that enhance the fund's overall portfolio risk and return profile (CAIA Association 2024). Whereas SAA is built on modern portfolio theory and capital market equilibrium models that construct portfolios based on expected returns and volatilities for each asset class, TPA demands market monitoring tools that can provide regime-aware assessments and portfolio construction tools that can transverse asset class silos (Elkamhi and Lee 2025). Complex systems approaches may complement TPA with a science-based framework that accords with TPA's need to model networks of moving parts spanning asset classes, public and private markets, and regime shifts, ultimately enabling dynamic and adaptive portfolio strategies.

[12] Smart beta strategies refer to a range of index-based investment products that incorporate factor exposures and are generally long only, though the term is used inconsistently (Doyle and Hayman 2024).

Complex Systemic Risk

In a financial context, **systemic risk** refers to "a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy" (Caruana 2010). Of particular concern are possible market crashes or systemwide crises affecting the real economy. However, there is neither an established rulebook for what kinds of shocks may be relevant nor ideal methods for calculating the effects produced by those shocks. Disruptions to a financial system, for example, may be caused by endogenous factors, such as a bank collapse or credit defaults, or by exogenous factors, such as political turmoil or extreme weather events.[13]

In addition, no standard measure or quantification of systemic risk exists, thus generating policy debates surrounding best practices for evaluating systemic risk (Dijkman 2010). Market-based measures of systemic risk include **conditional value at risk (CoVaR)** and **marginal expected shortfall (MES)**; both are derived from traditional risk estimates, such as **value at risk (VaR)** or **expected shortfall (ES)**.[14] Though used in practice, these measures inadequately capture the full complexities of systemic risk.

Systemwide VaR, for example, is more than the sum of the CoVaRs of institutions. Although "CoVaR may provide a realistic approximation for smaller banks," it "cannot capture the heteroscedasticity characteristic of financial assets, which may severely underestimate systemic risk" (Ellis, Sharma, and Brzeszczyński 2022). Likewise, CoVaR and MES alone are "unlikely to detect asymptotic tail dependence," which is fundamental for any systemic risk measure (Basilio, Oliveira, and Mahmoudvand 2020). As Hoffmann (2017, p. 184) described,

> Standard risk models cannot accurately model the risk posed by especially rare, systemic events, as the number of financial crises in the past two decades have shown. . . . Not only have such rare events occurred far more frequently than predicted, but they have brought with them strong interdependencies between institutions and rapidly increasing correlations between

[13] What counts as "endogenous" and "exogenous" are relative to where one wishes to draw the boundaries of a system. They are not absolute categories.

[14] CoVaR captures the VaR of the financial system "conditional on institutions being under distress" (Adrian and Brunnermeier 2008, p. 1). Both CVaR and CoVaR are sometimes expanded as "conditional VaR" and are based on value-at-risk concepts, but the "conditional" differs in each case: In CVaR (conditional value at risk or expected shortfall), it means the expected loss given that losses exceed the VaR threshold for an individual position or portfolio; in CoVaR, it means the VaR of the system conditional on another institution's distress. CVaR is a tail-risk measure used in portfolio risk management, while CoVaR is a systemic risk measure accounting for spillover risks, mainly used in financial stability studies and regulatory contexts.

MES refers to the expected equity loss of a financial institution conditional on the market or sector being in distress—specifically, when the aggregate return falls into its worst *q*% tail of the loss distribution (Acharya, Pedersen, Philippon, and Richardson 2017, p. 3). VaR is "a measure of the size of the tail of the distribution of profits on a portfolio or for an organization" (Chance and Edleson 2024, p. 31). ES offers the tail conditional expectation by integrating all losses with low probabilities across the distribution tail (Hoffmann 2017).

> markets, for example, that would, under '*normal*' circumstances, be deemed unrelated. . . . Conventional risk models have, therefore, all in all failed exactly where they were needed most (namely, when to address extreme risks) since they have proved to be conceptually inappropriate.

Contagion is commonly discussed in the context of regulatory analyses of systemic risk. Contagion occurs when the instability of an institution (e.g., a firm, market, or sector) spreads to other parts of the financial system, producing negative effects throughout the system and instigating a systemwide crisis (Smaga 2014, p. 11). Systemic risk can, therefore, be materialized as a contagion event.

The simplest forms of contagion may be represented as a domino effect. For example, a default by a major bank could immediately cause losses at other banks that lent it money, potentially causing those banks to fail, in turn. Empirical evidence shows that even mild market crashes in one country can increase the probability of crashes elsewhere as dominos fall (Fauzi and Wahyudi 2016; Markwat, Kole, and Van Dijk 2009).[15]

However, real financial contagion is often more complex. Propagation of negative effects throughout a system is often highly dynamic, nonlinear, and multidirectional, requiring more advanced techniques to model these interactions (Pacelli, Cananà, Chakraborti, Di Tommaso, and Foglia 2025). When a shock hits, relationships among market participants can change amid the crisis. For example, once Bank A starts struggling, Bank B might preemptively cut off credit to Bank C out of fear, even if Bank C was not yet directly affected. Meanwhile, Bank C might sell assets to raise cash, pushing prices down and hurting other firms holding those assets. These interactions can form a web of changing feedback loops that include indirect effects (Quirici and Moro-Visconti 2025).

Real financial networks also exhibit self-organization and adaptation, requiring ongoing assessments at the system level. Pacelli (2025) noted that if regulators only analyze each institution in isolation (a purely microprudential view), they critically miss the systemic picture: The system can self-organize into a fragile state even if each part seems stable. Neglecting the diverse web of interconnections can lead to "inappropriate, superficial and pro-cyclical regulatory prescriptions"—essentially, regulations that might inadvertently increase risk in the system by not accounting for complex interactions (Pacelli 2025, p. 14).

Macroprudential regulation, born out of the GFC, seeks to acknowledge features of network interconnection. Such policies aim to generate systemic resilience by assessing the structural integrity of the financial system as a whole and

[15] Markwat et al. (2009, p. 2000) acknowledged that "there are indeed higher-order dependencies in the dynamic patterns of crashes, especially concerning the more severe crashes" that do not strictly follow patterns of linear autocorrelation.

preventing the emergence of systemic crises. Still, even aggregate indicators of financial vulnerability used by regulators, central banks, and international institutions may miss important aspects of the complex financial system. For example, such measures as the Financial Conditions Index, the Financial Stress Index, or the Composite Indicator of Systemic Stress (CISS) may be useful to gain a combined snapshot of financial vulnerabilities; however, they cannot model future regime shifts or directly capture adaptive behavior in market participants as a crisis unfolds. Indeed, news of increased systemic risk could catalyze further investor panic, prompting sell-offs that lead to new vulnerabilities—a self-fulfilling loop (Pacelli et al. 2025).

Being able to map these multilevel feedback effects within the system is critical. Taking an example from Gai (2013), forced asset sales during periods of market stress—whether due to fire sales or funding liquidity shortfalls—can lead to losses that weaken banks' balance sheets. This, in turn, constrains their capacity to extend credit, leading to a credit crunch that dampens consumption, investment, and economic growth. As real activity deteriorates, borrower defaults rise and asset values decline further, feeding back into the financial system. Evaluations of systemic risk must therefore "address the non-linear consequences implied by the two-way relationship between the financial system and the real economy, together with the sizable externalities implied by the interconnectedness of financial firms for the system as a whole" (Gai 2013, p. 3).

In sum, systemic risk analysis must be sensitive to the highly interconnected dynamics of financial systems. It requires continual monitoring not only of individual financial entities but also of the network of dependencies that signal how shocks might cascade and amplify through patterns of feedback, **emergence**, and **self-organization**. Later, we introduce techniques used to model these dynamics to better understand and mitigate systemic risk in practice.

Systemic Risk vs. Systematic Risk

Because systemic risk is about systemwide effects, it differs from risks affecting a single entity, as well as systematic risk (market risk) in a portfolio context. **Systematic risk** typically refers to broad market risk that cannot be diversified away (e.g., the risk related to macroeconomic factors, such as interest rates or inflation). Typically, systemic risk is the focus of regulators, while systematic risk is the focus of investors pricing assets.

In the CAPM, for example, systematic risk is captured by beta, which measures an asset's exposure to market movements.[16] Investors expect to be compensated for bearing systematic risk—hence the concept of an equity risk premium (the excess return on the equity market over risk-free assets). Systemic risk, in contrast, is about the system's structural integrity.

[16] More precisely, beta measures the sensitivity of a stock's return to the equity risk premium.

It concerns regulators because it can lead to system collapse, not just asset price fluctuations.

Despite their differences, the two can be related. A systemic event such as a banking panic can trigger the realization of systematic risk, leading to broad market sell-offs as investors withdraw en masse or banks hoard cash, potentially freezing markets. Conversely, elevated systematic risk (i.e., high exposure of assets to common marketwide factors) can amplify the impact of adverse shocks. When widespread declines in asset prices occur, the losses can propagate stress through financial institutions with real-economy feedback loops, intensifying a systemic crisis (e.g., credit contractions and reduced consumption leading to widespread capital crunches, financial instability, and economic distress), which can further impact market prices (Borio, Drehmann, and Xia 2018; von Peter 2009).

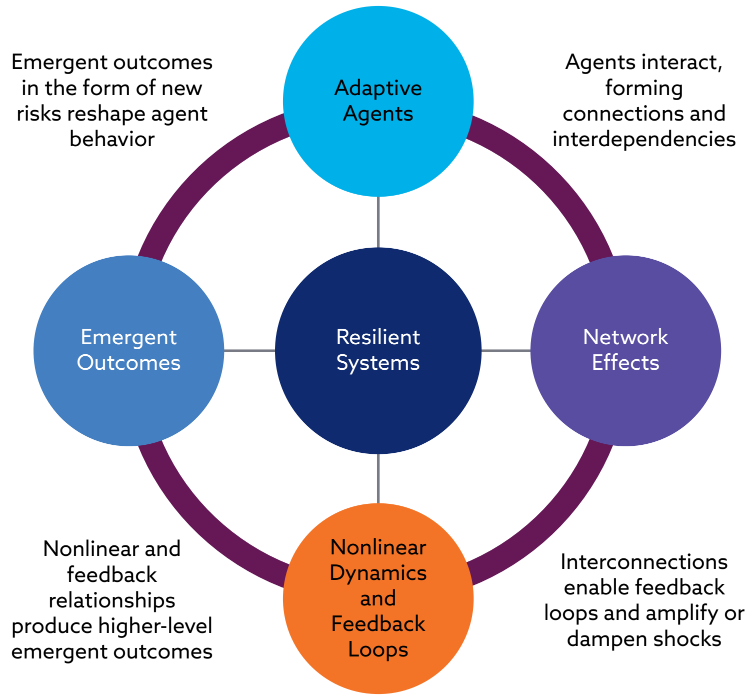
Asset owners are increasingly acknowledging the interplay between the systematic risk in their portfolios and the systemic—often existential—risks imposed by such threats as climate change, geopolitical instability, and socioeconomic inequality (see Impact Management Platform 2023). Although system-level investors may focus on different environmental, social, and governance (ESG) aspects, they share a commitment to the belief that investors not only respond to investment conditions but also directly contribute to shaping those conditions. In other words, investors do not just passively capture market beta; they actively influence how the market performs by managing systemic risks as systematic risks and building long-term resiliency into capital markets (Gordon 2021).[17]

Asset owners may exhibit influence through portfolio allocation strategies, stewardship activities, impact investing, and engagement on regulatory policies, all of which demand a systems-based lens to realize market impact and enhance long-term value creation. Such groups as The Investment Integration Project, the Predistribution Initiative, the Institute for Energy Economics and Financial Analysis, and the Shareholder Commons, as well as UN-supported Principles for Responsible Investment (PRI) signatories, among others, have launched initiatives aimed at facilitating system-level investing (PRI 2024; PRI forthcoming).

Complex systems analysis offers a framework under which regulators and investors can come together to understand how systemic risk and systematic risk mutually impact one another. As an interdisciplinary field, complex systems sciences have a history of fostering engagement between disciplines and point to opportunities for increased collaboration between asset owners,

[17] Lukomnik and Hawley (2021, p. 41) described those who adopt this view as "beta activists," maintaining that "in theory, the sum of all the investors' expectations about any systematic risk (e.g., climate change, lack of gender diversity, etc.) is built into the perceived riskiness of 'the market.' Therefore, if a beta activist can cause a reduction in the perceived riskiness of a systematic risk, the entire market re-rates. That is similar to what happens when the market re-rates a single security targeted by an alpha activist. However, because the systematic risk factor targeted by a beta activist impacts the entire marketplace, even a small systematic risk re-rating can have hundreds of billions of dollars of impact."

Exhibit 3. Resilience through a Systems Lens



policymakers, and investment professionals by bringing together concerns, perspectives, data, and forecasting techniques.

Exhibit 3 shows how enhancing resiliency from a complex systems lens emphasizes the capacity of financial systems to absorb shocks, adapt to disruptions, and recover without collapsing. This perspective acknowledges the inherent unpredictability and interconnectedness of financial ecosystems and shifts the focus toward strengthening underlying structures and enabling flexible, adaptive responses to emergent risks and nonlinear dynamics. In essence, building resilient systems requires attention to the following aspects of the system:

- *Adaptive agents:* Systemic risk in a complex system is dynamic, with agents adapting and evolving, sometimes generating new exposures as they adjust their strategies in response to market conditions and regulations. This process can make the system more prone to unexpected risk concentrations and hidden vulnerabilities over time.
- *Network effects:* Rather than viewing institutions or entities in isolation, complex systems analysis emphasizes the web of interconnections, including direct and indirect ties, which can amplify or dampen shocks. The emphasis is on how risk propagates through these connections, as seen in network models.

- *Nonlinear dynamics and feedback loops:* Complex systems exhibit nonlinear behaviors and feedback loops, where small shocks can sometimes lead to disproportionate, cascading failures or, alternatively, be absorbed without significant disruption. Relevant to this approach is the identification of "tipping points," where the system's state reaches a critical point prompting a regime change.
- *Emergent outcomes:* Agents (e.g., banks, funds, regulators) interact and adapt to each other's actions, often leading to emergent patterns that can be unpredictable (e.g., periods of heightened volatility or regime shifts). These emergent patterns generate systemic risks that cannot be fully estimated by the sum of individual risks.

HOW TO MODEL COMPLEX FINANCIAL SYSTEMS

The theoretical shifts embracing systems thinking in finance demand new ways of modeling complex phenomena. In practice, market analysis methods have often relied on the mathematics of calculus with stochastic differential equations and regression models (Konstantinov and Fabozzi 2025). Though these techniques alone may be sufficient for capturing simple multivariate problems, many macroeconomic and market-level behaviors of interest to analysts and regulators rely on key structural elements observed in complex systems. In other words, to study complex financial systems, we need modeling approaches that can stretch beyond assumptions of linearity and normal distribution for how losses propagate through the system (Farmer 2024). Traditional models—such as the CAPM, the Black–Scholes option pricing model, or dynamic stochastic general equilibrium (DSGE) models—provide important insights but typically require simplifying assumptions (e.g., representative agents, linearization around equilibrium, or normal distributions) that make it hard to simulate crises, contagion, or adaptive behavior.

Combined with a new era of big data and computing power, we are starting to see innovative techniques in the investment industry that do more than explain features of complexity; they explicitly map and simulate the dynamics of complex financial systems. Two of these approaches, agent-based modeling and network theory, provide distinct yet complementary insights. ABMs simulate interactions among heterogeneous, adaptive agents to reveal emergent phenomena, such as herding behavior, which can lead to volatility clustering. Network theory maps structural interconnections, highlighting contagion channels, systemic vulnerabilities, and key leverage points.

Although often used in practice for distinct purposes, these methods capture complementary perspectives. Within a system, agent interactions will endogenously form network patterns (e.g., hubs of influence or feedback loops) that constrain their subsequent behaviors, permitting further evolution of the interaction dynamics that lead to changes in the network structure. What this means for the practitioner is that simulating complex systems requires attention to both the dynamics of individual agent interactions and the structural (i.e., network) features that emerge from those interactions.

ABMs and network theory are just two of several commonly used modeling techniques in systems sciences (see Appendix B). While no single technique can model every aspect of a system of interest, each can highlight important features of the system that can be used to inform portfolio construction or systemic risk modeling. In practice, techniques can be combined or used in complementary ways to better understand and simulate the complex dynamics of a system. Ultimately, however, these modeling techniques all reflect a burgeoning theoretical shift away from models of static equilibrium and efficient markets and toward embracing financial markets as complex adaptive systems.

Agent-Based Models to Capture Complex Dynamics

Agent-based models (ABMs) are computational models that simulate the interactions of autonomous “agents” to assess their effects on the system. ABMs model individual agents (which could be investors, banks, traders, etc.) with certain behaviors or decision rules. The ABM’s topology represents the interactions between agents that can unfold according to their defined rules. During the simulation, the agents interact step by step (often randomized and repeated thousands of times). The goal is to see what emergent phenomena result from the bottom-up interactions. As such, ABMs can capture multiple features of complex systems, including heterogeneous adaptive agents, emergence, and self-organization.

Thus, ABMs break away from traditional methods, such as DSGE models, many of which assume a unitary representative agent (Bookstaber 2017). Instead, a core feature of ABMs is the ability to model interactions between many heterogeneous agents with different risk preferences, investment strategies, or information. Agents interact within an environment, which can exogenously or endogenously introduce shocks, and analysts observe how the system evolves over time. Crucially, ABMs do not require the system to settle in equilibrium: They can generate booms, busts, cycles, or chaotic fluctuations as outcomes. As such, ABMs have been used across disciplines to model highly dynamic and volatile behavior, such as disease outbreaks and crowd behavior in crisis situations.

Because of their bottom-up design, ABMs would be less suited to forecasting the price of a particular asset, but they can be helpful in determining what trading activities might move the prices of assets or generate business cycles, price bubbles, clustered volatility, or the onset of “bear” or “bull” markets (Turrell 2016). A classic use of ABMs is to study material risk generated by contagion effects and herd behavior (see Bookstaber and Sharma 2022). For instance, an ABM might simulate a market where agents decide to buy or sell based on their connections (e.g., social network influence) or in reaction to recent news events. By manipulating how strong the herding tendency is, we can see at what point and under what conditions a small shock might lead to a major crash.

In building an ABM, one must identify the types of agents, their decision rules, and how they interact. These rules may be informed by data or theory. ABMs are often used without perfectly fitting to data; they are exploratory. That said, calibration to real market data can be performed or model parameters can be selected to reproduce known patterns in market data. Common software used to construct ABMs includes NetLogo, AnyLogic, Altreva Adaptive Modeler, MASON, Repast, and GAMA Platform.

Example: Agent-Based Stock Market Model with Fundamental and Technical Traders

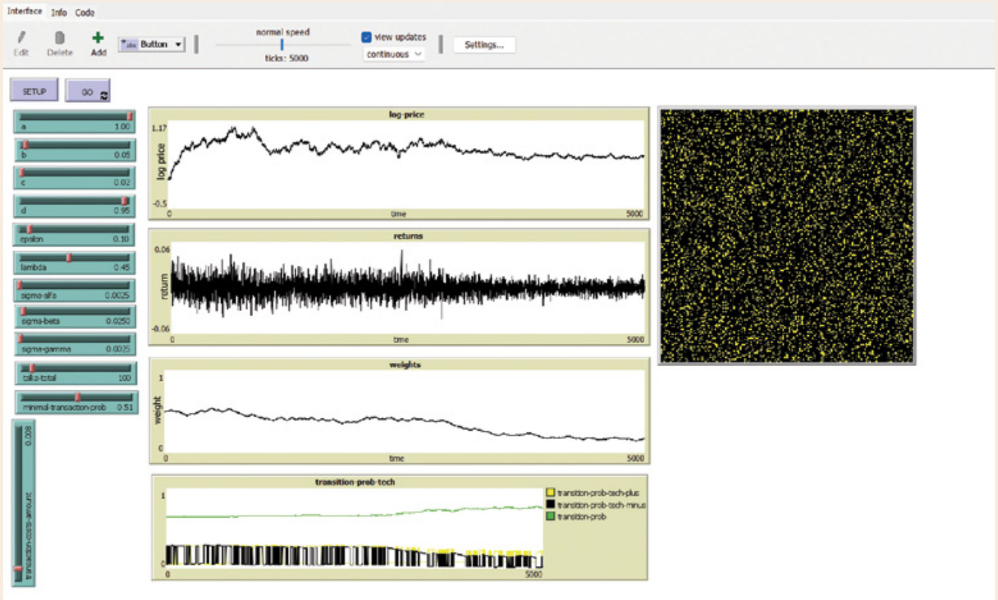
A simplified model by Šperka and Spišák (2013) assesses the influence of transaction costs on the stability of financial markets. The computerized simulation features two types of traders (agents): fundamental traders and technical traders. Fundamental traders purchase assets when prices are below their fundamental value. Technical traders buy based on recent price trends. However, traders also communicate at random, and the more successful traders (based on current and past profitability) can convince the other traders to adopt their strategy.[18] Agents can also change strategies independently, though at much lower probabilities. As such, the number of traders with a fundamental or technical strategy will change over time.

The base model runs using the computer simulation program NetLogo (see **Exhibit 4**). It features 10,000 agents trading over 5,000 days. Model parameters are located in the left panel of Exhibit 4 and are modifiable. The first three are price dynamics parameters that represent how strongly prices react to excess demand (a), how sensitive technical traders are to recent price signals (b), and how strongly fundamental traders respond to the gap between the market price and the fundamental value (c). Parameter d is a memory (discount) parameter, epsilon is the likelihood a trader will switch strategies independently, and lambda represents how strongly relative profitability differences influence switching when traders meet. Sigma-alpha, sigma-beta, and sigma-gamma represent stochastic parameters (introducing randomness or noise), and the last three parameters are baseline interaction and market microstructure calibrations.[19] The middle panel charts shown in Exhibit 4 represent evolving price values, returns (log price changes), weights of technical trading strategy, and probabilities for switching strategy. On the right side, fundamental (black) and technical (yellow) traders are represented by color.

[18] Successful "convincing" occurs at probability *K*, defined in Šperka and Spišák (2013).

[19] See Westerhoff (2009) for a complete overview of the parameters adopted in Spišák and Šperka (2014).

Exhibit 4. NetLogo Artificial Stock Market Simulation with Fundamental and Technical Traders



Source: Spišák and Šperka (2014).

Once the base model environment is established, transaction costs are introduced at a constant value of 0.015, which has a direct impact on asset prices. In the short run, this increases the number of technical traders and decreases fundamental trading, as prices increase relative to unchanging fundamental value, reducing the expected returns of fundamental traders. However, as the model continues to run, technical trading becomes less attractive, prices drop, and fundamental traders dominate, eventually leading to lower price volatility and market stabilization. Šperka and Spišák (2013) run the simulation once more at a higher transaction cost (0.03). Under this scenario, a return to stability was not observed, and technical traders continued to dominate, indicating that if transaction costs are high enough, technical trading becomes more attractive than fundamental strategies and the market continues to be unstable.

Example: Simulating Banking Network Risk with ABMs

The International Monetary Fund developed an agent-based model called ABBA to analyze systemic risks in the banking system (Chan-Lau 2017). ABBA simulates interactions between three types of agents: savers, loans, and banks. Savers are distributed across global regions, each of which is dominated by one bank. Following payments of principal and interest, savers may withdraw their deposits from the bank and relocate to another region to open an account with another bank. Savers accounts remain solvent as long as the bank does not default. Loans are also distributed across regions, with each loan featuring several risk characteristics (i.e., probability of default, risk weight, rating, recovery rate in case of default, and fire sale loss rates). Based on the credit risk characteristics of the loan, banks will produce a loan rate quote and lend the amount as long as the bank can meet its capital and reserve requirements. Meanwhile, each bank agent is making multiple business decisions based on its financial health and regulatory environment. Banks consistently evaluate their loan portfolio solvency, assess net income, optimize loan portfolio composition to meet capital requirements, and decide whether to pay dividends (Chan-Lau 2017). In ABBA, therefore, banks are the primary agents that exhibit adaptive behavior and can learn and modify as they go. The decision-making process of banks can therefore influence the flow of interactions within the system.

As banks interact in the form of interbank lending, an endogenous network forms (i.e., links are established between banks, loans, and savers). As the simulation runs and banks modify their decisions following loan defaults and indirect effects on capitalization, new network structures emerge. Analysts then simulate shocks, such as a change in capital requirements or a liquidity shock from savers withdrawing en masse, to see how the shock propagates.

Ultimately, ABBA is useful insofar as it can capture immense heterogeneity (banks of different sizes/strategies) and adaptive behavior (banks reacting to stress by deleveraging), illustrating how regulatory policy changes or shocks can lead to nonlinear outcomes in system stability. Indeed, tightening capital requirements might paradoxically increase short-term systemic risk if many banks deleverage simultaneously but may also improve long-term resilience (Chan-Lau 2017). Such insights are difficult to obtain from equilibrium models but emerge naturally in an ABM. Central banks and regulators are increasingly exploring ABMs like ABBA to complement traditional stress tests.

In some cases, ABMs use reinforcement learning to model agent behavior, adding additional layers of adaptability and insight. In these models, agents operate within a system of learning algorithms and reward structures that guide activity. Agents learn and adapt their behavior as the system evolves under changing demands and conditions. Such models are useful in realistically modeling the dynamics of pricing strategies and market competition (Alonso 2024). In addition, new "AI agents" with capabilities to follow complex, multistep decision-making patterns could be integrated as simulated agents within ABMs that would model more adaptive and potentially realistic interactions (Borsos et al. 2025). For a comprehensive review of current applications of ABMs in finance and economics, see Chudziak (2025). For a summary of ABMs, see **Exhibit 5**.

Exhibit 5. Agent-Based Models Summary

Key Features

- ABMs are well suited to capture emergent market phenomena. A well-known example showed that even if all agents trade with simple rules, their interactions can produce heavy-tailed return distributions and volatility clustering, mirroring real markets (LeBaron, Arthur, and Palmer 1999).
- Agents in ABMs are heterogeneous and can take up individual strategies or heuristics as well as adapt their strategies as environments evolve (Bookstaber and Sharma 2022).
- ABMs can incorporate behavior rules drawn from behavioral finance or observed trading patterns to model realistic bottom-up interactions. For instance, analysts could program agents to underweight recent losers or to panic sell after a certain loss threshold.
- No requirement of equilibrium or closed-form solution: The model "solution" is the simulated outcome.

Example Use Cases

- Simulate how herd behavior or feedback trading can lead to market bubbles and crashes.
- Model traders with varying individual risk tolerance levels and trading strategies to see how fluctuations in investor risk affect market trends and performance.
- Conduct dynamic stress tests (e.g., represent banks as agents who might withdraw lending when their capital falls to see systemic liquidity impacts and amplification events).
- Run "what-if" scenario simulations (e.g., the introduction of a new tax) that can inform policy creation and implementation.

Challenges

- *Requires significant computational power*. Large-scale simulations with many agents (especially if each agent is complex) can be computationally heavy and slow. However, increasing computing power can mitigate this issue over time.
- *Sensitive to assumptions*. Results can depend heavily on how agents are specified. If we miss an important behavior or constraint, the model might mis-predict outcomes (for example, omitting that agents have leverage limits could ignore a key feedback in a crisis).
- *Can be difficult to calibrate and validate*. Ensuring the agent rules are realistic and that the model's output aligns with real data patterns is nontrivial. There is a risk of "overfitting" to known outcomes or, conversely, using overly simplistic rules that fail to capture realistic behaviors.

Network Theory and Graph Models to Capture System Structure

While ABMs are useful for capturing systemwide patterns that emerge from dynamic interactions of heterogeneous agents, depicting the overall structure of the system can be challenging. System structure is significant to complex systems since the heterogeneity of agents implies that not all system components possess equal importance and understanding of where control points (hubs of influence or key leverage points) lie within the system can surface hidden vulnerabilities or areas for intervention. Additionally, simulating every dynamic interaction via an ABM is impractical, so mapping key relationships within the system is an effective first step for determining what parts of a system are most relevant for generating systemwide effects of interest (e.g., market return, volatility, or crashes) and how information or influence is distributed throughout the system.

Mapping the structure of a system is possible through network theory. **Network theory** is an area of mathematics used to analyze relationships and interactions of interconnected entities (Konstantinov and Fabozzi 2025). In practice, network theory provides a set of techniques for analyzing graphs. **Graph models** consist of nodes (vertices) and links (edges) connecting nodes. They range from simple models containing a small number of nodes to widely distributed and highly interconnected networks with weighted connectivities.

In finance, many structures can be represented as networks: interbank lending networks, counterparty exposure networks, cross-shareholding networks, payment flows, asset correlations, and so on. Each node might be a firm, bank, asset, or country, and each link represents some connection, such as a financial contract, correlation coefficient, or transaction. As such, network analysis provides a systematic method for analyzing relationships and flows between interconnected entities.

In practical terms, network analysis in finance often starts with constructing a matrix of connections, referred to as an adjacency matrix. For instance, an interbank network can be derived from exposure data: Matrix entry (i, j), for example, would represent the amount bank i is owed by bank j. From this adjacency matrix, the user can create a weighted graph and compute, for example, systemic risk metrics or simulate defaults (see Konstantinov and Fabozzi 2025).

From there, network models allow us to use such metrics as connectivity, centrality, clustering, and path lengths to understand the architecture of a financial system. For example, centrality measures can identify which institutions are "too central to fail" (because they serve as important hubs in the network; see Hüser 2015; Minoiu, Kang, Subrahmanian, and Berea 2014).[20]

[20] See Rodrigues (2018) and Wan, Mahajan, Kang, Moore, and Cho (2021) for an overview of network centrality measures. See also Lerman, Ghosh, and Kang (2010); Piraveenan, Prokopenko, and Hossain (2013); and Ghanem, Magnien, and Tarissan (2019) for centrality metrics applied to dynamic or evolving networks.

Clustering can reveal communities of banks or stocks that are tightly knit and could have contagion within the cluster. Network paths might illuminate how a shock could propagate from one node to another through intermediate connections. As such, network models address the interaction structure across many nodes. Even if initial edge weights are derived from linear measures (as they often are in adjacency matrices), the heterogeneous geometry of the graph (e.g., hubs, communities, bottlenecks) creates system-level behavior (or risks) that may be nonlinear.

The application of machine learning techniques, such as deep learning, on graph data has allowed for improved analyses of highly interconnected and multidimensional networks, such as those of complex financial markets. Among these techniques, graph neural networks (GNNs) have emerged as particularly well suited for various graph-based tasks, including node classification, graph classification, and edge prediction (Wang, Zhang, Xiao, and Song 2021).

In risk management, network contagion models complement traditional stress tests. A stress test might assume one bank's failure and then exogenously impose losses on others. A network model, in contrast, would identify how the failure causes losses through a web of endogenous exposures, possibly uncovering nonintuitive contagion paths (such as Bank A's failure hurting Bank C via Bank B's distress discussed earlier). The Office of Financial Research in the United States, for instance, has worked on network models for the credit default swap market to see how the default of one large counterparty would affect others in the web of credit default swap contracts (Chen and Wang 2013).

Example: Stock Market Analysis Using Networks

Namaki, Shirazi, Raei, and Jafari (2011) used network analysis to examine both a mature market, the Dow Jones Industrial Average (DJIA), and an emerging market, the Tehran Stock Exchange (TSE), to see whether stock correlation patterns have unique structural features. The researchers constructed a stock correlation network where nodes represent stocks and edges represent correlations. Both networks exhibited a "market mode," captured by the largest eigenvalue of the correlation matrix, reflecting the collective movement of most stocks. The largest eigenvalue tends to surge during crises, signaling stronger marketwide co-movement.[21]

[21] See Jolliffe and Cadima (2016) for an overview of principal component analysis, which is a linear dimensionality reduction technique.

However, Namaki et al. (2011) wanted to uncover genuine stock relationships, so they used random matrix theory (RMT) to filter out the “market mode” from the correlation matrices.[22] For the DJIA, this process significantly altered the mean correlation coefficient distribution, indicating that optimizing using raw correlations can overemphasize systematic risk while obscuring idiosyncratic features of the stocks. Results from the TSE analysis demonstrated scale-free properties within the stock network, meaning that a few highly connected “hub” stocks influence many others. These hubs are critical in understanding the market’s systemic risk profile and the impact of market shocks. By adjusting correlation thresholds (what correlation value is enough to constitute an edge), the authors demonstrated how the market connectivity structure can change, which could influence asset allocation and portfolio diversification strategies. Similar applications of network analysis could assist financial professionals in identifying key points of market influence and systemic vulnerabilities.

Network models can also be applied at a micro level to better understand portfolios or funds. For example, portfolio managers may use network algorithms to enhance diversification, as demonstrated by the case study that follows this section. Through identifying clusters of highly interconnected assets, portfolio managers can restructure portfolios to avoid concentrating assets within one cluster. This method can reveal hidden factor exposures that a simple asset-based or sector-based classification might overlook; for example, companies in different sectors may be tightly linked through supply chains or co-ownership within major indexes and ETFs.

In summary, network theory offers powerful analytical tools to map and evaluate the architecture of financial systems, shedding light on channels of risk transmission that are often obscured in traditional aggregate models (see **Exhibit 6**). This approach is becoming increasingly vital as financial networks become more densely connected and systemically complex.

[22] RMT, originally developed to explain the energy levels of complex nuclei, is now used to filter noise in financial time series (Daly, Crane, and Ruskin 2008). The technique involves comparing eigenvalues of an empirically derived covariance or correlation matrix with those of a corresponding purely random matrix, thus allowing for the removal or replacement of “noisy” eigenvalues.

Exhibit 6. Network Theory Models Summary

Key Features

- Represents key structural features of highly interconnected networks that exhibit amplification or diminishing effects. For example, a "star" network—one central hub connected to many periphery nodes—is vulnerable if the hub fails. A highly clustered network might trap a shock in one cluster but keep it from spreading globally (or vice versa, if clusters are linked by a few bridges).
- Can be used to identify changes in network structure (e.g., banks might alter trading partners, leading to emergent hub structures). Ongoing monitoring of network clusters can help predict where risks are forming.
- Different types of connections can be represented in separate layers (e.g., an overlap of a credit network and a derivative network), which can interact. This is advanced but increasingly relevant for assessing how a liquidity freeze (one network) can trigger fire sales (another network of correlated assets), for example.

Example Use Cases

- Identify which bank failures would cause the greatest cascade, using network centrality metrics or simulating default contagion (Jo 2012; Giansante 2010).
- Gauge how a disruption at a key node (such as a major bank that conducts clearing or a critical supplier firm) could ripple through counterparties.
- Map how portfolios overlap via common asset holdings to see if many investors unwittingly form an interconnected sell-off network (relevant for crowded trades and liquidity risk).
- Examine cross-border capital flows through a network of countries to see how financial shocks could transmit internationally.

Challenges

- *Connections are dynamic*. Financial networks are not static. Connections form and dissolve over time. Analyzing an evolving network (time-varying graph) is more complex than a static snapshot, and many network metrics are harder to interpret as the network changes.
- *Some parameters must be inferred*. The "edges" in financial networks are often not directly observable. For example, bilateral exposures between banks might be confidential. Analysts must infer networks from partial data or proxies (e.g., using correlations as edges).
- *Can be hard to interpret*. Even if we can compute centrality metrics, such as **closeness centrality*** or **eigenvector centrality**,** for firms in a network, translating that into an actionable risk assessment or investment strategy can be tricky. There is also a danger of oversimplifying (e.g., just because a bank is central does not guarantee its failure will be catastrophic; it depends on the context and buffering mechanisms). Still, these metrics provide valuable signals.

*Closeness centrality is defined in terms of the average distance of each node to all others (Rodrigues 2018).

**Eigenvector centrality is a measure of a node's centrality (i.e., importance) given the centrality of its neighbors (Konstantinov and Fabozzi 2025).

CASE STUDY: NETWORK ASSET ALLOCATION

This case study illustrates how network theory can be applied to asset allocation purposes. We emphasize that this example is merely illustrative, where the effectiveness of such methods depends on a multitude of factors, including the asset class and the quantity of data available. Moreover, we offer this case study as a demonstration of how to begin adopting systems thinking within traditional portfolio management contexts. It does not reject established approaches, such as mean–variance optimization; rather, it extends the norms of current practice to incorporate network theory. While fully embracing markets as complex systems likely means going beyond traditional financial approaches, both conceptually and methodologically, we acknowledge the need for a starting point—a place where practitioners can easily adopt new approaches that appeal to a systems perspective. With this in mind, we developed the following case study, which considers portfolio construction in the sovereign fixed-income asset class. The code for this case study can be found by visiting the RPC Labs GitHub repository at https://github.com/CFA-Institute-RPC.

Portfolio construction is central to the investment process, involving asset allocation and security selection to achieve targeted returns. In the case of fixed-income assets, the presence of highly correlated bond yields (the expected yearly return on the bond until maturity) introduces diversification risks. Specifically, if bond yields move closely together, the portfolio can face heightened sensitivity to interest rate shifts or macroeconomic changes, potentially magnifying risk exposure. Rising yields across correlated bonds lead to declining bond prices, negatively impacting the portfolio's value. Conversely, falling yields lead to an increase in portfolio value. Hence, the correlation of bond yields can significantly influence portfolio risk.

While the amplification of gains or losses from high correlation in bond yields can be individually assessed for a few assets, it becomes challenging for hundreds or thousands of assets. One systematic approach to portfolio construction that minimizes the risk associated with highly correlated bond yields is a minimum-variance optimization. For selected assets, portfolio weights are assigned such that the portfolio variance (representing the risk objective) is minimized.[23]

However, issues may arise regarding the data used to derive portfolio weights. Specifically, the optimization may assign weights based on abnormal bond yields that are idiosyncratic to the specific sample period. This may result in overfitting, where the allocation results in the minimum-variance portfolio on in-sample data but is suboptimal on out-of-sample data. Overfitting can decrease the robustness of backtesting when evaluating portfolio performance

[23] With additional constraints, including that the weighted returns of the portfolio equal a given value, portfolio weights are nonnegative and the sum of all portfolio weights is equal to 1.

based on historical data, where results are sensitive to noise. To address these issues, we use network analysis, specifically a spanning tree methodology. With a spanning tree, we identify key correlations between the historical movements in bond yields, where the subset of correlations represents a network. Then, from the network, we can use properties from the network topology to inform constraints for bond holdings under the minimum-variance optimization.[24] Using such approaches, the portfolio variance can be reduced by controlling for portfolio weights assigned to highly correlated assets (as correlations with volatility represent the covariance of bond yields), thereby reducing overfitting from other correlations. Again, we emphasize that this case study only illustrates the network methodology; implementing the results as constraints in a portfolio optimization approach can be conducted in future work.

Data

We used European 10-year sovereign bond data obtained from LSEG with daily closing yield-to-maturity values during the year 2024. In total, we chose bonds from the following countries: Austria (AUT), Belgium (BEL), Germany (DEU), Spain (ESP), Finland (FIN), Ireland (IRL), Italy (ITA), the Netherlands (NLD), and Portugal (PRT). Sovereign bonds associated with these developed EU countries have high liquidity, thus facilitating the collection of reliable data to support our analysis.

Exhibit 7 presents summary statistics for the mean, volatility (standard deviation), skewness (the degree of asymmetry in the distribution of yield-to-maturity values), kurtosis (the level of tailedness in the distribution, relative to a normal distribution), and maximum and minimum yield-to-maturity values

Exhibit 7. Summary Statistics of Daily Yield to Maturity (%)

Country	Mean	Volatility	Skewness	Kurtosis	Max.	Min.
AUT	2.843	0.152	−0.095	−0.457	3.191	2.485
BEL	2.932	0.131	0.065	−0.493	3.269	2.652
DEU	2.341	0.144	0.078	−0.67	2.683	2.017
ESP	3.152	0.164	−0.341	−0.524	3.493	2.756
FIN	2.81	0.153	−0.002	−0.549	3.179	2.463
IRL	2.735	0.166	−0.115	−0.733	3.129	2.366
ITA	3.705	0.194	−0.427	−0.276	4.112	3.194
NLD	2.623	0.151	0.11	−0.481	2.994	2.278
PRT	2.952	0.188	−0.29	−0.719	3.324	2.51

[24] This process is denoted either as a minimum or maximum spanning tree approach, depending on the metric used to compute edge weights.

for each sovereign bond in 2024. The table shows that the average yield-to-maturity values over the year remain similar across all fixed-income instruments. The lowest average yield to maturity is for Germany, 2.341, which is reflective of German bonds being considered a "safe-haven" instrument and a benchmark bond for the eurozone. Conversely, the average yield to maturity is highest for Italy, 3.705, which also has the highest volatility value, 0.194. The volatility for bonds from Ireland and Spain is also relatively high.

Sovereign Bond Correlations

We provide a heatmap of the correlation between sovereign bonds, where correlations are calculated with daily yield-to-maturity values over the January to December 2024 period (**Exhibit 8**). Across all bonds, we find a high correlation between sovereign bonds, reflecting the financial dependencies between eurozone countries. The high correlation is reflected in the correlation values of Austria and Finland and of Austria and the Netherlands, where correlation values between sovereign bonds are equal to 0.99, suggesting almost perfect positive correlation. There are entries in the correlation matrix where correlation values between sovereign bonds are high but not almost perfectly positively correlated, as observed between Germany and Italy, where the correlation value between the daily yield-to-maturity values of sovereign bonds is equal to 0.74. Note that while we identify high correlations among different bonds, not all correlations will be included in the network analysis; we include only a subset of correlations as part of the spanning tree.[25]

Exhibit 8. Correlation Heatmap of Daily Bond Yields

	AUT	BEL	DEU	ESP	FIN	IRL	ITA	NLD	PRT
AUT	1.00	0.97	0.96	0.95	0.99	0.98	0.88	0.99	0.95
BEL	0.97	1.00	0.97	0.90	0.98	0.95	0.81	0.98	0.89
DEU	0.96	0.97	1.00	0.86	0.96	0.96	0.74	0.98	0.87
ESP	0.95	0.90	0.86	1.00	0.95	0.93	0.97	0.91	0.98
FIN	0.99	0.98	0.96	0.95	1.00	0.97	0.88	0.99	0.95
IRL	0.98	0.95	0.96	0.93	0.97	1.00	0.83	0.97	0.94
ITA	0.88	0.81	0.74	0.97	0.88	0.83	1.00	0.82	0.94
NLD	0.99	0.98	0.98	0.91	0.99	0.97	0.82	1.00	0.91
PRT	0.95	0.89	0.87	0.98	0.95	0.94	0.94	0.91	1.00

[25] If numerical algorithms for correlation network construction are used, then the potential error should be considered if correlation values are high between securities where a unique network is not formed.

Spanning Tree

Using a spanning tree approach, a minimum number of correlations between assets with the highest magnitude is chosen, where each asset has an associated correlation with another asset in the portfolio. The subset of correlations can be described under a network, where nodes represent assets and correlations represent edges connecting those nodes. We provide further details on how the network topology of the correlation spanning tree can be used to inform constraints on portfolio weights in the minimum-variance optimization approach to improve portfolio robustness.

In the minimum-variance optimization approach, the portfolio variance is calculated by the correlations in the yield to maturity, the volatility of these yields, and the portfolio weights assigned to each bond. The portfolio variance increases as correlation values and portfolio weights of assets associated with these correlations increase. While applying the optimization approach, portfolio weights are calculated by accounting for all correlation values between assets, even if these correlations arise from noise in the data. To address this issue, we focus on the subset of correlations identified under a spanning tree, where we can decrease overfitting under the optimization approach by controlling for portfolio weights based on the most "significant" correlations—specifically, correlations between assets we believe could lead to an increase in portfolio risk over time.

However, because all assets are represented in the spanning tree, we cannot account for all correlations in the spanning tree by decreasing the portfolio weights of all assets, because this would violate other constraints in the portfolio optimization approach. We therefore need to prioritize the decrease in portfolio risk for some of the correlations in the spanning tree. Hence, we choose a subset of assets that are the most interconnected in the spanning tree—specifically, nodes with the most edges. With edges representing correlations between assets, the greater the number of edges associated with this subset of assets, the greater the ability to lower the portfolio risk from these correlations in the minimum-variance optimization.

To identify these assets with a high number of correlations in the spanning tree, we rely on centrality metrics. Centrality measures how connected a node is to other nodes. For the spanning tree, the more central an asset is, the more correlations it has with other assets and thus the larger its influence on portfolio variance. Hence, reducing the weight of such assets decreases the contribution of spanning tree–selected correlations to portfolio risk.

While centrality can be defined in multiple ways, we use eigenvector centrality (defined in the glossary). The eigenvector centrality represents how central a node is to other nodes, accounting for the centrality of those nodes, where at equilibrium, the eigenvector centrality of a node accounts for the centrality of all other nodes in the network. The eigenvector centrality differs from other measures (such as degree centrality) that account for only first-order connectivity.

To illustrate this approach, consider a portfolio of four bonds. In the minimum-variance optimization, where no spanning tree constraints are applied, assume for this portfolio that the optimal weights are evenly distributed across all four bonds (0.25, 0.25, 0.25, 0.25), with the first entry representing Bond 1, the second entry representing Bond 2, and so forth. Now, suppose from the spanning tree, constructed from correlations with high positive magnitude, we find that Bonds 1 and 2 are the most central. To limit the portfolio variance from correlations with Bonds 1 and 2, we impose an upper bound constraint of 0.2 on their combined weight. This means that, subject to all other constraints, no more than 20% of the portfolio can be allocated in total to Bonds 1 and 2. The maximum allocation of portfolio weight to Bonds 1 and 2 reduces the increase in portfolio risk from correlations associated with Bonds 1 and 2. The choice of 0.2 (i.e., 20%) is illustrative; in practice, the bound would depend on the magnitude of correlations and the network topology of the spanning tree.

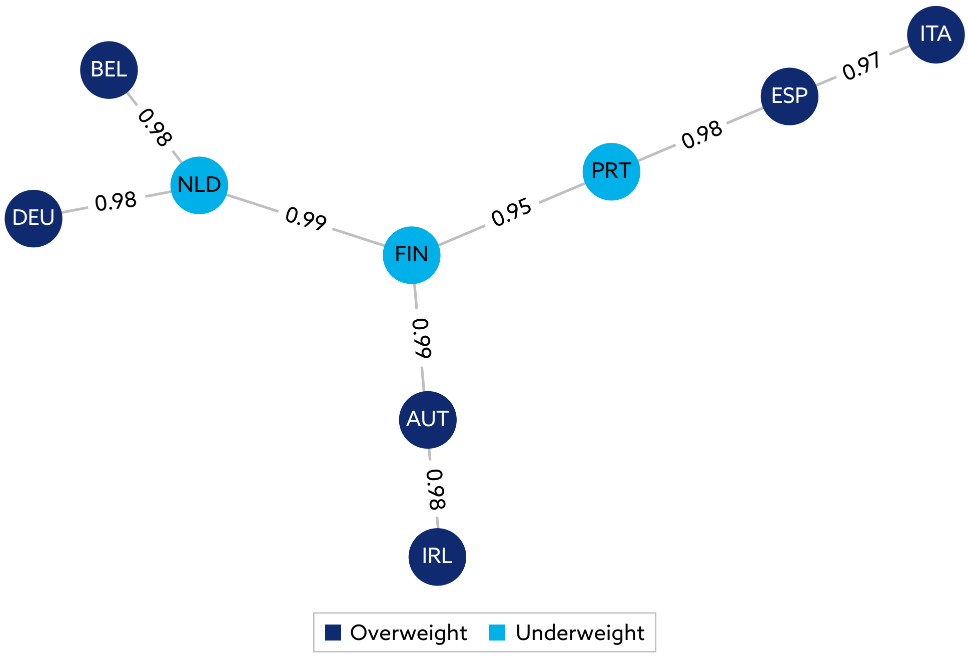
Establishing an upper bound of 0.2 on Bonds 1 and 2 leads to a corresponding lower bound constraint of 0.8 on the combined weights of Bonds 3 and 4, ensuring that at least 80% of the portfolio is allocated to them. Because the total portfolio weight must equal 1 under the minimum-variance optimization approach, any upper bound on one set of bonds necessitates a lower bound on the complementary set. This lower bound ensures a minimum allocation to Bonds 3 and 4.

With these spanning tree–informed constraints, one feasible allocation could be (0.1, 0.1, 0.4, 0.4). Other allocations, such as (0.2, 0.0, 0.8, 0.0), also satisfy the constraints. Crucially, across all feasible solutions, the constraints reallocate portfolio weights away from the most central, highly correlated bonds—here, Bonds 1 and 2, whose total weight decreases relative to the unconstrained (0.25, 0.25, 0.25, 0.25)—and toward less central, less correlated bonds (here, Bonds 3 and 4, whose weights increase). If applied in practice, the number of bonds subject to upper bound constraints should be calibrated through backtesting to ensure portfolio robustness.

Exhibit 9 shows which assets to apply either an upper or lower bound constraint on. We designate assets (light blue nodes) with an upper bound constraint as being underweighted, as the associated portfolio weights for this set of assets are lower with the spanning tree–informed constraint. For all other assets (dark blue nodes), we designate assets with a lower bound constraint as being overweighted, with higher portfolio weights under the portfolio optimization. We use our centrality metric to determine these constraints. Specifically, we include assets in the upper bound constraint if the total normalized eigenvector centrality sum of assets exceeds 0.5, representing (light blue) nodes where at least 50% of the network centrality is contained.[26] All other nodes are therefore subject to the lower bound constraint.

[26] This assumption can be adjusted to include nodes where 40% or 80% (for example) of the centrality is represented.

Exhibit 9. Correlation Spanning Tree of 10-Year Sovereign Bonds



In Exhibit 9, we can identify small clusters of connected assets, where these connections can be related to financial and economic similarities. For example, we find Austria, Finland, and the Netherlands are interconnected in the spanning tree; these countries have relatively low fiscal debts. We also find that Spain and Italy are connected; both of these countries have relatively high debt-to-GDP ratios.

Based on eigenvector centrality, as Finland, the Netherlands, and Portugal are the most central in the network, and as part of a portfolio optimization approach, an upper bound on the total portfolio weight would be applied to these assets; a lower bound constraint would be applied on all remaining assets. Applying an upper bound constraint to portfolio weights for Finland, the Netherlands, and Portugal in the portfolio optimization problem would have the largest impact on decreasing the total portfolio risk because the assets accounting for 50% of the centrality are associated with 75% of the total number of correlations in the spanning tree. However, the difference in the correlation magnitude of these edges compared with periphery node edges is small because correlations were chosen from a set of correlation values that are high, on average. In this regard, the difference in the change in portfolio weights based on correlations under the spanning tree would be small. Using network approaches, we can establish additional constraints for the minimum-variance portfolio optimization, addressing potential overfitting issues that may arise.

Other Considerations

Here, we highlight several points relating to network analysis for portfolio allocation that did not appear in our results. The first is short selling, where network methods can inform negative correlations. Short selling can increase the value of the portfolio. In the case of two assets that are negatively correlated, by observing the historical data on yield to maturity, the asset for which there is a decrease in yield to maturity over time can be longed (positive asset allocation weighting) and the asset for which there is an increase in yield to maturity over time can be shorted (negative asset allocation weighting). However, increasing the range of weights can increase portfolio variance and risk, where losses can be unbounded. Hence, extensions to short selling would require more detailed analysis and backtesting to build effective long-term strategies.

In our case study, we use a one-year horizon of daily yield-to-maturity values for sovereign bonds. However, correlations can vary significantly depending on the length and frequency of the observation window (e.g., daily, weekly, or monthly). Shorter windows may capture more timely dynamics but risk producing unstable correlations, particularly during periods of market stress. In contrast, longer windows provide stability but may smooth over temporal changes that are important for portfolio risk management. Thus, the appropriate time window should reflect both the type of assets in the portfolio and the investment horizon, which ultimately are at the discretion of the portfolio manager.

Another consideration is the choice of method used to construct the network. A spanning tree method was used in this example, where the minimal amount of information was such that all nodes representing assets were connected through correlations. However, the minimal information may not encompass all the relevant information, where one could argue that key information on correlations between assets was missing from the network. Hence, how informed network constraints perform under portfolio optimization and out-of-sample data will vary depending on the assets and the methodology used to construct the correlation network, which should be tested.

We motivate the use of networks for asset allocation under a minimum-variance optimization problem, where networks serve as a constraint on portfolio weights. However, the use of minimum-variance optimization has limitations, including the objective for asset allocation, which accounts for only the portfolio risk and how such risk is defined (i.e., only the portfolio variance). In this regard, other approaches that do not depend only on historical information or objectives that account for other criteria for portfolio allocation (e.g., ESG considerations) could also be included in the network approach.

Finally, we assume in this analysis that the portfolio is self-financing, with a margin equal to 100% of the portfolio value with no portfolio leverage. However, borrowing on margin can significantly increase portfolio leverage, in addition to taking short positions. Such financing conditions will require further constraints on the risk side in asset allocation, accounting for correlations across all assets that can increase portfolio risk.

CONCLUSION

This report reviewed a foundational shift in how capital markets can be understood and analyzed using the lens of complex systems. Traditional financial paradigms—rooted in neoclassical economics, equilibrium-based models, and assumptions of fully rational agents—often prove inadequate in capturing the dynamic, nonlinear, and interconnected nature of contemporary financial systems. In contrast, complexity science offers a robust and interdisciplinary framework capable of addressing these limitations by foregrounding emergent phenomena, adaptive behavior, feedback dynamics, and systemic interdependencies.

Integrating such tools as agent-based modeling and network analysis into portfolio management and risk management provides both theoretical depth and practical utility. These methodologies enable practitioners to simulate heterogeneous agent behavior, model contagion pathways, identify structural vulnerabilities, and assess resilience in the face of exogenous and endogenous shocks. Such approaches are increasingly relevant for understanding and managing systemic risk, forecasting regime shifts, and designing investment strategies responsive to evolving market environments.

The complex systems perspective presented in this report aligns with existing and emerging investment frameworks, including multifactor strategies, TPA, and systems-level investing—the latter emphasizing the interconnectedness between financial returns and the broader socioeconomic and environmental systems within which markets operate. However, adopting a complex systems approach is not just a methodological enhancement but also constitutes a paradigmatic shift with significant implications for portfolio construction, risk management, regulatory oversight, and long-term capital stewardship. The full range of implications extends well beyond the scope of this report.[27] Yet, we hope it is clear that acknowledging capital markets as complex systems demands shifts in how we think about investments, investors, and risk. As such, if we fully adopt a systems perspective, new models will be needed that challenge inherited assumptions and embrace the complexities of our current and future world.

The introduction of complex systems into investment management represents a timely evolution. By transitioning to a new analytical framework, investment professionals and policymakers can be further equipped to navigate uncertainty, anticipate structural transformations, and contribute to collectively developing more resilient and adaptive financial systems.

[27] For a more detailed account, see Bookstaber (2007) and Farmer (2024).

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APPENDIX A. A BRIEF HISTORY OF COMPLEX SYSTEMS IN FINANCE

While complex systems analysis is not new, its evolution has taken many paths, intersecting with economics and finance at multiple points. Understanding this history can illuminate how we arrived at current practices and where we might be headed.

Early Insights from Mathematics and Physics (1950s–1960s)

What would become complex systems theory was in its infancy with such researchers as applied mathematician Norbert Wiener (1948), who focused on early cybernetics, and biologist Ludwig von Bertalanffy (1968), who introduced general systems theory (GST).[28] Along with other contributors, systems approaches spread across such disciplines as engineering, physics, biology, and psychology (see van der Leeuw 2019).

At the same time, approaches used to study particle motion and geometric features of nature were applied to financial markets, with Maurice F. Osborne (1959) applying Brownian motion[29] to stock prices and Benoît Mandelbrot (1963) applying fractal geometry to price movement self-similarity across time scales. While Osborne's work reinforced the random walk hypothesis and the development of the Black–Scholes option pricing model, which dominated financial theory for decades, Mandelbrot's analysis suggested that markets are nonrandom and non-Gaussian and retain memory effects, an early indicator that finance could be understood through complexity science.

Complexity Science Meets Financial Markets (1970s–1980s)

Complex systems theory continued to develop in such fields as physics and ecology, where researchers studied how interactions among components within a system could lead to emergent, unpredictable behaviors. These developments were slowly introduced to economics and finance. Key early work came from such researchers as mathematician E. C. Zeeman (1974), who introduced catastrophe theory to model sudden market transitions, arguing that investor sentiment shifts could drive abrupt crashes.[30]

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[28] GST refers to a general science of fundamental principles governing the origin, function, and maintenance of natural and social systems (Issitt 2024). GST emphasizes the study of systems as a whole and identifying how the underlying behaviors of interconnected elements generate isomorphisms and emergent properties across different levels of the system (Hofkirchner and Schafranek 2011).

[29] Such application of Brownian motion can be traced further back to the seminal work of Louis Bachelier (1900).

[30] Catastrophe theory is a mathematical framework used to describe discontinuous transitions between the states of a system, given smooth variation of the underlying parameters (Roopnarine 2008).

In 1984, the Santa Fe Institute (SFI) opened as a hub for complexity research. Economists, physicists, and biologists, such as Murray Gell-Mann, John Holland, and W. Brian Arthur, collaborated at SFI to model financial markets as complex adaptive systems. Scheinkman and LeBaron (1989) applied nonlinear dynamical methods to financial time-series data, identifying nonrandom, nonlinear dependencies in stock returns.

By the end of the 1980s, the overlap of complexity and finance had gained momentum on two fronts. First, SFI and other institutions fostered conferences and books, such as *The Economy as an Evolving Complex System* (Anderson, Arrow, and Pines 1988), where economists and physicists exchanged ideas. Second, a growing body of empirical work hinted that markets might exhibit complex system dynamics, including nonlinear feedback patterns. The stage was set for rising interest in the 1990s as computing power and interdisciplinary collaboration grew.

Finance Begins Embracing Complex Systems Frameworks (1990s–2000s)

The 1990s witnessed a convergence of complexity and finance in multiple areas. Economists began to build computational models of markets as evolving ecologies of agents, an example of which is SFI's "artificial stock market" (Ehrentreich 2008). Using agent-based modeling, researchers simulated a market in which heterogeneous, adaptive agents traded with each other. They found that as the model ran, agents produced unpredictable outcomes not captured by traditional equilibrium models but reminiscent of the emergent behavior of financial markets, such as periodic bubbles and crashes, herd-driven volatility clusters, and regimes of high and low volatility. These features arose endogenously and illustrated that markets naturally self-organize into complex, nonequilibrium states.

At the same time, physicists brought a data-driven, "law-finding" approach, treating markets like physical systems to be empirically studied. The growing influence of physics into economics took shape as "econophysics"—a term coined in the mid-1990s to describe the trend. Physicists such as Rosario Mantegna and H. Eugene Stanley (1999) applied methods from statistical mechanics to asset prices and other financial data. Although mainstream economists had previously adopted some computations from physics (e.g., Brownian motion, mentioned previously), a common belief among econophysicists was that standard economic theory was unable to explain the non-Gaussian (i.e., heavy-tailed) distributions of empirical market data (Rosser 2021, pp. 69–70). Econophysicists confirmed and extended Mandelbrot's earlier observations, identifying heavy tails and other scaling phenomena across individual stocks, stock indexes, and company size growth rates (Stanley, Amaral, Canning, Gopikrishnan, Lee, and Liu 1999). Researchers also discovered long-range correlations in volatility and clustering of market activity, suggesting self-organizing behavior. While these ideas did not immediately hit mainstream economics, they planted seeds for future quantitative finance techniques.

In the 2000s, complex systems approaches to finance gained practical relevance. Researchers began applying concepts of self-organized criticality, examining whether markets operate near critical points (Johansen, Ledoit, and Sornette 2000). Around the middle of the decade, some economists and policymakers acknowledged the growing complexity of financial systems, driven by exotic derivatives, global banking networks, and algorithmic trading. A few stakeholders warned that this complexity posed systemic risks (see Bookstaber 2007; Buffett 2003; Haldane 2009; May, Levin, and Sugihara 2008). The 2008 GFC solidified attention to complex systemic risk. The crisis unfolded as a network cascade in which feedback loops and interbank failures amplified shocks—dynamics traditional risk models failed to capture. Instead, such concepts as network contagion, heavy-tail risk, and adaptive behavior were introduced. By the end of the decade, financial markets were increasingly recognized as a deeply interconnected complex system, necessitating new analytical tools to understand and mitigate systemic risk.

Contemporary Developments and Advanced Applications (2010s to Present)

Following the GFC, additional economists and regulators adopted complexity science concepts, such as “tipping points,” “networks,” “feedback,” and “resilience,” though complexity science’s quantitative and modeling tools remained underutilized (Battiston et al. 2016). Stakeholders such as Andrew Haldane, chief economist at the Bank of England (from 2014 to 2021), and John Rutledge, chief investment strategist at Safanad (a global principal investment firm), called for real-time “financial weather maps” (weather patterns are classic examples of complex systems) to dynamically track systemic risks (Nordrum 2016; Rutledge 2020). In recent years, complex systems theory in finance has been further bolstered by advances in computing and data. The rise of big data and machine learning enabled the calibration of more sophisticated models that capture nonlinear relationships and emergent patterns.[31]

The COVID-19 pandemic in 2020 further highlighted the need for complex systems approaches. Researchers have been working on models that integrate epidemiological dynamics with economic networks to understand how such events as a virus outbreak can trigger a financial crisis via behavioral responses and policy reactions.

There is also growing interest in multilayer network models, where different network layers might represent financial, supply chain, and information links simultaneously (Pacelli 2025). These models can help capture how a shock in one domain (e.g., a disruption in trade networks) can compound with shocks in another (financial networks).

[31] For example, reinforcement learning algorithms (a type of machine learning) are now used in adaptive trading strategies, effectively allowing trading agents to learn and evolve in response to market feedback. Such algorithms echo the idea of markets as complex adaptive systems: They do not assume a static optimal strategy but, rather, continually adapt to new data.

APPENDIX B. COMMON MODELING TECHNIQUES FOR COMPLEX SYSTEMS

Systems scientists use multiple techniques to analyze complex systems. This report focuses on ABMs and network theory models. Other notable models include nonlinear dynamical systems modeling and system dynamics or causal loop diagrams. Importantly, no model will provide a complete picture of a complex system, and different techniques will be better at capturing certain system features over others. For example, ABMs capture heterogeneous agents and interaction dynamics, whereas network theory focuses on network structure. Likewise, other models are useful in cases of highly nonlinear phenomena (i.e., sensitive to initial conditions) or to qualitatively identify feedback loops within a system. The technique selected will depend on the functional purpose of the study and what aspect of market phenomena one wishes to capture. While these models are not exhaustive of the full range of tools used by systems scientists, they demonstrate additional methodologies used in investigating different features of complex systems.

A dynamical systems model is one that evolves over time according to rules expressed as mathematical equations (primarily differential equations; see Ackley, Lessler, and Glymour 2022). Model formalizations are represented as vectors across a phase space, S, capturing all possible states of the system across time, t, which may be continuous or discrete (Boccara 2010). The evolution law(s) determines the state of the system at a point in time based on previous states of the system.

For example, a formal dynamical systems model would consist of the following:

- A set of state variables describing the system at time t (e.g., price, volatility, interest rate)
- An evolution law that tells you how those state variables change from t to $t + 1$, generally written as a differential function
- Additional parameters and external inputs

A nonlinear dynamical system is one in which the evolution rules are nonlinear such that they produce disproportionately large or complex responses to small changes in initial conditions or parameters. Nonlinearity is a key ingredient for modeling such phenomena as chaos (sensitive dependence on initial conditions) and complex oscillatory behavior. Analysts might study trajectories through the phase space to identify attractors (states or cycles the system gravitates toward) or repellers. In finance, dynamical systems theory can be used to model business cycles, asset price dynamics, or other time series where feedback loops exist.

Likewise, based on the concepts of cybernetics, Jay Forrester of MIT developed system dynamics techniques to model the interactions within systems (Hester and Adams 2014, p. 53). Unlike dynamical systems modeling, which is centered on formalized mathematical models, system dynamics is an approach used to represent high levels of aggregation, focusing on interrelationships and feedback loops between stocks (entities that accumulate or deplete) and flows (rates of change) within a system. Causal loop diagrams are the main analytical tool used to capture system dynamics, usually represented through arrows between system components. Relationships depicted in causal loop diagrams may be defined by mathematical equations derived from systematized data, though they are often derived from qualitative sources. (See **Exhibit B1** for a comparison of four common modeling techniques used in complex systems analysis.)

Exhibit B1. Complex Systems Modeling Techniques

	What Is It?	What Aspects of Complex Systems Are Emphasized?	Challenges
Agent-based models	Simulations of autonomous agent interactions that affect the system as a whole	Heterogeneous adaptive agents, emergence, self-organization	Computational requirements; sensitive to assumptions; difficulties calibrating and evaluating
Network theory and graph models	Representations of interconnected or dependent entities along with relative strength of connections	Interconnected networks	Real connections in data are dynamic; parameters must be inferred from data; can be challenging to translate into actions
Nonlinear dynamical systems modeling	Vectors across a possibility space that mathematically represent states of the system as it evolves	Emergence, nonlinearity, and regime shifts	Model specifications may not be obvious from the data; does not provide neat analytical solutions; can be hard to interpret
System dynamics and causal loop diagrams	Diagrams of causal flow within a system	Feedback loops and interconnected networks	Uses aggregated metrics; parameters difficult to estimate; risk of oversimplification

GLOSSARY

Adaptive agents: Market participants who respond to each other's behavior and environmental conditions as they evolve.

Agent-based models (ABMs): Computational models that simulate the interactions of autonomous "agents" to assess their effects on the system.

Bounded rationality: Individuals aim for satisfactory solutions rather than optimal ones, given cognitive and information limitations (Simon 1955).

Closeness centrality: The measure of centrality of a node defined in terms of the average distance of the node to all others (Rodrigues 2018).

Conditional value at risk (CoVaR): Captures the VaR of the financial system "conditional on institutions being under distress" (Adrian and Brunnermeier 2008, p. 1).

Contagion: When the instability of an institution (e.g., an instrument, market, sector, or infrastructure) spreads to other parts of the financial system, producing negative effects throughout the system and instigating a systemwide crisis (Smaga 2014, p. 11).

Econobiology: Also called "evolutionary economics"; an application of complex systems to financial markets that uses lessons on complexity from evolutionary biology to understand economic and market behavior (Rickles 2011).

Econophysics: An application of complex systems to financial markets inspired by complexity frameworks and statistical modeling in physics and applied to economic and market behavior (Rickles 2011).

Eigenvector centrality: A measure of a node's centrality given the centrality of its neighbors (Konstantinov and Fabozzi 2025).

Emergence: Higher-order features or patterns arise from lower-level interactions.

Expected shortfall (ES): The tail conditional expectation by integrating all losses with low probabilities across the distribution tail (Hoffmann 2017).

Graph models: Network representations that consist of nodes (vertices) and links (edges) connecting nodes; used in network analysis.

Marginal expected shortfall (MES): A financial institution's "losses in the tail of the aggregate sector's loss distribution" (Acharya et al. 2017, p. 3).

Networks: Webs of relationships through which entities or agents are linked; a network view looks at how connections between entities/agents transmit and in some cases amplify shocks.

Network theory: An area of mathematics used to analyze relationships and interactions of interconnected entities (Konstantinov and Fabozzi 2025).

Nonlinearity: A property of a system in which the output is not proportional to the input; small changes can have outsized effects.

Resilience: The capacity to absorb shocks and reorganize; how a system's interconnected relationships and structural vulnerabilities might mitigate shocks.

Self-organization: Structure or order can emerge from the bottom up; lower-level activity creates patterns at higher levels.

Stylized facts: A set of properties common across many instruments, markets, and time periods and observed by independent empirical studies, which any theory of markets should explain (Cont 2001).

Systematic risk: Broad market risk that cannot be diversified away.

Systemic risk: "A risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy" (Caruana 2010).

Value at risk (VaR): "A measure of the size of the tail of the distribution of profits on a portfolio or for an organization" (Chance and Edleson 2024, p. 31).

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