INDUSTRY FUTURE

CFA Institute
Research & Policy Center

Artificial Intelligence and the Future of Finance: A Framework for Structural Change

Mona Naqvi

Introduction

Since the rise of modern capital markets, finance has been organized around informational scarcity. In every area, from competitive advantage to price discovery and fiduciary responsibility, success depended on who could access, interpret, and act on information with greater precision and speed than other market participants. This organizing logic has shaped how markets function, how investors allocate capital, and how professional judgment is exercised.

Artificial intelligence (AI) is redefining this logic. As analytical capability scales and becomes embedded across markets, the scarcity assumptions that underpin the financial system are being reconfigured.

A structural transition is underway in how information is generated, processed, and acted upon across the capital markets ecosystem. The implications extend beyond productivity gains and reach into price formation, capital allocation, and the integrity and stability of the financial system itself. The key question, therefore, is not whether AI adoption will continue but *how* capital markets will reorganize as AI becomes increasingly abundant, automated, and embedded in investment decision-making.

This paper provides an organizing framework for understanding the pathways and channels through which AI is reshaping capital markets and surfaces strategic questions facing the investment industry. In doing so, it lays the foundation for the CFA Institute Research and Policy Center AI agenda. It is targeted at senior leaders in institutional investment organizations responsible for investment strategy, portfolio construction, capital allocation, and AI integration.

July 2026

CONTENTS

Technological Turning Points in Capital Markets

Major economic transitions have been driven by general-purpose technologies that redefined the sources of value creation and the mechanisms by which markets price and allocate capital. As markets evolved from agrarian economies to industrialization to the digital age, each transition created not incremental efficiency but structural reallocation. With each major shift, productivity gains were uneven and competitive advantages were redistributed. These inflection points generated both growth and displacement in market economies, concentrating advantage in new infrastructures and capabilities. Governance followed, often belatedly, as markets recalibrated around new foundations.

The current transition to AI belongs in this lineage but differs in important respects. AI not only automates tasks but alters how judgment itself is formed and exercised in capital allocation. The deeper issue is not technology, per se, but the assumptions and norms that organize around its use: how information is priced, how risks are managed, how skill is identified, and how accountability is assigned. Such principles are reflected in prevailing tenets from modern portfolio theory (MPT) to the efficient market hypothesis, collectively shaping performance measures, incentives, and institutional design. But when the mechanisms informing judgment fundamentally change, the assumptions that sustain these tenets inevitably come under review.

AI in Context

AI is neither monolithic nor new to modern finance. Quantitative models, algorithmic trading systems, and machine learning techniques have been embedded in investment processes for decades (López de Prado 2018). What distinguishes the current phase is the scale, adaptability, and generality of analytical capability through AI. Recent advances reflect the convergence of breakthroughs in model architecture, data availability, and computational capacity. Systems can now ingest vast volumes of unstructured information, generate structured analysis, and operate across multiple cognitive tasks that were once considered distinctly human.

Unlike earlier task-specific systems, many contemporary AI models are increasingly general-purpose, capable of transferring knowledge across domains and interacting with external tools and workflows. So-called agentic systems are also emerging that can interact with external tools and perform multi-step processes with varying degrees of autonomy within defined parameters. The widespread availability of AI models, along with the ability to scale human capacity with agentic systems, reduces barriers to entry for firms and creates opportunities to reshape competitive dynamics across industry segments, including within financial services.

Nevertheless, experts remain divided on the long-term trajectory of AI. Some anticipate the emergence of artificial general intelligence (AGI), defined as systems capable of performing a broad range of cognitive tasks *at or beyond* human levels, within years or decades. Others predict more gradual evolution, with capabilities remaining specialized but still powerful. These uncertainties reflect genuine constraints: Scaling advanced models depends on access to high-quality data, specialized hardware, energy-intensive compute infrastructure, and sustainable economic incentives. Yet, across credible trajectories—whether toward highly capable but specialized systems or more generalized intelligence—one conclusion remains consistent: Analytical capacity is scaling at a pace and magnitude that will materially reshape decision-making environments within the professional lifespan of today's investment practitioners (Kaplan et al. 2020; Bengio et al. 2024).

A Framework for Navigating Structural Change

Notwithstanding the arrival of AGI, the capability improvements occurring through AI technology, combined with institutional adoption and competitive pressures throughout the investment industry, can generate structural shifts in the world of finance. Markets respond to incentives, cost structures, and relative advantages. The relevant question for capital markets is not *whether* or *when* an AI-related milestone will occur. Instead, the question is how scaled analytical capability may fundamentally alter professional norms, competitive dynamics, and systemic risk.

Rather than attempt to resolve debates over AGI timelines or technological end states, this paper examines the structural forces already in motion and their implied trajectories. This approach enables market participants to prepare for multiple potential future scenarios in the financial industry.

Structural transitions are inherently path dependent and shaped by both institutional and professional responses. Early decisions about governance design, professional standards, and institutional architecture can materially influence competitive positioning and system resilience. The framework presented here combines structural force analysis with scenario logic, drawing on push–pull dynamics from innovation economics and path dependence from institutional theory. Its goal is to equip investment professionals to engage with structural change deliberately—before adaptation becomes reaction.

Core Assumptions Under Pressure

As AI alters the conditions under which information is produced and acted upon, the doctrines built around those conditions come under strain. Of course, the theoretical foundations that anchor modern finance did not emerge absent technology. Indeed, markets have long incorporated tools for calculation, modeling, and execution—from early computational devices to more recent algorithmic systems and high-frequency trading infrastructure. The key distinction now, however, is that although prior analytical capacity remained constrained by human direction, interpretation, and oversight, today's advances in AI meaningfully alter the scale, distribution, and autonomy of analytical capacity in finance. As this capacity increases, the boundary conditions under which existing theories operate could shift.

Today, the investment profession is guided by five prevailing tenets that frame behaviors and institutional design: informational efficiency, diversification and risk premia, skill and persistent outperformance, accountability and fiduciary responsibility, and market structure and systemic interaction.

Informational Efficiency

The efficient market hypothesis (EMH) holds that asset prices reflect available information (Fama 1970). It has never implied perfect rationality or the absence of asymmetry. Markets have always contained informational imbalances, behavioral biases, and episodes of mispricing. Yet competitive pressures, arbitrage activity, and institutional learning have historically worked to incorporate new information into prices over time and limit opportunities for alpha generation.

AI alters the scale and speed at which information is processed and disseminated. As analytical systems generate, filter, and prioritize signals across large segments of the market, the dynamics of information integration shift. Inefficiencies will not likely disappear; instead, the question is whether and how their character and persistence may change under conditions of scaled intelligence.

Diversification and Risk Premia

MPT assumes that diversification across imperfectly correlated assets reduces volatility and that risk is compensated through identifiable premia (Markowitz 1952; Sharpe 1964). Correlation regimes, however, have never been static. Market stress, liquidity shocks, and macroeconomic cycles have historically altered cross-asset relationships. AI may influence these dynamics by accelerating signal diffusion and the timeframes through which these dynamics manifest, encouraging convergence around similar predictive architectures. Diversification continues to function, but the drivers

of correlation and the structure of premia evolve as capital flows become increasingly model mediated.

Skill and Persistent Outperformance

Active management has long relied on the premise that differentiated judgment predicated on superior information can produce persistent excess returns—a premise that has always been contested (Carhart 1997; Fama and French 2010). Even today, informational advantages decay and competitive pressures compress margins, and outperformance has historically proven difficult to sustain. AI proliferation does not eliminate the possibility of investor skill, but it may alter how and where such skill is expressed. As the cost of generating structured analysis declines and analytical tools become widely accessible, differentiation may depend less on information production and more on system design, data governance, model oversight, and institutional integration (Vayanos and Woolley 2013). In other words, persistent alpha, if it exists, may take different forms.

Accountability and Fiduciary Responsibility

Financial markets at their core depend on identifiable agents who can articulate the rationale behind investment decisions and be held accountable for their consequences. Fiduciary duty presumes that responsibility can be traced to human judgment and institutional process. Although technology has long supported decision-making, ultimate authority and accountability have thus far remained human-centered. As analytical systems become partially autonomous and more deeply embedded with AI tools, the distribution of responsibility may become more complex. Hybrid decision environments do not remove accountability, but they do require clear delineation of oversight, validation, and governance to preserve stakeholder trust.

Market Structure and Systemic Interaction

Capital markets have always exhibited feedback loops, liquidity cycles, and shifting correlation regimes. Episodes of stress have revealed fragilities, and convergence around similar strategies has periodically amplified volatility (Brunnermeier 2009; SEC and CFTC 2010). Market structure has never been static, and systemic risk has never been absent.

AI may influence these dynamics by accelerating signal diffusion and increasing the likelihood of convergence around similar analytical architectures. For instance, if large segments of capital rely on overlapping models trained on similar data, feedback loops may intensify and exacerbate liquidity dynamics such as herding and momentum. Such dynamics may evolve more rapidly than before, amplifying risks. Will the mechanisms that previously moderated convergence operate in the same way under conditions of scaled and increasingly automated analysis (Daníelsson and Uthemann 2025)?

Implications for the Future

Together, these pressures signal not the collapse of the industry's intellectual foundations but rather a reconfiguration. Although the doctrines of modern finance endure, the scarcity conditions under which they operate do not. The concepts of informational efficiency, diversification, skill, accountability, and market stability may continue to define the system, but their expression will continue to evolve as analytical capability continues to scale and become more autonomous.

The trajectory of the industry's evolution will also not be determined by doctrines alone. It will be shaped by a complex interaction of technological capability, institutional adoption, task reallocation, and structural recomposition across markets. The more visible changes may occur in workflows and competitive dynamics. The more consequential shifts, however, may unfold more gradually, as assumptions harden or adapt beneath the surface of daily practice. It is this deeper layer of structural evolution, rather than surface-level technological change, that could shape the long-term character of capital markets.

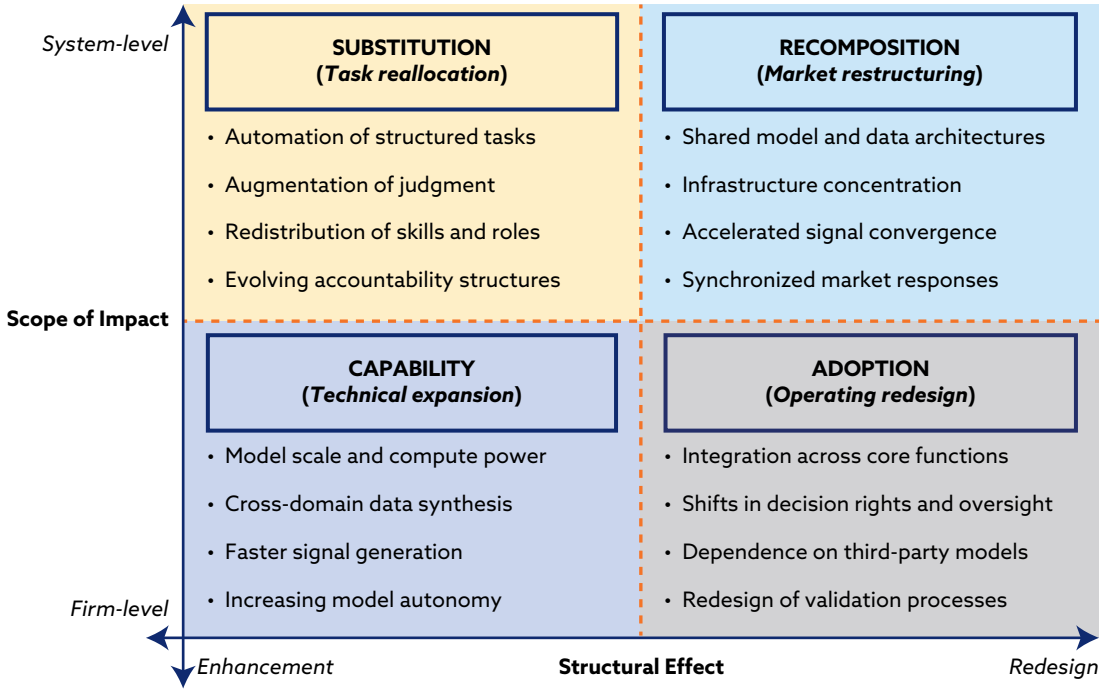
Structural Forces of AI Integration

To equip the profession with a shared vocabulary for examining this transition, we introduce the **CFA Institute Structural Forces of AI Integration** framework. This framework is organized around four interacting structural forces: *capability*, *adoption*, *substitution*, and *recomposition* (see **Exhibit 1**). Capability expands what is technically possible. Adoption determines how widely those capabilities are embedded. Substitution reallocates agency within decision systems. Recomposition reflects the cumulative market-level consequences of those shifts.

These four forces define the principal dimensions along which AI integration unfolds. Although analytically distinct, these forces intertwine to shape how analytical power scales, how institutions respond, how professional roles evolve, and how markets adapt over time. They therefore reflect how the financial system itself could evolve.

This framework seeks to isolate the mechanics of the AI transition. Subsequent sections use it to examine how varying configurations of these forces may produce distinct structural states of capital markets, place prevailing assumptions under strain, and necessitate new forms of institutional stewardship. The purpose is to clarify the forces at work, ultimately enabling practitioners, regulators, and fiduciaries to assess where pressures in the financial system are accumulating and where adaptation may be required.

Exhibit 1. The CFA Institute Structural Forces of AI Integration



Source: CFA Institute.

Interaction and Escalation Dynamics

Although distinct from each other, the four structural forces interact. Expanding technical capability enables investment firms to adopt AI more deeply. As adoption spreads, tasks are reallocated between humans and machines. When this reallocation occurs across many institutions simultaneously, market structure begins to shift. In turn, changes in market structure influence future investment decisions, governance practices, and competitive incentives. Additionally, these dynamics are not linear. Firms advance at different speeds, and technical capability alone does not ensure market transformation. Regulatory boundaries, institutional risk appetite, and professional norms will shape how far and how quickly this integration progresses. As such, the forces are better understood as a system of interacting pressures than as an inevitable sequence.

The Dynamics of AI Transition: Push, Pull, and Path Dependence

The four structural forces of AI integration presented do not advance uniformly or independently. They are governed by push and pull factors that interact to generate path dependence, to either accelerate, moderate, or redirect the trajectory of AI integration across capital markets.

Push Dynamics

Push dynamics originate from within the technology and competitive environment. Declining compute costs, expanding model capabilities, and intensifying competitive pressure create persistent incentives for both firms and individuals to deepen AI integration, regardless of broader institutional readiness. A firm that adopts more capable analytical systems gains measurable advantages in speed, cost, and scalability. This competitive logic generates adoption pressure across the industry, even among institutions that might prefer a more measured pace of integration. Left unmoderated, push dynamics create structural pressure toward convergence.

Pull Dynamics

Alternatively, pull dynamics originate from the institutional and professional environment itself and include regulatory frameworks, governance expectations, fiduciary standards, and professional norms. Collectively, they shape how far and how quickly push dynamics translate into structural change. Pull dynamics do not operate automatically but require active investment, coordination, and institutional will. Where governance frameworks are robust, where professional standards set proper expectations for model oversight and accountability, and where regulatory clarity reduces uncertainty, pull dynamics can help shape the trajectory of AI adoption, determining not only the pace of integration but also its character.

Interaction Effects

The interaction between push and pull forces generates path dependence. Early decisions about model governance, vendor reliance, infrastructure design, and professional standards constrain future options. Institutions and regulators that establish governance frameworks early tend to operate from positions of greater flexibility and resilience as integration deepens. Those that defer governance decisions until AI adoption advances further may face a more constrained set of options, inheriting structural dependencies that are difficult to unwind. Path dependence, therefore, implies that the profession's most consequential decisions may be the earlier ones that determine whether governance evolves ahead of adoption or whether firms are forced to govern a system already shaped by the choices it deferred.

These dynamics also have system-level implications. One consequence of the push–pull interaction is what this paper terms **cognitive convergence**: the progressive alignment of model architectures, training data, and decision frameworks across institutions. This convergence produces correlated analytical outputs that compress the interpretive diversity that markets rely on for resilience. The process mirrors what researchers have characterized as "monoculture risk," defined as the systemic vulnerability that arises when institutions converge on shared analytical foundations (ECB 2024; Frimpong 2026).

Alternative Future States of Capital Markets in the AI Era

The four structural forces of capability expansion, institutional adoption, task substitution, and systemic recomposition define the dimensions along which AI integration might unfold. The states that emerge are not technologically predetermined but instead reflect how push and pull dynamics interact over time, shaped by competitive incentives on the one hand and governance, standards, and regulation on the other. This section outlines four alternative future states for how these four structural forces may combine to shape competitive dynamics, market behavior, and professional practice as AI integration deepens.

Augmented Markets

AI integration enhances workflow efficiency without materially reshaping market architecture. In this state, technical capability expands significantly and adoption is widespread, yet substitution and recomposition remain contained. AI becomes deeply embedded across research, portfolio construction, and risk management as an augmentative layer rather than a structural redesign.

For asset managers, this implies productivity gains and incremental fee compression rather than existential disruption. Analytical output increases and risk management becomes more dynamic, while allocation decisions retain human oversight. Active management remains viable, though informational advantages decay as similar tools become broadly accessible. Asset owners benefit from greater transparency, faster reporting, and enhanced performance attribution, while governance frameworks remain largely unchanged.

Overall, market behavior accelerates but does not fundamentally shift. Liquidity dynamics, correlation regimes, and price discovery evolve gradually. AI strengthens resilience and operational efficiency without materially reordering capital allocation or market structure.

Competitive Divergence

Uneven AI adoption creates widening dispersion in performance, cost structure, and competitive positioning. In this state, technical capability expands, but adoption remains uneven. Firms diverge in the depth of AI integration, with some embedding it across portfolio construction, risk modeling, and trading infrastructure, while others remain constrained by legacy systems, capital limitations, or regulatory hesitation. Substitution occurs in leading institutions, without market-level recomposition. AI-leading asset managers benefit from lower marginal analytical costs and more scalable decision frameworks, while lagging firms face margin compression, talent migration, and declining relative performance.

Asset owners increasingly differentiate between AI-enabled and legacy managers, while smaller intermediaries confront strategic choices: to invest, partner, specialize, or exit. Infrastructure dependence rises but remains fragmented, while regulators observe growing disparities in operational resilience and model governance. The defining feature of this state is asymmetry. Markets do not reorganize around a shared analytical architecture, as competitive divergence reshapes the landscape.

Platform Convergence

AI capability is broadly adopted through shared infrastructure, which compresses differentiation and concentrates influence within common analytical platforms. Adoption is increasingly mediated through foundation models, centralized data, and shared compute ecosystems. Substitution expands, and recomposition begins reshaping market structure. As asset managers rely on shared model environments, convergence accelerates. Signal generation and portfolio construction standardize, informational dispersion compresses, and alpha opportunities narrow. Competitive advantage shifts toward scale, governance quality, cost efficiency, and preferential access to infrastructure. Asset owners interact more directly with centralized analytical platforms, while exchanges and data providers integrate more tightly into AI-enabled trading systems. This scenario is already visible in the growing reliance on a small number of foundation model providers and cloud-based AI platforms. Market behavior becomes more synchronized. Liquidity remains accessible, but correlations adjust more rapidly as common signals propagate across overlapping systems. Regulatory attention increasingly focuses on infrastructure concentration and systemic interdependence.

Model-Mediated Markets

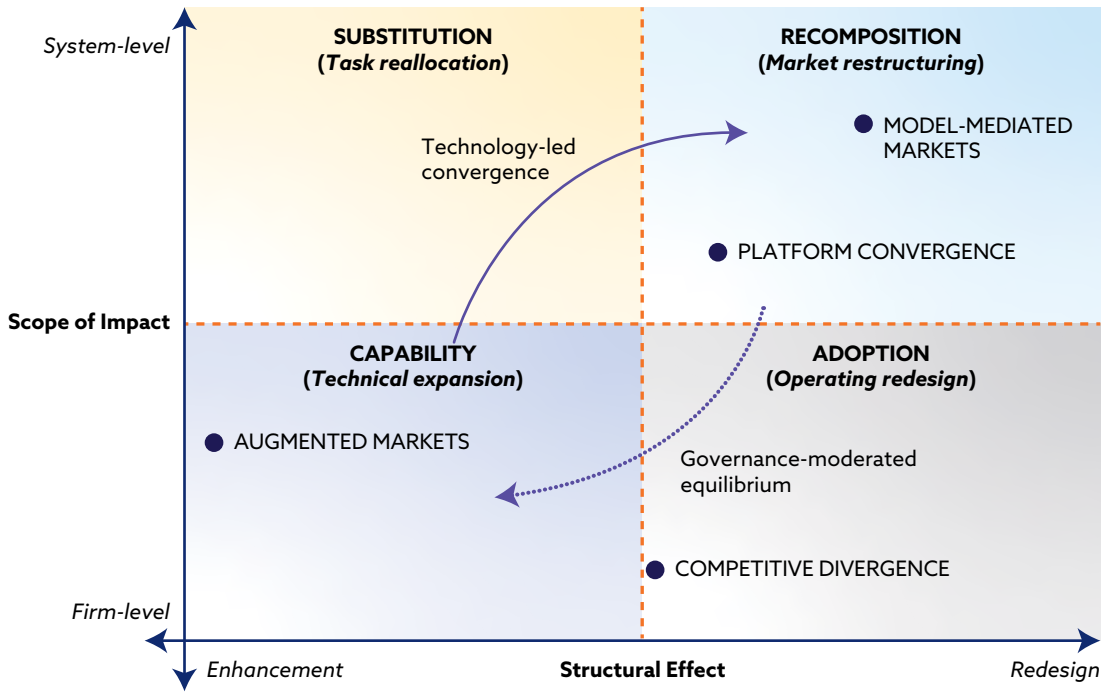
AI systems assume primary responsibility for signal generation, allocation decisions, and risk calibration across large segments of capital. Distinctions between discretionary and systematic strategies blur as portfolio construction becomes predominantly model mediated, compressing traditional informational advantages. Analytical production becomes increasingly commoditized, while governance credibility becomes a key differentiator. Asset owners rely more heavily on automated allocation frameworks and real-time diagnostics, while exchanges, clearinghouses, and liquidity providers operate within tightly synchronized environments. In such conditions, portfolio construction, execution, and risk calibration may be largely automated, with oversight focused on model governance and constraint setting. Markets become highly synchronized: Signal diffusion accelerates, correlations adjust abruptly, and informational dispersion compresses, reshaping price discovery. Systemic oversight centers on shared analytical dependencies and infrastructure resilience. Model-mediated markets represent a highly transformative configuration in the AI era, in which AI becomes embedded within market

architecture itself, reshaping how information is produced, capital is allocated, and fiduciary responsibility is exercised.

Exhibit 2 shows how each alternative state within the four structural forces framework reflects not only the level of AI integration but also the balance of forces that produced it. States toward the upper right (Platform Convergence, Model-Mediated Markets) represent configurations where push dynamics have driven integration to systemic scale, reshaping market architecture and competitive structure in fundamental ways. States toward the bottom left (Augmented Markets) reflect configurations where pull dynamics have slowed the pace and nature of adoption, preserving greater continuity. Critically, these "stages" are neither fixed nor sequential. Markets may exhibit characteristics of more than one state simultaneously, and the trajectory between them is neither linear nor inevitable.

Although no single configuration is predetermined, declining marginal analytical cost and infrastructure scale effects create structural pressure toward convergence around shared architectures, whatever they may be. Whether that convergence enforces resilience or amplifies fragility will depend on governance and professional standards. In other words, the future of capital markets will depend on the institutional and professional choices that follow.

Exhibit 2. Alternative States Across the Four Structural Forces of AI Integration



Source: CFA Institute.

Stress Testing Core Assumptions Across Alternative Future States

The alternative future states are not predictions but rather are structured environments through which the core assumptions of modern finance can be stress tested. As AI alters the scarcity conditions under which information is produced, interpreted, and acted upon, the theories and assumptions built upon those conditions reconfigure depending on how AI integration unfolds. **Exhibit 3** assesses how the foundations of modern finance are expressed under each scenario—each representing a different mix of the four structural forces of capability, adoption, substitution, and recomposition.

What the Stress Test Reveals

Across configurations, core assumptions of modern finance remain but operate under altered conditions as AI integration deepens. Informational efficiency strengthens as information is rapidly priced in, although synchronized models introduce new systemic sensitivities. Diversification remains foundational, but its reliability increasingly depends on signal diversity. Investment skill persists, shifting from information discovery toward capital allocation and system

Exhibit 3. Comparative Stress Test of Market Assumptions Under Various AI Integration Scenarios

Prevailing Assumption	Augmented Markets	Competitive Divergence	Platform Convergence	Model-Mediated Markets
Informational Efficiency	Accelerated repricing; EMH modestly strengthened	Efficiency uneven; firm-level asymmetries widen	Informational edge lessens; arbitrage windows collapse	Frictions minimal; episodic but potentially systemic mispricing
Diversification and Risk Premia	Diversification broadly reliable; premia intact	Diversification uneven across firms; premia dispersion widens	Correlations tighten with shared signals; premia reprice faster	Model-driven correlations; diversification less reliable
Skill and Persistent Outperformance	Skill augmented; alpha pressured but still viable	Alpha concentrated among AI-integrated firms	Durability of alpha lessens; execution and scale differentiate	Alpha rooted in allocation and governance quality
Accountability and Fiduciary Duty	Human-centered decision authority; oversight expanded	Governance quality uneven; accountability fragmented	Model validation central; fiduciary duty is procedural	Responsibility is diffuse; system architecture is key
Market Structure and Stability	Feedback loops stabilizing; faster adjustment cycles	Uneven resilience; consolidation pressures rise	Infrastructure concentration elevates correlated exposure	Synchronized models risk amplifying systemic shocks

governance. Accountability remains central, even as responsibility shifts from judgment toward system design and oversight. What changes across states is not the relevance of these doctrines but the scarcity conditions under which they operate. Under more moderate configurations, these assumptions bend but remain operative. In platform convergence and model-mediated markets, the conditions under which they function diverge more markedly from those in which they were conceived, with implications for how the profession understands risk, accountability, and advantage.

Structural Tensions Across Alternative Future States

Cutting across all states are five structural tensions that intensify as AI integration deepens, regardless of configuration. These tensions emerge from the interaction of the four structural forces at the level of competitive structure, institutional behavior, and systemic design. Across configurations, competitive advantage shifts from insight toward architecture, while cognitive convergence—the alignment of model architectures and decision frameworks—compresses interpretive diversity. More broadly, diversification comes under strain as correlations reflect shared signals, accountability becomes more diffuse across models and governance structures, and value creation shifts toward system design and oversight as analytical production becomes increasingly commoditized. Although firms may seek to differentiate through proprietary models and data, these efforts operate within shared technological and institutional constraints, limiting the extent to which divergence can offset broader convergence pressures. **Exhibit 4** illustrates five structural tensions that will likely shape markets in the AI era.

Exhibit 4. Structural Tensions Shaping Capital Markets in the AI Era

Structural Tension	Transmission Mechanism	Institutional Implications	Acute Scenarios
Competitive Dynamics			
Advantage shifts from insight to architecture	As analytical tools become widely accessible, the informational component of differentiation narrows, shifting emphasis toward the design, governance, and integration of the systems that deploy it.	Process quality, data infrastructure, and execution consistency become more prominent sources of differentiation alongside, and increasingly relative to, research intensity.	Competitive Divergence
			Platform Convergence
			Model-Mediated Markets

(continued)

Exhibit 4. Structural Tensions Shaping Capital Markets in the AI Era *(continued)*

Structural Tension	Transmission Mechanism	Institutional Implications	Acute Scenarios
Concentration pressure rises, even as adoption spreads	Market incentives favor shared infrastructure, channeling adoption through a small number of dominant providers and concentrating critical data, model development, and compute in ways that amplify asymmetry and systemic interdependence simultaneously.	"Cognitive convergence" introduces systemic risk for which existing regulatory frameworks have no established template. Vendor dependency and infrastructure resilience require explicit treatment as risk management priorities, not solely operational ones.	Platform Convergence Model-Mediated Markets
Cost compression accelerates, but the basis of value shifts	As analytical production costs decline, competitive pressure transfers from research output toward governance credibility, execution quality, and institutional trustworthiness, thus reshaping the bases on which mandates are awarded and retained.	Active managers face a strategic inflection: compete on scale, specialize where human judgment remains distinctive, or differentiate around governance. Fee pressure on research-intensive strategies intensifies as analytical commoditization broadens.	Competitive Divergence Platform Convergence Model-Mediated Markets
Market Structure Dynamics			
Speed and synchronization reshape market dynamics	Shared model architectures generate correlated signals that propagate simultaneously, compressing time between signal identification, portfolio response, and market-wide repricing in ways existing liquidity and circuit-breaker frameworks cannot absorb.	Infrastructure concentration risk and behavioral synchronization risk are becoming distinct regulatory disciplines. Institutions must stress test correlation assumptions under model-driven repositioning, not only under historical stress scenarios.	Augmented Markets Platform Convergence Model-Mediated Markets
Professional Dynamics			
Professional accountability becomes more contested, not less	What constitutes expertise is redefined at the same moment that responsibility becomes harder to trace. Professional standards and credentialing frameworks must evolve to reflect where human judgment remains most consequential—and most at risk of displacement.	Expertise is redefined at the same moment responsibility becomes harder to trace. Professional standards and credentialing frameworks must evolve to reflect where human judgment remains most consequential.	Augmented Markets Competitive Divergence Platform Convergence Model-Mediated Markets

Competitive pressures surface first among leading institutions under competitive divergence before diffusing more broadly as integration deepens. As cognitive convergence advances, interpretive diversity compresses and overlapping signals become more likely, increasing sensitivity to shared assumptions embedded within analytical systems. Firms that underestimate these pressures risk embedding structural dependencies that become difficult to unwind.

Strategic Questions for the Investment Profession

The structural tensions identified here extend beyond operational adjustments. They raise fundamental questions about how finance functions when intelligence becomes abundant, automated, and embedded within market infrastructure. How the investment profession responds to these questions will shape competitive structure, capital allocation, fiduciary accountability, and systemic stability for years to come. The questions that follow address issues that remain unresolved.

1. The nature of advantage
   - *When informational edge compresses, where does durable alpha come from?*
   - *If arbitrage windows shorten, does alpha increasingly reflect capital allocation skill rather than the speed of information capture?*
2. Price discovery and fundamental value
   - *How does price discovery function when automated systems operate at scale?*
   - *If signals converge faster across firms, what anchors long-term valuation?*
3. The structure of competition
   - *If analysis is widely accessible, what differentiates one asset manager from another?*
   - *Does AI favor scale and concentration, or does it enable durable specialization?*
4. Infrastructure and systemic risk
   - *When reliance on common models and data increases, does convergence in analytical frameworks introduce new forms of systemic risk?*
   - *Could shared optimization and signal processing amplify synchronized mispricing or market instability?*

5. Governance and accountability
    - *How should ethics and oversight be exercised in a model-driven investment process?*
    - *Who is accountable when automated allocation decisions fail?*
6. The future of the profession
    - *In a system where intelligence is automated, what defines professional competence, and how does the profession identify, develop, and recognize it?*
    - *Does the locus of expertise shift from research production toward model oversight, system governance, and fiduciary stewardship, and what does that mean for how institutions build and allocate human capital?*

The answers to these questions will shape not only competitive outcomes but also the future integrity and resilience of the financial system. They will define the terrain for the profession's response to AI integration, as well as the agenda that the following sections seek to address.

Governance, Regulation, and Systemic Risk

AI tests capital market governance not at its margins but at its foundations—redistributing accountability, concentrating infrastructure, and synchronizing behavior in ways existing controls were not conceived to address (Daníelsson, Macrae, and Uthemann 2022). As investment decisions become increasingly model mediated, the chain of responsibility that fiduciary frameworks were designed to trace grows more diffuse. Responsibility is distributed across models, data providers, oversight functions, and governance structures, often with unequal visibility and control. Governance is thus not ancillary to this transition; it is the mechanism through which market integrity is preserved as analytical authority becomes increasingly model mediated.

Cognitive convergence presents a distinct but related challenge. As adoption increasingly flows through a small number of dominant model providers and data platforms, the system accumulates dependencies that prudential regulatory frameworks were not built to assess. Traditional oversight focuses on the solvency and liquidity of individual institutions, not on shared analytical infrastructure spanning large segments of capital simultaneously (IMF 2024). The frameworks, data, and institutional mandates required to govern AI remain nascent (ECB 2024). Emerging regulatory responses reflect both the urgency of the challenge and the genuine difficulty of meeting it. Bodies including the International Organization of Securities Commissions (IOSCO), the Financial Stability Board (FSB), and national regulators have published substantive guidance on model risk management, algorithmic transparency, and responsible AI deployment (see FSB 2017, 2024; IOSCO 2025, 2026). Three areas warrant focused attention.

1. **Traceability in hybrid decision systems:** Human oversight must remain documentable and auditable. Governance frameworks must ensure that model-assisted conclusions can be explained, challenged, and attributed to identifiable human judgment where consequential.
2. **Model validation frameworks suited to adaptive architectures:** AI systems that learn, adapt, and generalize across domains require validation that is continuous, adversarial, and sensitive to distributional shift—disciplines most institutions and regulatory frameworks are still developing.
3. **Oversight of shared analytical infrastructure:** When a small number of providers underpin large segments of capital, concentration risk migrates from individual institutions to the infrastructure itself—a form of systemic exposure that prudential frameworks have not yet developed the tools to assess.

These priorities face real implementation challenges. Regulatory frameworks remain fragmented across jurisdictions, adaptive models resist traditional oversight, and the specialist talent required to govern them remains scarce. The risk of over-regulation stifling innovation is real, but the more immediate risk is under-governance of a transition already underway.

For the investment profession, these imperatives also reinforce the continued relevance of the CFA Institute Code of Ethics and Standards of Professional Conduct (www.cfainstitute.org/standards/professionals/code-ethics-standards)—particularly around model oversight, explainability, and suitability. These imperatives also signal that professional standards must evolve as AI integration deepens.

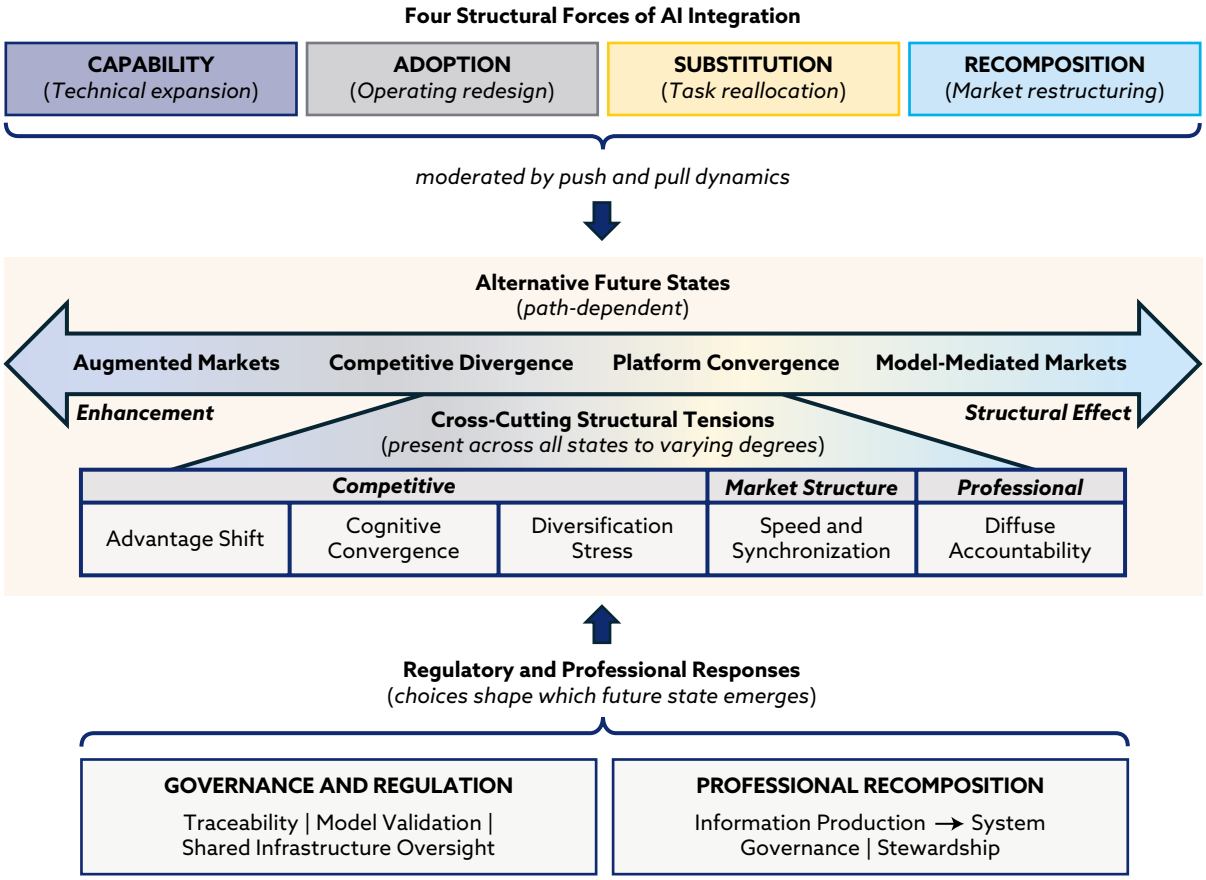
The Architecture of AI Transition

The four structural forces, alternative future states, and structural tensions together describe an integrated system in which technological capability transmits through competitive dynamics and institutional design to shape system-level configurations of capital markets. These configurations coexist across the system and are subject to cross-cutting tensions that intensify as integration deepens. Regulatory and professional responses shape how they evolve. The CFA Institute AI Transition Framework, shown in **Exhibit 5**, synthesizes these elements into a unified architecture for interpretation by clarifying how analytical abundance interacts with market structure, how convergence pressures accumulate, and how institutional choices will shape the capital markets that emerge.

The framework is not a forecast. Each element is already observable across today's capital markets. It is the choices the investment profession makes throughout the AI transition that will shape the industry's future.

This transition will be uneven and nonlinear. Firms, jurisdictions, and market segments will move at different speeds and in different directions, sometimes simultaneously. A large systematic manager may already operate under

Exhibit 5. The CFA Institute AI Transition Framework



Source: CFA Institute.

model-mediated market conditions, whereas a smaller active manager may remain in augmented markets. Jurisdictions with more-developed governance frameworks may moderate convergence pressures that others amplify. These configurations will coexist and interact rather than resolve into a single global state.

Although convergence pressures may intensify, the scenarios described in this paper are neither inevitable nor predetermined. The future may well be more nonlinear and depend more heavily on human agency than any single trajectory in this framework suggests.

Next Steps: Reimagining the Future of Finance in the Age of AI

The AI transition underway in capital markets is not simply a technological upgrade. It is a structural reordering of the conditions under which information is produced, expertise is valued, and accountability is assigned. The four structural forces discussed here are already in motion, and the alternative

futures they may produce are not distant hypotheticals but live trajectories being shaped by the institutional and professional choices made today. The most consequential decisions may be the earlier choices about governance and standards that determine whether the system that emerges is one society can trust. The window for shaping those choices remains open, although not indefinitely.

What the AI transition framework ultimately reveals is an inversion at the heart of modern finance. For generations, information scarcity was the central organizing principle of financial markets: Those who could access, interpret, and act on information faster than others captured value. As AI scales, however, that scarcity inverts: Intelligence becomes abundant, and judgment about how to govern, deploy, and constrain information becomes the scarce resource. The profession must therefore build a new identity around the capacity to steward systems more powerful than any individual practitioner in service of markets that remain fair, stable, and accountable. These conditions call for independent, evidence-based analytical leadership grounded in the long-term integrity of the profession, rather than the short-term imperatives of any single institution or jurisdiction.

A Strategic Compass for the Profession: Navigating the AI Transition

This paper is the first in a flagship series under the CFA Institute *Reimagining the Future of Finance in the Age of AI* research program. The paper provides the foundation for a connected body of work addressing the dimensions of market structure transition as AI integration deepens. The research will pursue several priorities: professional recomposition as analytical production scales, accountability in model-mediated environments, the systemic implications of cognitive convergence, and the institutional conditions required to preserve fair, resilient, and accountable markets. Each priority will produce practitioner-relevant guidance, inform professional standards, and support engagement with regulators across jurisdictions.

The decisions made in the years immediately ahead will determine whether society can trust the financial system that emerges from this transition. That is the standard against which the profession's response to AI integration will ultimately be judged—and the horizon toward which this research program is directed.

References

Bengio, Y., G. Hinton, A. Yao, et al. 2024. "Managing Extreme AI Risks amid Rapid Progress." *Science* 384 (6698): 842–45. doi:10.1126/science.adn0117.

Brunnermeier, M. K. 2009. "Deciphering the Liquidity and Credit Crunch 2007–2008." *Journal of Economic Perspectives* 23 (1): 77–100. doi:10.1257/jep.23.1.77.

Carhart, M. M. 1997. "On Persistence in Mutual Fund Performance." *Journal of Finance* 52 (1): 57–82. doi:10.1111/j.1540-6261.1997.tb03808.x.

Daníelsson, J., R. Macrae, and A. Uthemann. 2022. "Artificial Intelligence and Systemic Risk." *Journal of Banking & Finance* 140 (July). doi:10.1016/j.jbankfin.2021.106290.

Daníelsson, J., and A. Uthemann. 2025. "Artificial Intelligence and Financial Crises." *Journal of Financial Stability* 80 (September). doi:10.1016/j.jfs.2025.101453.

ECB (European Central Bank). 2024. "The Rise of Artificial Intelligence: Benefits and Risks for Financial Stability." *Financial Stability Review* (May): 104–19. www.ecb.europa.eu/press/financial-stability-publications/fsr/html/ecb.fsr202405~7f212449c8.en.html.

Fama, E. F. 1970. "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance* 25 (2): 383–417. doi:10.2307/2325486.

Fama, E. F., and K. R. French. 2010. "Luck Versus Skill in the Cross-Section of Mutual Fund Returns." *Journal of Finance* 65 (5): 1915–47. doi:10.1111/j.1540-6261.2010.01598.x.

FSB. 2017. "Artificial Intelligence and Machine Learning in Financial Services." (1 November). www.fsb.org/2017/11/artificial-intelligence-and-machine-learning-in-financial-service/.

———. 2024. "The Financial Stability Implications of Artificial Intelligence." (14 November). www.fsb.org/2024/11/the-financial-stability-implications-of-artificial-intelligence/.

Frimpong, V. 2026. "Model Monoculture Risk: Systemic AI Convergence in Banking and Financial Markets." Working paper (5 March). http://dx.doi.org/10.2139/ssrn.6583923.

IMF (International Monetary Fund). 2024. "Chapter 3: Advances in Artificial Intelligence: Implications for Capital Market Activities." In *Global Financial Stability Report, October 2024*. doi:10.5089/9798400277573.082.

IOSCO. 2025. "Artificial Intelligence in Capital Markets: Use Cases, Risks, and Challenges." IOSCO Consultation Report (March). www.iosco.org/library/pubdocs/pdf/IOSCOPD788.pdf.

———. 2026. "Supervisory Toolkit for AI Use in Capital Markets." IOSCO Final Report (May). www.iosco.org/library/pubdocs/pdf/IOSCOPD823.pdf.

Kaplan, J., S. McCandlish, T. Henighan, et al. 2020. "Scaling Laws for Neural Language Models." Working paper (January). doi:10.48550/arXiv.2001.08361.

López de Prado, M. 2018. *Advances in Financial Machine Learning*. Wiley.

Markowitz, H. 1952. "Portfolio Selection." *Journal of Finance* 7 (1): 77–91. doi:10.1111/j.1540-6261.1952.tb01525.x.

SEC and CFTC (Commodity Futures Trading Commission). 2010. "Findings Regarding the Market Events of May 6, 2010." SEC/CFTC Joint Advisory Committee (30 September). www.sec.gov/files/marketevents-report.pdf.

Sharpe, W. F. 1964. "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk." *Journal of Finance* 19 (3): 425–42. doi:10.1111/j.1540-6261.1964.tb02865.x.

Vayanos, D., and P. Woolley. 2013. "An Institutional Theory of Momentum and Reversal." *Review of Financial Studies* 26 (5): 1087–145. www.jstor.org/stable/23470044.

Author

Mona Naqvi
Managing Director, Research and Policy Center
CFA Institute

ABOUT THE RESEARCH AND POLICY CENTER

CFA Institute Research and Policy Center brings together CFA Institute expertise along with a diverse, cross-disciplinary community of subject matter experts working collaboratively to address complex problems. It is informed by the perspective of practitioners and the convening power, impartiality, and credibility of CFA Institute, whose mission is to lead the investment profession globally by promoting the highest standards of ethics, education, and professional excellence for the ultimate benefit of society. For more information, visit https://rpc.cfainstitute.org/en/.

First page photo credit: Getty Images/iStockphoto/Claudio, Ventrella

CFA Institute

PROFESSIONAL LEARNING QUALIFIED ACTIVITY

This publication qualifies for 0.75 PL credits under the guidelines of the CFA Institute Professional Learning Program.