CHAPTER 3

ADVANCES IN ARTIFICIAL INTELLIGENCE: IMPLICATIONS FOR CAPITAL MARKET ACTIVITIES

Chapter 3 at a Glance

- Generative artificial intelligence and related breakthroughs have the potential to dramatically increase the efficiency of capital markets—trading, investment, and asset allocation—through artificial intelligence–assisted process automation and analysis of complex unstructured data, and evidence suggests these effects are already beginning to be felt.
- New evidence from labor markets and patent filings suggests that the adoption of artificial intelligence (AI) in capital markets is likely to increase significantly in the near future, and analyses of pricing patterns and trading dynamics already show changes in some markets consistent with the adoption of these new technologies.
- In addition, AI could cause large changes in market structure through the greater and more powerful use of algorithmic trading and novel trading and investment strategies, which in turn may increase turnover and asset correlations and drive prices to reflect new information at an ever-increasing speed.
- However, based on outreach conducted with both market participants and regulators, most current use of AI appears to be an extension of existing trends in the use of machine learning and other advanced analytical tools; more significant changes are a medium- to long-term concern.
- AI may actually reduce financial stability risks by enabling superior risk management, deepening market liquidity, and improving market monitoring by both participants and regulators. At the same time, new risks may arise:
    - Increased market speed and volatility under stress, especially if trading strategies of AI models all respond to a shock in a similar manner or shut down in response to an unforeseen event.
    - More opacity and monitoring challenges, as AI spurs further migration of market-making and investment activities to hedge funds, proprietary trading firms, and other nonbank financial intermediaries and creates uncertainty about how AI models used by different investors and traders could interact.
    - Increased operational risks as a result of reliance on a few key third-party AI service providers that dominate computational power and large language model services.
    - Increased cyber and market manipulation risks, particularly in generating fraud and social media disinformation.
- Many of these risks are addressed by existing regulatory frameworks, but important new and unforeseen developments may arise. To ensure relevant authorities are prepared for these potentially transformative changes, they should consider additional policy responses:
    - Undertake the calibration of circuit breakers and a review of margining practices in light of potentially rapid AI-driven price moves.
    - Enhance monitoring and data collection of the activity of large traders, including nonbank financial intermediaries.
    - Address dependency on data, models, and technological infrastructure by requesting a risk mapping from regulated entities (that is, data on the internal and external interconnections and interdependencies that are necessary to deliver the institutions' critical services).
    - Adopt a coordinated approach for the definition of critical AI third-party service providers and continue to strive for resilience in capital markets by enhancing cyberattack protocols.
    - Adopt measures that ensure continued market integrity, efficiency, and resilience of over-the-counter markets when AI use proliferates.

The authors of this chapter are Nassira Abbas (co-lead), Gabriela Elizabeth Conde Vitureira, Mohamed Diaby, Gonzalo Fernandez Dionis, Andrew Ferrante, Dirk Jan Grolleman (co-lead), Johannes Kramer, Xiang-Li Lim, Benjamin Mosk (co-lead), Puja Singh, and Richard Stobo, under the oversight of Charles Cohen and Jason Wu. Markus Pelger served as an external advisor.

Introduction

Artificial intelligence (AI) has the potential to reshape the world and transform industries, including financial services. This chapter focuses on the use of AI and GenAI[1] in capital markets, which may see deep changes in market structure changes from network effects and increased speed of market functioning. Financial services are well poised to take advantage of recent advances in AI given the industry's long-standing focus on data collection and analysis and early adoption of techniques such as machine learning (ML). Recent surveys of financial institutions reported that a vast majority of respondents expect a significant expansion of the use of GenAI-driven models (IIF and Ernst & Young 2023), and more than half of investment managers said that they planned to use GenAI in the future (Mercer Investments 2024). Hence, it is important to understand the potential financial stability implications of these developments and to ensure regulators are ready for these changes.

Further adoption of AI may contribute positively to financial stability, and can provide clear benefits to financial institutions, such as efficiency improvements and higher productivity (Boukherouaa and others 2021), refined portfolio investing frameworks (Park and others 2023), improved return forecasting (Chen, Kelly, and Xiu 2023), and quantification of crash risks (Swinkels and Hoogteijling 2022). There are also AI applications benefiting SupTech and RegTech.[2]

However, AI could also introduce new forms of financial stability risks and accelerate well-established financial stability concerns such as leverage, liquidity strains, and interconnectedness. This chapter considers and finds indicative evidence for four broad categories of potential risks, which could transmit stress to the real economy through loss of market confidence, higher borrowing costs, and potentially significant financial system outages:

- **Increased market speed and volatility under stress**, especially if AI trading strategies become highly correlated
- **Opacity and monitoring challenges** as extreme behaviour of AI systems becomes increasingly difficult to anticipate and AI activities also migrate to nonbank financial intermediaries (NBFIs)
- **Increased operational risks** as a result of reliance on a few key third-party AI service providers
- **Increased cyber and market manipulation risks**, particularly through fraud and disinformation

GenAI is already seeing widespread "evolutionary" adoption—use cases that build upon existing analytical methods and investment strategies—across the financial sector. As in other industries, GenAI is increasing efficiency across a host of tasks: helping analysts write code, improving customer-facing activities, and generating new investment ideas. Large language models are being used as inputs into existing analytical models to improve the forecasting power of textual analysis, likely improving the predictive power of quantitative investment strategies. It could also lower barriers to entry for quantitative investors into less liquid asset classes (such as corporate or sovereign bonds) that require extensive analysis of indentures and other legal documents. GenAI is also likely to increase the speed of market reactions to new information through the real-time processing of unstructured data, such as textual central bank announcements. Numerous other use cases in asset allocation, trading, and risk management have been noted by market participants (Figure 3.1).

The more "revolutionary" uses of GenAI—radically new investment strategies and processes using cutting-edge AI technology—remain mostly speculative. Although many observers envision scenarios involving autonomous AI generating and executing trades without human oversight, most market participants that responded to IMF outreach are quite uncomfortable with this idea (Box 3.1). They view AI-generated strategies that are not understood by humans as a nonstarter. In addition, for regulatory, risk management, liability, and ethical reasons, most participants view having a "human in the loop" as an essential part of any AI-based strategy.

[1]For the purpose of this chapter, AI or "machine learning (ML) models" (AI/ML) refers to well-established predictive analytics, including shallow neural networks, clustering algorithms, textual analysis tools natural language processing, decision trees, and so on; and "sophisticated AI models" refers to their move recent and advanced counterparts, such as deep neural network architectures addressing reinforcement learning, and natural language processing (large language models). This includes GenAI models capable of generating text, codes, images, and other content.

[2]SupTech and RegTech are advanced financial technology applications used by supervisors and regulated institutions.

Figure 3.1. Recent and Potential Use Cases for Artificial Intelligence and Machine Learning in Capital Market Activities: Investment Decisions, Trade Execution, and Monitoring Processes

Potential benefits include enhanced accuracy, efficiency, and market insights through multidimensional analysis from unstructured data sources, delivering customized, and actionable outputs.

Key Processes	Client/Institution Profiling	Asset Allocation			Trading	Risk Management	
	Identification of Needs and Constraints	Asset Class Allocation	Sectoral Allocation	Security Selection	Orders Placement and Execution	Risk Monitoring	Reporting
Potential Benefits from Adopting AI	**Enhance client's profile assessment** • Analyze unstructured or alternative clients' data to understand unique objectives, idiosyncratic needs, and risk preference • Generate simulated scenarios and visualization of potential outcomes of different asset mix	**Enhance optimization and forecast techniques for strategic allocation** • High dimensional forecasting and predictor selections • Deep learning methodologies for dynamic multiperiod portfolio optimization • Clustering/network analysis to analyze multidimensional interactions/ correlations		**Improve analysis precision** • Feature extraction (beta, momentum, and so on) • Network/ multidimension analysis for relative value analysis and identify price dislocation	**Minimize market impact** • Structured trade execution algorithms to minimize market impact • Analyzing unstructured data and cross-market indicators to identify prevailing liquidity conditions **Assist price discovery** • Modelling executable prices for illiquid secu-rities through multiple market indicators **Improve liquidity management efficiency** • Forecast liquidity needs (margin management, collateral, etc.) through clustering/network analysis	**Dynamic risk sensing** • Generate risk hypothesis • To identify performance drivers and anomalies through multidimensional analysis **Generate risk scenario** • Value-at-risk estimation through generative adversarial networks to capture temporal dynamics in time-series data	**Customize insights** • Customized content generation, reports, and dashboards • Chatbot **Ease compliance monitoring** • Screening, flagging, and reporting of anomalies
		Derive signals from unstructured and alternative data • Natural language processing models for sentiment analysis to identify thematic opportunities • Polarity detection, microtext analysis, aspect extraction, or sarcasm detection to improve signal quality					

Sources: Academic studies; IMF outreach discussions (see Box 3.1); prospectus from third-party services; and IMF staff compilations.

Note: The figure presents recent and potential artificial intelligence (AI) and machine learning (ML) use cases across investment decision, execution, and monitoring processes. The information may not be exhaustive of all possible AI/ML use cases, as adoption continues to evolve.

For emerging markets, AI is widely seen as a positive development, although it may create fragmentation risks. The IMF's outreach effort found that market participants widely viewed GenAI as a tool to enable technological leapfrogging and increase financial development and inclusion for many emerging market and developing economies through increased access to credit and a deepening of local financial markets. However, if high fixed costs lead to different speeds of adoption across regions, emerging market and developing economies may be less able to benefit from the migration to AI-driven activities than advanced economies.

As adoption is still at a relatively early stage, this chapter gives a forward-looking assessment of the impact of AI (and GenAI specifically) on capital markets. To compensate for the lack of readily available data in this area, the chapter draws on a combination of extensive IMF staff market outreach (Box 3.1) and analytical work that leverages novel data sources. By understanding the current levels and speed of adoption of AI, the chapter posits where and how AI-related risks may arise. It analyzes how AI is transforming market structures and dynamics and examines the financial stability implications for liquidity, leverage, and interconnectedness as well as other potential novel risks. The chapter concludes by offering policy recommendations that focus on monitoring and the sufficiency of current or forthcoming guidelines.

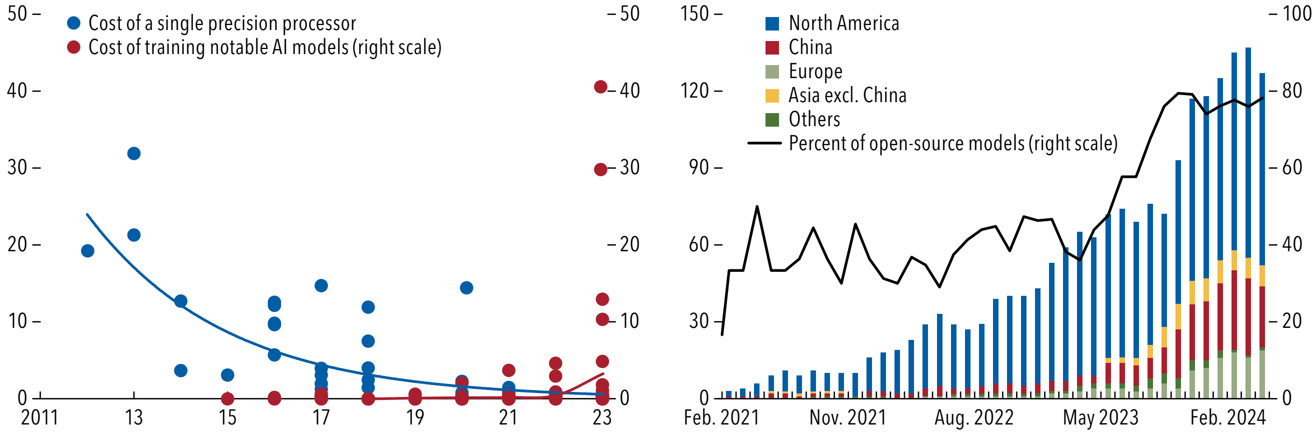
Figure 3.2. The Cost of Compute and the Artificial Intelligence Market Structure

Cost per unit of calculation has declined but models are increasingly complicated …

1. Cost of a Single Precision Processor and the Cost of Training Notable AI Models
(Inflation-adjusted 2023 US dollars per exa floating point operation; millions of inflation-adjusted 2023 US dollars, right scale)

… but most large, foundation models are being developed by a concentrated number of countries.

2. National Affiliation of Foundation Models and Access Type
(Trailing six-month count of published models; trailing six-month percentage of open-source models, right scale)



Sources: Epoch AI; Stanford University's Ecosystem Graphs; and IMF staff calculations.

Note: Training compute is measured using floating-point operations. Estimated costs for panel 1 were derived from Epoch AI's data sets and the methodology to estimate costs of training notable artificial intelligence models and graphics processing unit price-performance data. Foundation models are artificial intelligence/machine learning models developed that can be used for various applications. Exa denotes a factor of 10^{18}. The blue and red lines in panel 1 are best-fit lines. AI = artificial intelligence.

Current and Future Adoption of Artificial Intelligence in Capital Market Activities

Mainstream use of GenAI only dates back a few years, but financial institutions have been actively using ML and other AI-related computation methods for approximately 20 years, and these methods are now well integrated into their investment processes. Robo-advising, AI-based exchange-traded funds (ETFs), and applications related to GenAI are only in their infancy, but labor market data, patent filings, and investor outreach all suggest that institutions are rapidly gearing up for significant integration of these technologies.

Technological Change and the Rise of Artificial Intelligence

Although the unit cost of training AI models has dropped dramatically as a result of recent advancements in algorithmic efficiency and computation hardware, "notable" models of the type used in leading GenAI applications have simultaneously become much more complex, leading to much higher overall costs (Figure 3.2, panel 1).[3] The high fixed costs of the infrastructures and talent enabling development and distribution of sophisticated AI systems may exacerbate market concentration, whereby the few private sector developers with existing commercialization channels could continue to dominate the space (noting that the growing number of open source models may challenge this paradigm). Concentration often arise also because of data monopolies, whereby some players have access to superior nonpublic data, which would allow them to train more effective models or have the capacity to process huge volumes of data. This is especially pertinent in the financial sector, where some players have vast amounts of trading and client data. Development of foundation models has predominantly been based in the United States (Figure 3.2, panel 2).

Current Adoption: Evidence from the IMF's Market Outreach

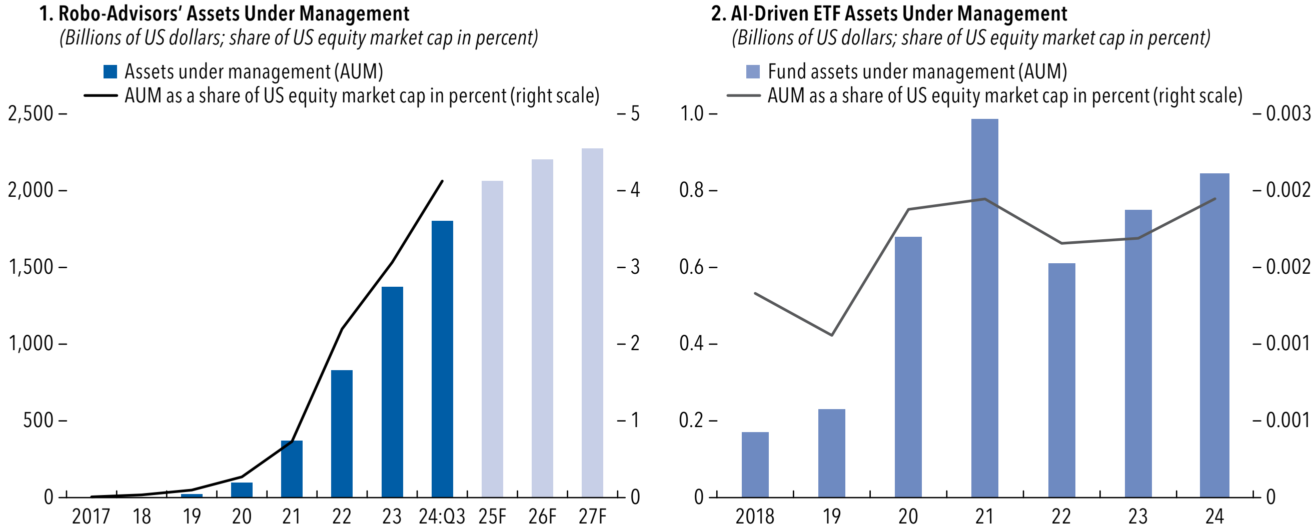
From a capital market perspective, the expansion and considerable scale of robo-advising highlights a move toward automation by the investment industry (Figure 3.3, panel 1). However, genuinely AI-driven strategies are still in their early stages. For instance, AI-powered ETFs—where AI is used to construct and adjust an ETF's portfolio—still account for a very small share of the market, with less than $1 billion in assets under management (Figure 3.3, panel 2). This indicates that

[3]Notable models are models in the running for the top 10 largest training compute, expressed in terms of required floating-point operations (FLOP) (Epoch AI 2024).

Figure 3.3. Investment Strategies Driven by Artificial Intelligence

Robo-advisor assets under management have grown explosively and are projected to grow further.

AI-driven exchange-traded fund (ETF) investment has grown, but it remains tiny compared to the market's size.



Sources: Bloomberg Finance L.P.; Statista Digital Market Insights; and IMF staff calculations.

Note: In panel 1, the light blue bars are the forecasts for 2025, 2026, and 2027. The share of assets under management as a percentage of the US equity market capitalization is based on the MSCI US Equity Index market capitalization. AI = artificial intelligence; ETF = exchange-traded fund.

although technology has begun to alter the landscape of investment management, the penetration of advanced AI applications is relatively modest.

To complement the analytical work based on an extensive literature of review and data collection, IMF staff conducted a qualitative assessment with main players in the industry directly involved in AI-related strategy to further assess how AI advances have been adopted and are transforming capital markets. The IMF staff outreach aimed to shed light on how financial institutions—both buy-side and sell-side firms—are harnessing AI technologies. While acknowledging that AI is not a new phenomenon, all market participants highlighted the accelerating pace of AI adoption in various areas, mainly driven by the proliferation of GenAI tools (Box 3.1).

Prospects for creating value through AI appear to be most promising in publicly traded liquid asset classes (Figure 3.4, panel 1).[4] Equities, government bonds, and listed derivatives offer a wealth of real-time data and transparency. The high volume of transactions and the dynamic nature of these markets enable AI systems to continuously learn and adapt, potentially offering more accurate and timely insights. Results from the IMF's outreach to stakeholders point to equities and derivatives as being the most likely areas where AI will be adopted in the investment process, followed by fixed income and foreign exchange (which are primarily traded in over-the-counter markets) (Figure 3.4, panel 2). However, some market participants also highlighted that advances in AI and its unprecedented processing capabilities could benefit less-liquid markets such as private credit and some emerging markets segments.

The IMF's outreach also reveals a number of AI use cases in the investment process. For instance, AI is used in the incorporation of alternative data sets,[5] the development of forward-looking indicators, and market analysis.[6] More specifically, buy-side firms employ AI/ML for productivity enhancement, including exploration of new asset classes,[7] extraction of signals from data to support their investment decisions, and

[4]For a thorough description of capital market structure (for example, type of instruments, actors, trading venues, and central counterparties), see US Securities and Exchange Commission (2020).

[5]Alternative data sets include content from social media platforms and other public forums where market participants share their opinions and engage in discourse. Sentiment analyses, although various natural language processing methodologies, are also conducted on regulatory filings or relevant public statements.

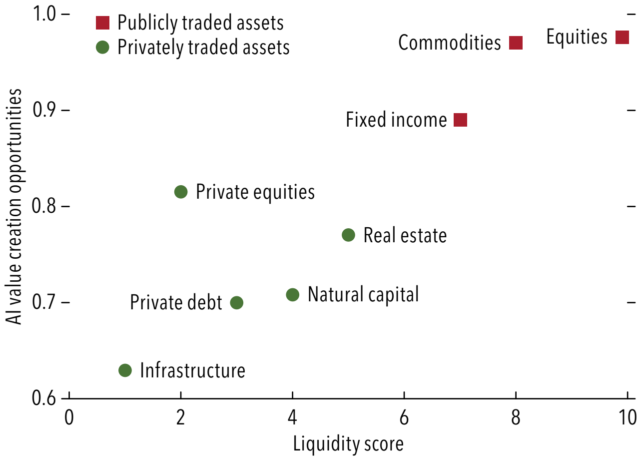
[6]Some market participants also employ AI techniques on price movements from other asset classes or instruments to estimate valuation and executable prices for some illiquid instruments.

[7]AI is primarily adopted for asset-class research, focusing on summarizing research documents from various sources and extracting key information relevant to assessing risk and return profiles or requirements that are unique to individual investors.

Figure 3.4. Opportunities for Artificial Intelligence to Create Value: Asset Classes

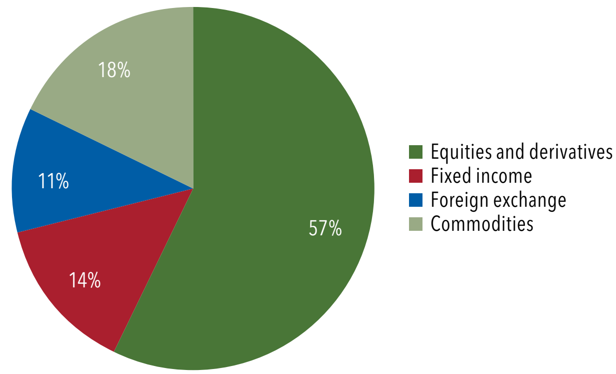
There is a strong correlation between market liquidity and current adoption of AI by investment managers.

1. AI Opportunities and Asset Class Liquidity
(Value creation opportunity index; liquidity score)



The IMF's outreach to stakeholders suggests equity markets as most likely to see AI implementation.

2. Which Markets Are Incorporating Machine Learning and Generative AI?
(Percent of participants' scores)



Sources: IMF, October 2024 *Global Financial Stability Report* market intelligence; Mercer Investments (2024); and IMF staff analysis.

Note: In panel 1, the liquidity score is assigned by asking a large language model to assign a liquidity score between 1 and 10 to each asset class, whereby the model is prompted to assign an ordinal score, distinct for each asset class, reflecting the liquidity of the given asset classes, and 1 reflects the least liquid asset class and 10 the most liquid. The AI value creation opportunities score is a ratio based on survey responses, whereby the numerator is equal to difference between the respondents that do see value creation opportunities and those that do not; the denominator is equal to the number of respondents that expressed a view. Details on the market intelligence outreach in panel 2 can be found in Box 3.1. AI = artificial intelligence.

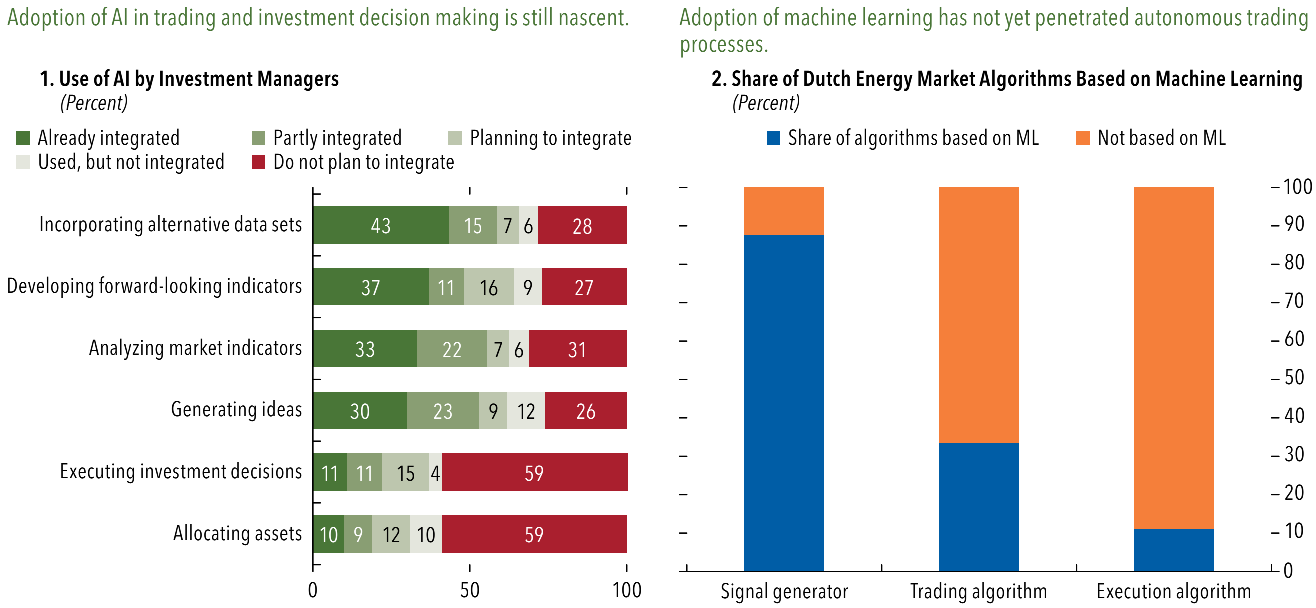
portfolio optimization and allocation, as well as for back-office activities. Meanwhile, sell-side institutions use AI/ML for risk assessment, pricing and forecasting, and customer service and to improve trading automation. Market infrastructure providers and academia note that AI/ML models, including sophisticated AI models, are aiding the democratization of techniques such as code writing and prototyping as well as information extraction and summarization.

Participants in the IMF's outreach to stakeholders widely observed that recent breakthroughs, particularly in GenAI, are catalyzing broader AI/ML adoption across capital markets. Within a three- to five-year horizon, participants expect greater integration of sophisticated AI in investment and trading decisions. One use case gaining traction in asset management is the AI-powered exploration of alternative and text data to uncover causal relationships in markets that are previously unknown, which could lead to new investment strategies. Another would be the adoption of traditional AI/ML applications to increase the robustness and accuracy of existing models, especially in terms of forecasting. A recent survey by Mercer Investments (2024) shows that the adoption of AI in core investment processes such as trading and the execution of investment decisions is still nascent (Figure 3.5, panel 1). Concentrating on the more specialized area of algorithmic trading, evidence is mixed. Survey data among participants of a major energy market (The Netherlands) suggest that more autonomous algorithms may still be based on simpler methods (Figure 3.5, panel 2).[8]

Meanwhile, there is evidence that sophisticated AI has not yet been implemented widely to build autonomous AI trading agents (Authority for Consumers and Markets 2024, p. 18). It is instead more frequently used to generate a signal that is then used as an input in an existing analytical system where a human trader may ultimately make the trading decision. There was a consensus among the IMF outreach participants on the increasing benefits of AI/ML, including improved efficiency and productivity, cost savings in designing

[8]The Dutch Authority for the Financial Markets found that on the Euronext exchange, "trading firms tell the Authority for the Financial Markets that machine learning is implicitly or explicitly used in 80 to 100 percent of their trading algorithms." It should be noted however, that "explicit" use cases may include applications that are not autonomous, such as signal generators (Authority for the Financial Markets 2023).

Figure 3.5. Artificial Intelligence Advances: Use Cases and Adoption in Investment Processes



Sources: Authority for Consumers and Markets; IMF, Mercer Investments (2024); and IMF staff analysis.

Note: Panel 2, statistics are derived from survey responses regarding algorithms that are already in use; survey responses regarding planned use cases are not included. AI = artificial intelligence; ML = machine learning.

trading algorithms, better processing of unstructured data, and more compressed bid-ask spreads.

Financial supervisors included in the IMF's staff outreach indicated that they were beginning to reap the benefits of AI. They use AI-driven SupTech tools to monitor financial markets and institutions, including ones that detect anomalies in large data sets to identify risks early, and other tools that can help check regulatory compliance of supervised entities. For their part, banks have used RegTech tools to manage regulatory compliance and to enhance and boost efficiency of their "anti-money laundering/know your customer" process by, for instance, automating some tasks to ensure higher accuracy in clients' data, monitor transactions, and detect fraud.

Looking ahead, market participants expect a rise in the use of AI in trading and investment, and a higher degree of autonomy of AI-based decisions, especially in the equity market, where high-frequency, AI-driven trading is expected to account for a more substantial share. However, all participants in the IMF's outreach expected a "human in the loop" approach to persist in the near term (three to five years), especially for large capital allocation decisions. Although the trend is toward less human interaction, complete autonomy is not anticipated soon, and models will continue to operate within predefined rules. Some participants mentioned the potential for agent-to-agent trading and the development of complete AI-driven workflows in trading.

Future Adoption: Evidence from Patent Filings and Labor Markets

The relationship between financial innovation and patents has been an area of growing interest in the literature (Lerner and others 2024). Financial innovations have become more significant and economically impactful, with a notable increase in patent grants today compared to the 1990s. This trend provides valuable insights into the evolving nature of financial innovation. In this regard, the evolution of AI patent filings may serve as an indicator of AI adoption in capital market activities, providing insights into future trends.

The number of filings that reference AI/ML terminologies in the context of high-frequency or algorithmic trading has increased (Figure 3.6, panel 1). Over the past year, filings lean toward improving operational efficiency of brokerage or trading platforms and on developing systems that compute trading signals with low latency and high throughput. AI/ML-related filings have also driven a surge in patents in the area of asset management (Figure 3.6, panel 2). Filings related to

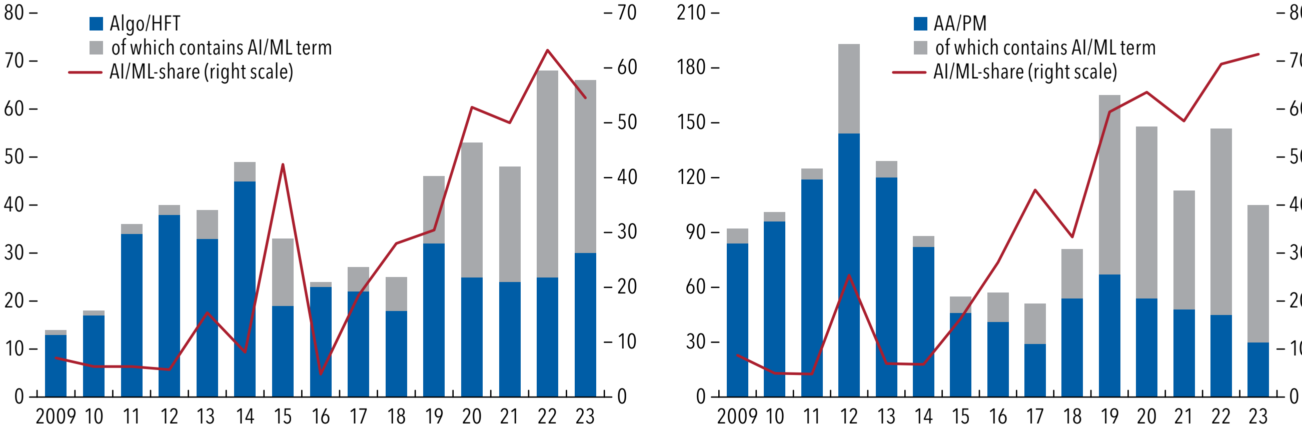
Figure 3.6. Artificial Intelligence/Machine Learning Innovations: Evidence from Patent Applications

Filings relating to high-frequency or algorithmic trading incorporating AI/ML are increasing ...

1. Patents Related to High-Frequency/Algorithmic Trading
(Number of patents; percent of patents)

... with a similar trend observed for applications relating to broader asset management practices.

2. Patents Related to Asset Allocation or Portfolio Management
(Number of patents; percent of patents)



Sources: World Intellectual Property Organization, PATENTSCOPE; and IMF staff calculations.

Note: Aggregated values are limited to filings with specific mention of financial or capital markets and the relevant terminologies. Aggregate patents may not be unique patents, as some patents may be filed in multiple jurisdictions. Aggregate patents may not be exhaustive of all patents filed with respective national authorities and are limited to those available in the PATENTSCOPE database. These filings may or may not translate to actual patents granted by national authorities, and the review process may take time depending on the complexity of the invention. In panel 2, asset management practices also include asset allocation and portfolio management applications. AA = asset allocation; AI = artificial intelligence; HFT = high-frequency trading; ML = machine learning; PM = portfolio management.

asset management detail the use of ML techniques to enhance the efficiency of cash flow and liquidity management, automate asset class rebalancing, improve valuation and forecasting methods, and determine capital requirements tailored to individual needs. Several innovations focus on interpreting unstructured data and designing systems to process information from alternative data sources. In addition, some filings incorporate techniques to access and manage alternative asset classes, such as methodologies for trading emissions and managing digital assets, as well as evaluation methods for validating cryptographically signed transactions.

Although only a small share of workers claims to have AI skills (Figure 3.7, panel 1), the talent pool, specifically within the financial services industry, appears to be growing. Quantitative researchers and analyst profiles in the US financial industry increasingly feature AI skills. ML, natural language processing, and deep learning are among the top 30 competencies listed in their profiles.[9] Demand for AI skills is on the rise and, according to the IMF's outreach, competition to attract talent is one of the most important challenges that could limit the acceleration of developments in AI. The incorporation of AI skills in job postings for typical front office roles with direct influence on investment decision making or responsible for financial market transactions has been increasing,[10] and the share of job postings for these front office roles and the financial services industry requiring AI skills has outpaced the overall share of AI-related job postings for the broader US economy (Figure 3.7, panel 2). Unsurprisingly, AI talent concentration[11] within the US financial services industry also exceeds the broader economy.

According to participants in the IMF's outreach, AI could bring greater financial opportunities in emerging markets and developing economies. Cited key benefits include improvements in access to financial services, credit scoring, loan origination, robo-advising, and

[9]Ranking is based on LinkedIn's statistical measure using Term Frequency-Inverse Document Frequency, a natural language processing algorithm that evaluates how representative a word/terminology is. Specifically, ML ranks among the top five skills in this cohort, highlighting the industry's expanding focus on AI/ML applications.

[10]Also known as "front office" roles, including traders, portfolio managers, portfolio strategist, asset allocation analysts, and programmatic traders. Job postings containing AI terminology for these roles rose from a monthly average of 4.5 percent of front office roles in 2019 to 4.9 percent in 2023 and a peak of 6.6 percent in 2022.

[11]A LinkedIn member is considered AI talent if they have explicitly added AI skills to their profile and/or they are occupied in an AI occupation representative, which requires AI skills to perform the job.

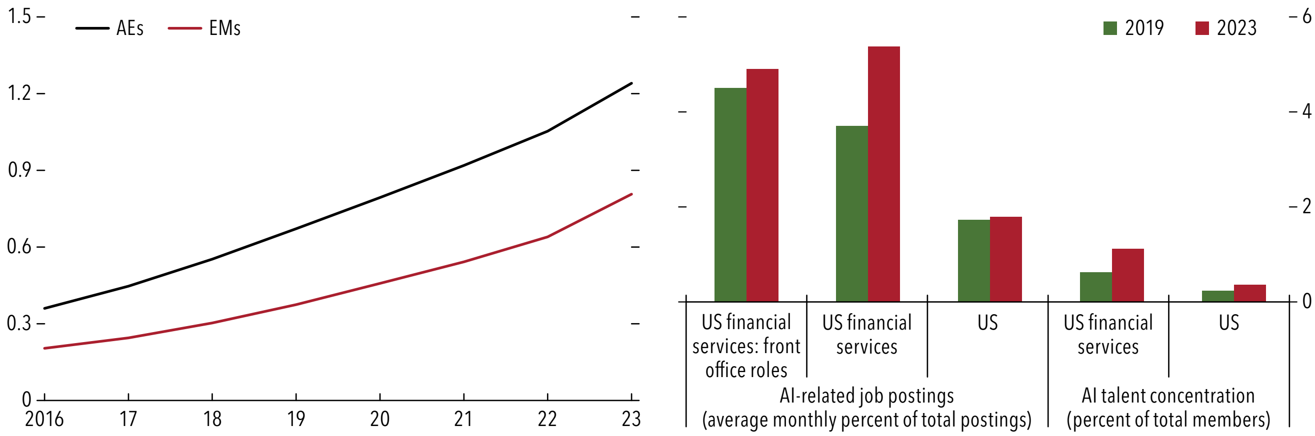
Figure 3.7. Adoption of Artificial Intelligence: Evidence from Candidate Profiles and Job Vacancies

While the existing workforce in the broader industry is steadily adopting AI skillsets …

… demand for these skills, particularly in the financial services sector, has increased in recent years and appears to outpace job postings of the broader US economy.

1. Concentration of LinkedIn Members in the Financial Services Industry with AI Skills
(Average percent of aggregated country profiles)

2. Job Postings Containing AI Skills and the Share of AI Talent
(Average monthly percent of total job postings, percent of total members)



Sources: Indeed Hiring Lab; LinkedIn Economic Graph; and IMF staff calculations.

Note: Financial services include entities that make financial transactions (creation, liquidation, or change in ownership of financial assets) and/or that facilitate financial transactions across 30 advanced economies and 14 emerging markets. Data from Indeed and LinkedIn were obtained through the Development Data Partnership (https://datapartnership.org/), a collaboration between international organizations and private sector companies to facilitate the efficient and responsible use of third-party data in international development. AEs = advanced economies; AI = artificial intelligence; EMs = emerging markets.

portfolio construction. GenAI-enabled parsing of fragmented and unstructured data could reduce investment barriers in these countries and improve the liquidity of some emerging market assets. Synthetic (AI-generated) data may also be helpful in training investment models where data are scarce, bearing in mind the caveats around the use of this technology. Overall, the combination of better liquidity and enhanced market efficiency could make some emerging markets more attractive to global investors and potentially lead to larger capital flows.

The use of a new generation of models should help address data gaps, thanks to the use of synthetic data in less-efficient markets, in turn enhancing market liquidity and lowering barriers to entry. Indeed, synthetic data being real data-like and generated by algorithms, can indeed offer valuable opportunities for training and testing AI. However, reliance on generated data should account for two key issues. First, the unintended over- or under-representation of certain values of real-world data distribution, undermining extreme event performance of AI systems. Second, potential biases perpetuated by synthetic data when the generation process fails to account for specificities and requirements of second-order applications.

Other market participants indicate possible differentiation between large and less-significant emerging markets, based on the extent to which AI technologies will be implemented. The risk of fragmentation between advanced economies and emerging market and developing economies seems to be limited, and some market participants reported that advances in AI could instead support greater financial inclusion. AI-driven financial services may facilitate access to credit using new data sets where traditional metrics are less developed, and robo-advising should reduce barriers to entry in investing, deepening local capital markets. However, others pointed to the risk of automation affecting lower-skilled jobs in some countries.

The Artificial Intelligence Transformation: Implications for Market Structures and Dynamics

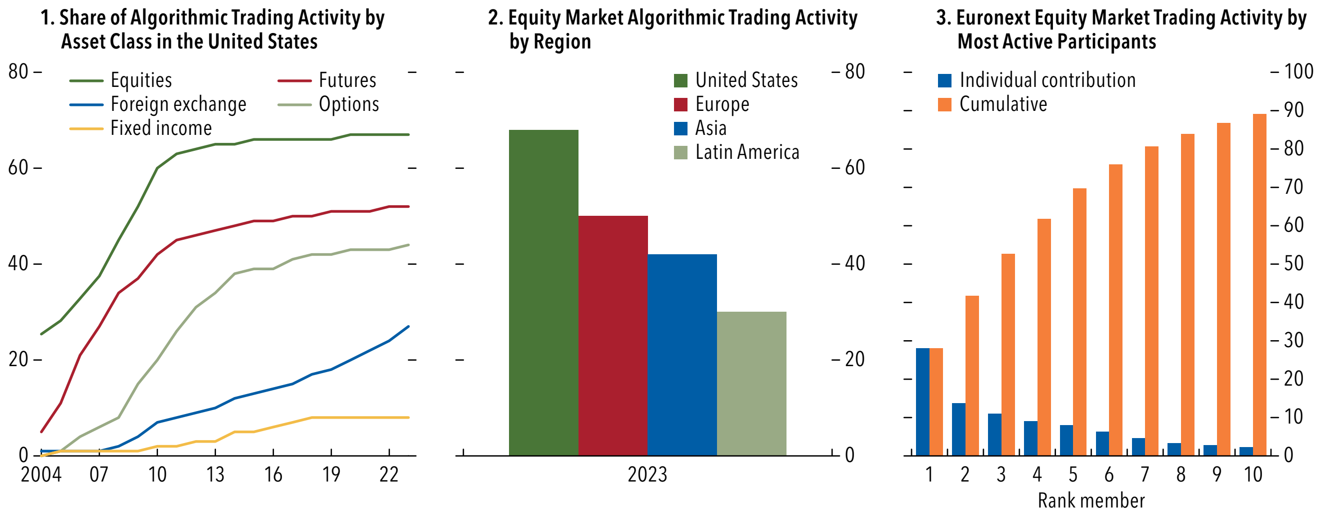
The adoption of AI in capital market activities has the potential to change the structure and dynamics of markets. Some of these changes are more evolutionary, whereby existing trends may be amplified. Other impacts could be more revolutionary: For example, the

Figure 3.8. Algorithmic Trading Activity and Concentration in Equity Markets
(Percent)

Algorithmic trading has expanded across asset classes.

The US equity market, being the largest and most liquid market, has seen the most aggressive adoption of algorithmic trading.

Activity in markets dominated by algorithmic trading tends to be dominated by a few players.



Sources: Authority for Consumers and Markets; Bank for International Settlements; Datos Insights; and IMF staff calculations.
Note: In panel 1, "equities" refers to US equities. In panel 3, statistics show trading activity by most active market participants on Euronext.

prospect of a market with competing and self-learning algorithms opens up a range of possible new market structure outcomes. This section first explores how AI could amplify existing trends and then turns to more revolutionary aspects.

A Larger Role for Nonbank Financial Institutions and More Algorithmic Trading

With the help of AI models, NBFIs may grow even more important, and the largest ones more important still. NBFIs now hold over half of all financial market assets globally. They are generally more agile and subject to fewer constraints with regard to the adoption of AI. By contrast, some of the larger banks may suffer from legacy infrastructure and may be subject to more stringent requirements in terms of model governance and accountability, and model explainability.

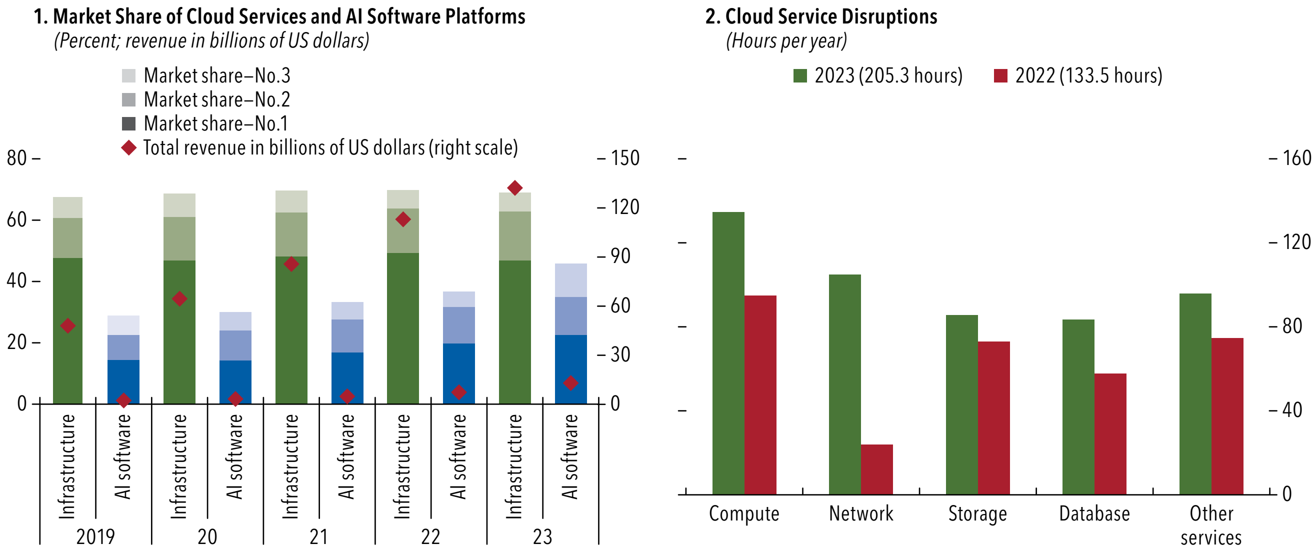
Over the past two decades, financial markets in advanced economies have experienced a significant transformation with the growth of algorithmic trading, with NBFIs rising to newfound importance. In the United States, algorithmic trading now constitutes about 70 percent of equities trading and more than half of futures trading (Figure 3.8, panel 1). Other jurisdictions are lagging behind in the share of algorithmic equities trading, but they could catch up briskly (Figure 3.8, panel 2). Increasing returns to scale seem to have resulted in those markets with a relatively high share of algorithmic trading activity also tending to see a concentration of activity among a limited number of players (Figure 3.8, panel 3). The high fixed costs associated with internal development or deployment of sophisticated AI let larger trading firms benefit from AI, while they could lead smaller players to resort to critical third-party service providers of cloud and AI software services, further amplifying outsourcing, market concentration and vendor lock-in risks (Figure 3.9).

Algorithmic trading now occupies a key role in many capital markets, and its evolution is likely to be driven by advances in AI. Strategies have already evolved from relatively simple trading rules to more complex algorithms and are now poised to use more sophisticated AI. This will provide new competitive advantages, primarily through the ability of AI to process large amounts of high-frequency and unstructured data in short amounts of time and to extract more value from it enabling automation of trading decisions. Algorithmic trading has already fundamentally altered the nature of capital markets, and the

Figure 3.9. The Risks of Artificial Intelligence: Dependence on Third-Party Providers

IT infrastructure remains strongly concentrated, and the AI software services market is becoming more concentrated.

There was longer outage time for IT infrastructure in 2023 than in 2022.



Sources: Bloomberg Intelligence; Parametrix Insurance; and IMF staff calculations.

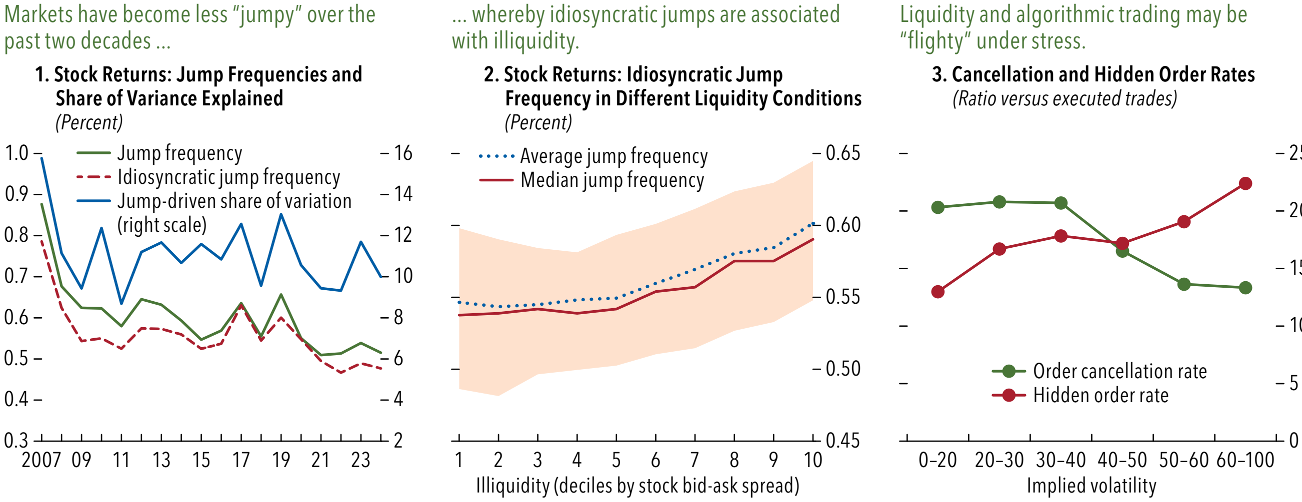
Note: In panel 1, infrastructure is represented by the aggregated revenue for the Infrastructure-as-a-Service segment, while AI software is represented by AI and predictive analytics Platforms-as-a-Service segment. In panel 2, disruption events only include critical events as defined by Parametrix and cover total outage, severe performance degradation, or other critical issues that require immediate action. As multiple groups may be affected by the same event simultaneously, the sum of the duration from each subcomponent is not equal to the total number of downtime hours. AI = artificial intelligence; IT = information technology.

finance literature has connected its history to provide valuable insights into the potential changes to come:

- Algorithmic trading is largely assessed to have a positive impact on market liquidity and efficiency, but there may also be some negative impacts, especially under stressed conditions. Research suggests that algorithmic trading enhances liquidity and informational efficiency, albeit at the cost of increased short-term volatility (Hendershott, Jones, and Menkveld 2011; Hendershott and Riordan 2012; Boehmer, Fong, and Wu 2021). However, algorithmic trading can also increase volatility following macroeconomic news and can disincentivize informed traders from participating in the market, potentially even harming market efficiency (Scholtus, van Dijk, and Frijns 2014; Yadav 2015). In the US Treasury market, one of the deepest and largest markets in the world, digitalization has dramatically improved liquidity on aggregate, but this may have come at the cost of rare but extreme bouts of illiquidity under stress (Bouveret and others 2015). Adrian, Fleming, and Vogt (2017) find that market liquidity is affected by the extent to which high-frequency traders are present in the market. This is relevant from a systemic perspective because most bonds are traded over the counter rather than on centralized exchanges where banks and securities dealers facilitate transactions.
- Algorithmic trading could minimize price swings that are not driven by new information (Chaboud and others 2014). A decomposition of high-frequency US stock returns into continuous and "jump" components (Online Annex 3.1) shows that idiosyncratic jumps in individual stock returns—which could be evidence of a reduced level of intermediation and lower liquidity—are less and less frequent (Figure 3.10, panel 1).[12] Further analysis suggests that idiosyncratic jumps are more frequent when liquidity conditions are poor (Figure 3.10, panel 2). This substantiates the notion

[12]See Box 1.4 in the October 2018 *Global Financial Stability Report*. Idiosyncratic jumps are identified by considering jumps in individual stocks that do not coincide with jumps in large and liquid passive ETFs that track the S&P 500 index (SPDR S&P 500 ETF Trust—SPY). The robustness of this identification is tested by also performing a jump decomposition of the residual stock returns, after regressing out the index return.

Figure 3.10. Algorithmic Trading and Market Efficiency



Sources: Bloomberg Finance L.P.; US Securities and Exchange Commission, Market Information Data Analytics System; and IMF staff calculations.

Note: In panel 1, the now-standard thresholding approach and time of the day indicator in Bollerslev, Todorov, and Li (2013) are used to identify jumps. Data consist of five-minute trading hour intraday data covering a balanced panel of 235 stocks between 2007 and 2024. In panel 2, the idiosyncratic jumps frequencies are computed per stock-specific deciles of the daily bid-ask spreads. Higher deciles correspond to higher illiquidity. See Online Annex 3.1 for further details.

that algorithmic trading may have helped reduce idiosyncratic jumps through its positive effect on liquidity and market efficiency. AI-driven algorithms could further facilitate this positive effect on market stability.

- Algorithmic risk limits may contribute to market destabilization under stress. Algorithmic trading strategies are often programmed to de-risk or even shut down during periods of high volatility, particularly when faced with price signals that have not occurred previously.[13] These measures are intended to protect individual trading firms from significant losses. However, under certain conditions they could contribute to market destabilization through a cascading and simultaneous triggering of limits, feedback loops, and the sudden evaporation of liquidity provided by algorithmic trading. These AI-driven strategies may then be "switched off." Data from US equity markets provide some evidence for the notion that liquidity provided by algorithmic trading diminishes under stress. High-frequency traders often make use of order cancellations (Weller 2017), but order cancellation rates drop significantly as implied volatility increases (Figure 3.10, panel 3). Simultaneously, hidden order rates increase. Hidden orders are typically used by large institutional investors to minimize the market impact of their trades when liquidity is limited. Both observations are consistent with the concept of "flighty liquidity-under-stress." Based on feedback received during the IMF outreach, AI-driven algorithmic trading strategies are also subject to the same measures under stressed conditions, especially when regular and predictable market patterns break down.
- GenAI could facilitate the proliferation of algorithmic trading across new asset classes, trading venues, and geographic regions.[14] GenAI can lower barriers to entry for algorithmic trading, as it facilitates coding, testing, and automation of trading in less technologically sophisticated trading venues. It could also help mitigate some of the obstacles that have previously impeded the proliferation of algorithmic trading. For example, in asset classes with highly diverse instruments (for example, corporate bonds) that do not

[13]These limits can include restrictions on the total volume of trades, maximum loss thresholds, or limits on exposures to specific assets or markets. A survey of energy traders conducted by the Dutch Authority for Consumers and Markets found that algorithms are subject to position limits (14/15), price limits (13/15), volume limits (12/15), and other limits (ACM 2024).

[14]See, for example, London Stock Exchange Group 2024.

Table 3.1. Potential Impact of the Adoption of Artificial Intelligence in Algorithmic Trading

	Negative Scenario	Positive Scenario
Market liquidity	**AI magnifies existing risks related to algorithmic trading by facilitating its growth.** AI could "democratize" and expand algorithmic trading activity to a broader set of assets and geographic areas. This could exacerbate risks related to sudden liquidity withdrawal under stressed conditions.	**AI increases the stability of algorithmic trading under stressed conditions.** AI-driven algorithms could operate in a wider set of market conditions than traditional algorithms, with lower flash-crash risk, and reduced liquidity-withdrawal under stress.
Leverage	**AI-driven strategies boost short-term leverage.** As arbitrage opportunities are exploited more efficiently by more advanced algorithms, remaining opportunities might require higher leverage to deliver similar returns.	**AI improves the management of leverage and related risks.** AI could facilitate more frequent and automated management of leveraged positions, based on more inputs, and mitigate operational lags.
Interconnectedness	**AI increases interconnectedness.** AI could proliferate algorithmic trading to other asset classes, geographic regions, and trading venues, and also operate in between different market segments; that is, in a multi-asset and multitrading venue approach.	
	Increased interconnectedness leads to higher correlations between capital market segments, facilitating spillovers and transmission of stress.	Market access, efficiency, and liquidity improve for some market segments, including emerging markets.

Source: IMF staff assessment.
Note: AI = artificial intelligence.

naturally lend themselves to automated trading, GenAI can facilitate the processing of complex text-based data (such as bond indentures) to enable more standardized risk analysis, and pricing tools can support liquidity.[15]

On balance, the impact of these changes from a financial stability perspective is highly uncertain. Given the nascent nature of the use of AI in algorithmic trading, multiple scenarios could materialize. Table 3.1 outlines the potential positive and negative scenarios related to liquidity, leverage, and interconnectedness in financial markets.

New Dynamics That Could Be Driven by Further Adoption of Artificial Intelligence

Beyond these traditional risk areas, AI could create new market dynamics and new risks to financial stability:

- *AI-driven strategies could drive higher and more procyclical trading volumes.* AI can quickly process vast amounts of new information and may therefore spur larger and more frequent portfolio adjustments, leading to higher trading volumes. Portfolio turnover for AI-powered ETFs[16] provides evidence for this scenario. ETFs with AI-driven strategies have experienced significantly higher turnover than other active or passive ETFs (Figure 3.11, panel 1), whose turnover has been relatively stable or slightly declining in recent years.[17,18] These higher trading volumes not only can enhance price discovery during stable market conditions but also can contribute to market instability in times of stress. Three sample AI-driven ETFs increased their portfolio turnover during the March 2020 market turmoil, providing some evidence for procyclicality (Figure 3.11, panel 2).
- *Markets could react faster to news.* There is some evidence of higher-speed adjustment based on an examination of historical releases of the Federal Open Market Committee minutes, usually a complex and lengthy document. Intraday market data suggest that, after the introduction of large language models, the initial market reaction following the release of the minutes (up to 45 seconds) tends to reflect its eventual impact more accurately than in the period before the introduction of these technologies (Figure 3.11, panel 3).
- *AI algorithms could collude or manipulate markets.* Risks in this area are currently being investigated through theoretical models of potential interactions

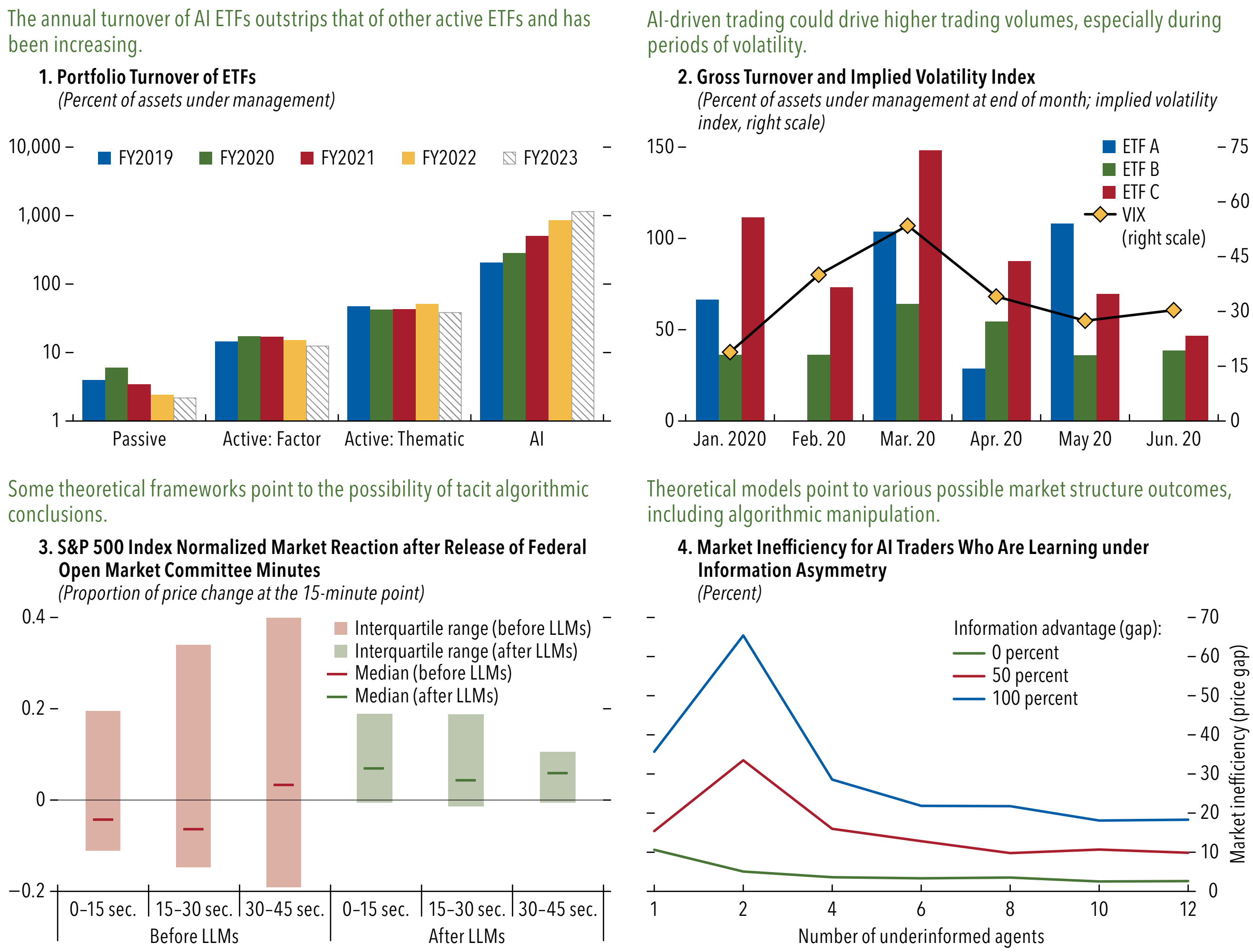
[15]Examples of AI-driven tools in bond markets include Overbond (https://overbond.com/) and BondGPT (https://www.ltxtrading.com/bondgpt).

[16]AI-powered ETFs are ETFs whose security selection and weights are optimized and periodically rebalanced using AI techniques with the objective to outperform their respective benchmarks.

[17]Bonelli and Foucault (2023) find that big data allows active asset managers to find new trading signals but that doing so requires new skills. Thus, big data can reduce the ability of asset managers lacking these skills to produce superior returns, and it has the potential to displace high-skill workers in finance.

[18]Chen and Ren (2022) find that AI-powered mutual funds do not outperform the market but that they do significantly outperform their human-managed peers through superior stock selection capability and lower turnover ratios.

Figure 3.11. New Artificial Intelligence Trading Dynamics



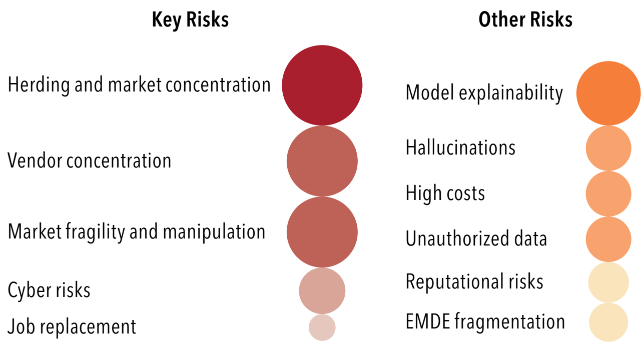
Sources: Bloomberg Finance L.P.; US Securities and Exchange Commission filings; and IMF staff calculations.

Note: In panel 2, ETF A, B, and C are samples of three AI-powered EFTs operating during the period. The implied volatility index is the VIX index. In panel 3, events have been included if the index price change surpassed 0.2 percent at the 15-minute mark. The periods before and after LLMs are separated by the publication of Vaswani and others (2017), which introduced the attention model and transformer architecture. Both the before and after LLM subsamples contain 15 qualifying datapoints. Panel 4 shows simulated scenarios from Fan, Pelger, and Yu (forthcoming), where deep learning-based reinforcement learning agents with different signals trade with each other. The panel displays the price gap between the market price and fundamental value. AI = artificial intelligence; ETF = exchange-traded fund; FY = financial reporting year; LLM = large language model.

Figure 3.12. Market Intelligence: Risks and Regulation

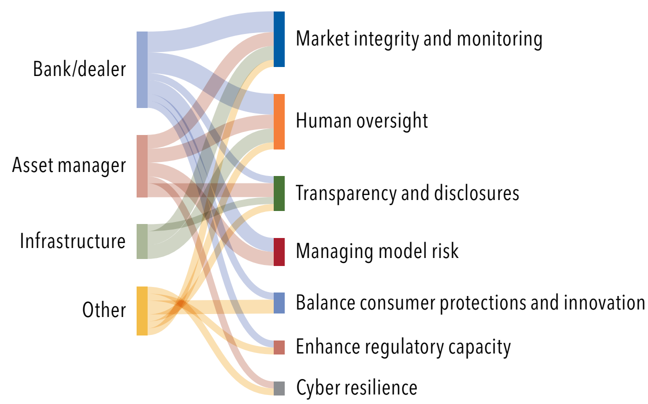
Some of the largest risks involve herding and market concentration as well as model explainability.

1. What Risks Are Associated with Using Generative AI?
(Share of participants)



Most market participants agree that regulators should ensure market integrity through monitoring and maintain human oversight of decision making.

2. How Do You Expect Regulatory Authorities to Respond to the Risks of Generative AI?



Sources: IMF, October 2024 *Global Financial Stability Report* market intelligence; and IMF staff calculations.

Note: For both panels, deepfake risks are included in the cyber categories, and additional information on market intelligence can be found in Box 3.1. In panel 1, the size and color of the bubbles represent the share of participants. Panel 2 shows that industry market participants expect regulatory authorities to intervene to limit the risks of generative AI. Infrastructure refers to market infrastructure firms. Other industry types in panel 2 include AI vendors, academia, and rating agencies. AI = artificial intelligence; EMDE = emerging market and developing economies.

between AI trading algorithms. Such models show a variety of different possible outcomes. In some cases, tacit algorithmic collusion could emerge (Dou, Goldstein, and Ji 2024). By contrast, the empirical literature points to the possibility of a "winner takes all" scenario (Baron and others 2017), which could result in market inefficiency—measured by the price gap between market prices and fundamental values—and manipulation. Manipulation is more likely if one algorithm has either an information or a latency advantage, and when the market has fewer players (Figure 3.11, panel 4).[19]

[19]Figure 3.11, panel 4, shows simulated scenarios from Fan, Pelger, and Yu (forthcoming). The panel displays the price gap between the market price and fundamental value based on a simulated market with informed and uninformed algorithmic traders that learn from each other's actions. One informed reinforcement learning agent holds one-eighth of the total market buying power, while the remaining buying power is evenly split among varying numbers of uninformed reinforcement learning agents. When the number of uninformed agents increases, it becomes harder for the informed reinforcement learning agent to manipulate the price, and hence, the equilibrium price gets closer to the fundamental value. The scenario with two uninformed agents makes it most likely to generate self-perpetuating trends, which are initiated by the informed reinforcement learning agent and take the form of local price bubbles.

Financial Stability Implications

Market Participants Are Most Worried about Concentration Risk

Participants in the IMF outreach cited potential herding and market concentration as a key financial stability risk that could result from wider and continued adoption of AI models in capital markets, especially those working at market infrastructure providers, assets managers, and academia (Figure 3.12, panel 1). This concern was viewed as especially pertinent if trading and investment strategies were to become largely derived from open-source AI and trained on similar data sourced from the same set of vendors. Correspondingly, vendor concentration was also viewed as a potential source of systemic risk, as overdependence on a limited number of AI model providers and data vendors could lead to mass disruptions to trading and investment were one or some of these vendors to fail.

Participants in the outreach also saw a possibility for widespread adoption of AI to introduce market manipulation (for example, through deepfakes or misinformation). Some participants mentioned market fragility issues—including the drying up of market liquidity, excess volatility, and flash crashes—arising from fast-paced decision making and ineffectiveness of guardrails that may result, for instance, from the poor design of such guardrails, the growing complexity of the AI system, or even a malicious intervention.[20] Other participants viewed threats such as cyberattacks on financial intermediaries and market utilities, and large-scale data poisoning as a potential source of systemic risk (Box 3.2). To a lesser extent, the acquisition of data scientists and other professionals that can work in an AI-driven environment was also raised as a concern.

Some participants raised concerns that the lack of model explainability and model hallucination[21] could be detrimental to trust in markets. Others expressed concern over high costs associated with fine-tuning sophisticated models using large data sets creating potential for an unlevel playing field, with large firms having an advantage. Few participants also worried that customer fraud, unauthorized use, and data access could pose risks and compliance issues, leading to reputational damage. To a lesser extent, the adoption of AI could exacerbate spillovers of advanced economy shocks to emerging market and developing economies,[22] particularly if AI models are more sensitive to price fluctuations and managed against a basket of various asset classes. Alongside increasing transactions and sensitivity to market news, cross-border capital flow volatility could also increase and be destabilizing, particularly for relatively smaller and less liquid markets with largely fragmented participants.

[20]Guardrails refer to various microstructure mechanisms (such as pretrade controls, circuit breakers, volatility parameters, and kill switches). Issues with participant systems may impact a trading venue's ability to maintain a fair and orderly market. This might necessitate a trading venue to introduce microstructure mechanisms and tools to manage these risks and address the issues that arise. For details, see IOSCO (2015).

[21]See Shabsigh and Boukherouaa (2023, p. 7), who explain how "GenAI's ability to generate new content based on training data comes with the risk that GenAI models could produce wrong but plausible sounding answers or output and then defend those responses confidently—a phenomenon broadly referred to as 'hallucination.'"

[22]A potential AI use case for emerging market and developing economy assets is on managing foreign exchange risk. Some corporate treasurers are experimenting with AI techniques to assess currency risk exposure, predict market trends, and calculate optimal foreign-exchange hedging ratios. See Lipsky, Cole. 2024. "Banks, Vendors Mine AI for Corporate FX Hedging." Risk.net, June 6. https://www.risk.net/markets/7959503/banks-vendors-mine-ai-for-corporate-fx-hedging.

Regulators Are Expected to Enhance Monitoring and Provide Guidance on the Risk Management of Artificial Intelligence Models

In response to the growing uncertainty and risks emerging from the adoption of AI/ML, participants in the IMF outreach expected regulatory authorities to provide clarity and guidance on model risk management, emphasize stress testing for extreme scenarios, and provide transparency and clearer disclosures (Figure 3.12, panel 2). Stakeholders also anticipated guidance on industry-specific regulatory structures to avoid violation of existing regulations, guidelines on AI use in consumer-facing applications, and accountability frameworks. Both buy-side and sell-side entities, along with academia and market infrastructure providers, emphasized the need for balanced regulation that ensures responsible use of AI without stifling innovation while at the same time ensuring adequate consumer protection. There was consensus that capital market supervisors should focus on providing guidelines and best practices rather than strict rulemaking, given the rapidly evolving nature of AI technology in financial markets. Some participants noted the importance of addressing bias in AI models and the potential need for supervisors to ensure better AI preparedness through continuous upskilling while integrating AI/ML (including sophisticated AI) in their supervision and market surveillance functions. Their overall sentiment was that the regulatory approach should be flexible and adaptable to keep pace with the rapid advancements in AI technology in the financial sector.

Summarizing the Financial Stability Challenges: Current and Prospective

The use of AI in capital markets is still relatively nascent, and currently the financial stability risks associated with its adoption appear contained. Even so, there are already well-documented instances of sophisticated AI being used to generate disinformation with the goal of manipulating markets, and more importantly, more malicious cyber threats (see Box 3.2).

The analytical work and the market participant responses to the IMF's outreach documented in this chapter demonstrate that rapid adoption of AI in capital markets is likely and that it may drive some transformative impacts on markets that lead to several financial stability challenges:

- ***Increased market speed and volatility under stress***
  - Continued growth of AI-enhanced algorithmic trading strategies could enhance market liquidity and bring efficiency gains, manifesting in the form of more prompt price adjustments in response to new information and also thinner margins for traders. But both could incentivize an increased use of leverage across the financial system and result in more amplification between falling asset prices, volatility, and deleveraging in periods of stress.
  - AI models may herd and produce rather similar decisions, especially during stress periods resulting in procyclical financial stability risks. During normal times, AI models may uncover new trading opportunities, leading to more diverse investment strategies that would be positive for financial market resilience. During adverse shocks, however, models could simultaneously rebalance portfolios toward safe assets, creating a self-fulfilling spiral of fire sales.
  - Novel adverse events—such as the COVID-19 pandemic in 2020—may drive AI model outcomes that are difficult to comprehend, or models may simply shutdown, requiring humans to make decisions on and process a voluminous number of trades. This vulnerability could be more heightened if AI trading algorithms collude with each other, resulting in a winner-dominated market that could be more easily upended by adverse shocks.
- ***More opacity and monitoring challenges***
  - AI may spur further migration of activities to NBFIs. Since the global financial crisis, trading and investment activity, and especially capital market activities, have steadily migrated out of the banking sector and into NBFIs (see Chapter 2 of the April 2023 *Global Financial Stability Report*). Some NBFIs have now built extensive expertise and technology to help them take advantage of new advances in AI. Regulatory requirements for banks regarding the explainability and transparency of internal models—compared to comparatively lighter requirements for NBFIs—give NBFIs a competitive advantage over banks in reaping the benefits of complex models, thereby raising systemic opacity.
  - AI models could generate portfolios across different asset classes, geographic regions, and trading venues, creating correlations and interconnectedness that are not relevant at the current juncture. This could undermine the ability of regulators to monitor financial risks holistically.
  - There will likely be emergent, new forms of risks (for example, potential complex interactions between autonomous AI agents not visible at the level of individual institutions or at the regulatory level).
- ***Increased operational risks as a result of reliance on a few key third-party AI service providers***
  - AI models and related information technology services currently reside with a handful of key providers with dominant computational power and established large language models. If capital markets activities become too reliant on these models, the failure of these providers may lead to market stress akin to the failure of key financial market utilities such as clearing houses.
- ***Increased market manipulation and cyber risks***
  - Fraud, disinformation, and deepfakes will likely become more sophisticated as AI advances and could be used by bad actors to manipulate financial markets and asset prices.
  - Data integrity and confidentiality could be compromised, leading to AI models producing suboptimal trading and investment decisions.

Regulatory and Supervisory Developments

International, National, and Supervisory Artificial Intelligence Initiatives

International organizations, standard-setting bodies, and financial sector authorities for larger capital markets have identified the use of AI/ML by market intermediaries and asset managers as a key priority, given the cautious but steady pace of its uptake. As capital markets are already subject to regulation and supervision, institutions are responsible for AI systems they deploy, whether internally developed or externally sourced. Existing regulatory and supervisory frameworks for capital markets are largely technology-neutral and are also applicable to AI systems. Ongoing work by financial sector authorities explores and provides guidance on application of existing prudential frameworks as well as the need for additional frameworks to effectively cover the risks specific to the use of AI,

Figure 3.13. Standard Setter, National, and Supervisory Artificial Intelligence Initiatives

Standard-setting bodies are designing frameworks by building on accepted practices, while considering their application to AI.

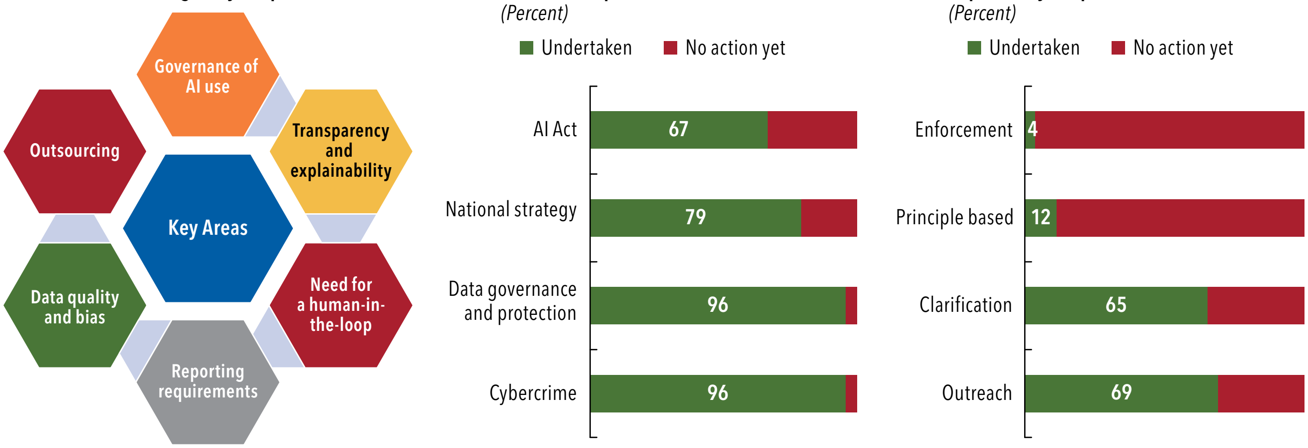
1. Standard-Setting Body Response

Governments with large capital markets are leveraging cyber and data frameworks to pivot to AI strategies ...

2. National Response
(Percent)

... whereas financial supervisors are cautious and respond through targeted outreach and clarification of existing standards.

3. Supervisory Response
(Percent)



Sources: Panel 1: IMF staff literature review of international standards and regulatory and supervisory publications. Panels 2 and 3: UN Institute for Disarmament Research AI Policy Portal; UN data protection and privacy legislation worldwide; and IMF staff analysis and review of AI-related initiatives taken by financial sector authorities.

Note: The analysis covers the jurisdictions with stock exchange operators with a market capitalization of listed companies exceeding $1 trillion as of March 2024. The sample consists of 24 jurisdictions, of which 11 are members of the European Economic Area, and 26 financial market authorities, of which 11 are from the European Economic Area and 3 are from the United States. AI = artificial intelligence.

which so far focus more on conduct issues such as ethics, fairness, and transparency.

Most current AI initiatives by standard-setting bodies begin by saying that financial sector authorities should remain vigilant on AI deployment by capital market participants and be prepared to respond to an acceleration in the pace of adoption. It is recommended that financial sector authorities update their skills and supervisory tools to monitor more complex investment strategies and process more granular data in real time. In addition, financial sector authorities should proactively question whether extant regulatory frameworks adapt to novel forms of AI with a comprehensive view of emerging risks.

In this context, standard-setters and financial sector authorities have issued or are revisiting assessments (FSB 2017b), guidance, and regulatory frameworks that take into account the various risks of AI deployment (Figure 3.13, panel 1) in a number of key areas. Existing frameworks issued by the Financial Stability Board (FSB), Bank for International Settlements, and national regulators address financial stability, market integrity, and investor protection concerns mostly by building on the principles of technology-neutral, results-based, and proportional regulation and supervision (Monetary Authority of Singapore 2018; Hong Kong Monetary Authority 2019).[23] The FSB issued guidance for managing third-party risk and cyber incidents (FSB 2020, 2023a). The Basel Committee frameworks for banking institutions that participate in capital markets include principles and recommendations on data governance and operational and cyber risk management (BCBS 2013; BIS 2023). The US National Institute of Standards and Technology (NIST) has recently issued a relevant AI framework (NIST 2024). The International Organization of Securities Commissions (IOSCO) has addressed algorithmic trading and market volatility (IOSCO 2018) and AI risks in market intermediaries

[23]While issued by the US Executive Power, the Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence (https://www.whitehouse.gov/briefing-room/presidential-actions/2023/10/30/executive-order-on-the-safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence/) encourages independent regulatory agencies to consider using their authority to prevent discrimination and address risks arising from the use AI to financial stability.

and asset management (IOSCO 2021). Currently, IOSCO is conducting a two-year project to assess risks and challenges associated with the use of AI, with potential policy guidance expected by the first quarter of 2025 (IOSCO 2024).

An IMF review of actions taken by 26 authorities in large capital markets finds that governments have already begun to formulate comprehensive AI strategies and act in the areas of data protection, governance, and cybercrime (Figure 3.13, panel 2). Some jurisdictions are also considering dedicated AI legislation to ensure robust governance for this rapidly evolving technology. However, supervisory authorities remain cautious in this area, and so far, have focused primarily on clarification and outreach, rather than on enforcement (Figure 3.13, panel 3).

Best Practices

Given the rapidly evolving and uncertain landscape of AI in capital markets, engagement through outreach is crucial. Establishing public/private forums to develop overarching principles (Office of the Superintendent of Financial Institutions 2023), partnering with the industry to build a risk framework (Monetary Authority of Singapore 2024), and conducting surveys on the applicability of existing frameworks are mechanisms that can be conducive to a safe adoption of AI (US National Archives 2021; Institute for Workplace Equality 2022; Bank of England 2024). Engagement also helps financial sector authorities assess whether existing risk management guidance takes into account the specific challenges of AI models, namely explainability, robustness, data bias/privacy, and cybersecurity, and to what extent AI is being used in the sector and for which particular services and activities. Other practices within the banking sector relate to requesting notification by banks prior to their adoption of certain technologies or arrangements with third parties (BCBS 2024).

AI is providing numerous opportunities for supervisors to generate efficiency gains by automating data quality checks to ensure completeness, correctness, and consistency. AI can also combine multiple data sources, even when original data lack a unique identifier, and help financial sector authorities detect anomalies in trading patterns, reflected in changes in prices, volume, and volatility (di Castri and others 2019). Other applications may aim to identify misleading information or perform real-time monitoring of market transactions. GenAI offers new possibilities to financial sector authorities because it enhances information retrieval, content creation, and code generation, debugging, and explanation, as well as legacy code optimization. These tools could enable financial sector authorities to accelerate the deployment of more traditional use cases such as fraud detection or monitoring of market activity, or streamline data management tasks.

While the adoption of new and emerging technology for supervisory processes (known as SupTech) continues to trend upward, the adoption rates between advanced economies and emerging market and developing economies are uneven (Cambridge SupTech Lab 2023).[24] Periodic upskilling and upgrading should help financial sector authorities identify AI use–specific issues like models designed to "game the regulation" and detect algorithmic coordination. Finally, existing cross-sectoral thematic reviews could reveal potential herding or material interconnectedness among market participants and also help identify best practices in the use of AI (Securities and Exchange Board of India 2019).

Policy Recommendations

Regulation and supervision in AI-related areas should be enhanced to address potential financial stability risks for both the banking and NBFI sectors. Regulatory and supervisory frameworks should follow a balanced approach, allowing financial sector participants to reap the potential benefits of AI while acknowledging its risks (IMF and World Bank 2018). Across sectors, supervisors should continue to strive for cyber resilience and address dependency on data, models, and third-party service providers by requesting risk mapping. Specific to capital markets, areas that could be strengthened further relate to over-the-counter markets and existing measures to address volatility. Implementation of these recommendations will require regulatory reporting to allow for continued structural assessment of the developments and accompanying risk, which is more achievable with an outreach or survey approach.

[24]In 2023, 79 percent of advanced economies and 54 percent of emerging market and developing economies had adopted SupTech tools, compared to 50 percent and 31 percent, respectively, in 2022.

Address Increased Market Speed and Volatility under Stress

Financial sector authorities and trading venues should determine whether designing new or modifying existing volatility response mechanisms is necessary to respond to crash events potentially originated in AI-driven-trading. Existing circuit breakers may need to be re-parameterized in light of changing market structures. However, poorly designed circuit breakers may exacerbate volatility and interfere with market efficiency and price discovery (Vereckey 2023). Testing algorithms in controlled environments could help financial sector authorities, trading venues, and market actors assess their behavior in extreme circumstances.

Financial sector authorities, trading venues, and central counterparties should review margining requirements and other buffers in light of potentially rapid AI-driven price moves. In line with policy proposals by the Basel Committee on Banking Supervision, the Bank for International Settlements' Committee on Payments and Market Infrastructures, and IOSCO, further international work is needed to (1) foster market participants' preparedness for the large variation margin calls that can occur during market stress; (2) identify good practices for variation margin collection and distribution by the central counterparty; (3) understand the degree and nature of the central counterparty margin models' responsiveness to volatility and other market stresses; and (4) review initial margin levels in non-stress times, including a review of the effectiveness of tools to reduce the procyclicality of margin models (BCBS, CPMI, and IOSCO 2022).

Address Increased Opacity and Monitoring Challenges

Financial sector authorities should ask financial institutions to regularly map interdependencies between data, models, and technological infrastructure supporting AI models.[25] These models may feed on shared or interdependent data sources; share a common architecture; and rely on a small number of providers for software, data, and cloud services. In addition, data sets may not cover a complete financial cycle, undermining the reliability of models built upon them (Gensler and Bailey 2020). Although regulatory frameworks require assessing the cumulative effects of models, they do not mandate a joint assessment of data dependencies. An updated view of these interdependencies will enable financial sector authorities to proactively manage risks and promote a resilient ecosystem.

Financial sector authorities should continue to strengthen their oversight and regulation of NBFIs by requiring them to identify themselves and disclose AI-relevant information. The authorities could monitor the activity of market participants that conduct a substantial amount of trading activity ("large traders") (IOSCO 2011). Each such large trader should be uniquely identified and provide information on its activities to its registered broker-dealer in its securities market, which would allow for monitoring by financial sector authorities. Other measures, such as those proposed by the FSB and IMF, and which also address risks of further adoption of AI in the NBFI sector, should aim to continue strengthening resilience there (see Chapter 2 of the April 2023 *Global Financial Stability Report*; FSB, n.d.). On that point, enhancing risk management and strengthening liquidity buffers could contribute to the resilience of NBFIs, thereby mitigating the effects of asset mispricing or liquidity runs.

Address Increased Operational Risks as a Result of Reliance on a Few Key Third-Party Artificial Intelligence Service Providers

Financial sector authorities should undertake a coordinated approach to the regulation and supervision of AI service providers. To this purpose, it is crucial to map the relationships and correspondences between critical AI service providers and essential IT infrastructure providers Failure or disruption of critical third parties may affect the stability of and confidence in the financial sector (Federal Reserve System, Federal Deposit Insurance Corporation, and Department of the Treasury 2023; see also European Securities and Markets Authority 2023). Comparable and interoperable regulatory approaches to critical service providers facilitate compliance across the financial sector and coordination among financial sector authorities (FSB 2023b). The authorities should also ensure that the definition of critical service providers is broad enough to capture the systemic use of common AI models (Bank of England 2024).

Financial sector authorities should continue to strive for resilience in capital markets by requiring protocols to avoid, protect against, respond to, and recover from attacks. AI systems are exposed to various types of attacks that can affect both the data used to train the

[25] Similar to, but expanded to data and AI systems, see Principle 4 of the BCBS "Principles for Operational Resilience" (BCBS 2021).

algorithm and the model itself, and that aim to either manipulate model results or extract their coding. AI systems are like other information technology systems, so cybersecurity needs should be contemplated at various stages—namely the design, development or procurement, deployment, and operations stages (National Cyber Security Centre 2023).

Address Over-the-Counter Monitoring Needs and Resilience Risks

Financial sector authorities should be prepared to adopt measures that ensure continued market integrity, efficiency, and resilience of over-the-counter markets when AI use proliferates. The authorities should consider collecting and disseminating more detailed information on over-the-counter transactions, requiring market participants to account for liquidity shifts in their risk management framework, establishing or expanding existing incentives for market-makers to enhance liquidity, improving incentives for central clearing, and establishing margin requirements for non-centrally cleared derivatives. In the event of shocks, backstop measures could include central bank liquidity provision to market-making banks or indirectly support nonbank dealers by easing market funding conditions (CGFS 2014).

Box 3.1. IMF Staff Market Outreach: Qualitative Assessment of Advances in Artificial Intelligence and Its Implications for Capital Markets

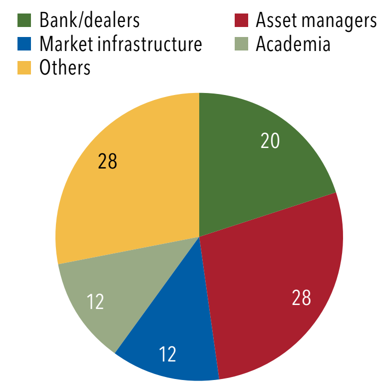
IMF staff conducted extensive outreach across various stakeholders to gather market intelligence on how financial institutions—both buy-side and sell-side firms—are harnessing advances in artificial intelligence (AI) for capital market activities, and on the potential impact of AI adoption. The objective was also to gain a forward-looking view on how the rise of sophisticated AI (including generative AI) technologies might influence financial activity in the future, especially in terms of the use of AI and machine learning (ML) for asset allocation and trading.

IMF staff engaged in a large number of meetings with bank/dealers, AI vendors, asset managers, academia, rating agencies, and market infrastructure firms, among others (Figure 3.1.1), and received detailed responses from 27 stakeholders directly involved in AI topics and business. While buy-side firms include asset managers, mutual funds, hedge funds, pension funds, private equity firms, and institutional investors, sell-side firms consist of investment banks, brokerage firms, market makers, and research analysts. Bilateral discussions focused on the use of AI/ML, including sophisticated AI for investing across various asset classes, expected use cases and benefits in investment and trading decisions, prospects around AI-based trading autonomy, risks and challenges (including potential systemic risks), and expected regulatory guidance on AI deployment. The outreach also sought feedback on the potential impact on emerging market and developing economies in terms of capital flows and potential fragmentation risk.

Given the challenge to identify a homogenous definition of AI and distinguish AI/ML from sophistication AI, IMF staff adopted the following definitions: "AI/ML models" referred to well-established predictive analytics, including neural networks, clustering algorithms, natural language processing, decision trees, and so on; and "sophisticated AI models" referred to the latest innovations, such as deep learning, reinforcement learning, and large language models. This includes generative AI models capable of generating text, codes, images, and other content. For certain topics for which questions can be asked consistently across participants (for example, asset classes for which AI is used, key risks that are top of mind), staff tabulated the results of answers to the questions.

The IMF's outreach was accompanied by an extensive literature review, data collection, and analytical work. In parallel, staff conducted a regulatory outreach with 10 capital market supervisors of advanced and emerging markets.

Figure 3.1.1. Participants in the IMF's Market Intelligence Outreach
(Percent)



Sources: IMF, October 2024 *Global Financial Stability Report* market intelligence; and IMF staff calculations.
Note: "Others" includes nonprofit financial organizations, artificial intelligence finance conferences, artificial intelligence vendors, and rating agencies. This figure does not include regulatory outreach.

Box 3.2. Manipulation and Cyber Risk: The Artificial Intelligence Arms Race

Generative artificial intelligence can be used by bad actors to manipulate markets or to conduct cyberattacks. Cyberattacks have been on the rise in recent years (Figure 3.2.1, panel 1), with the share of attacks on finance and insurance sector entities more than doubling over the past decade. Previous IMF work has shown one measure of potential maximum annual financial firm losses from cyber incidents has increased from $300 million to $2.2 billion since 2017 (see Chapter 3 of the April 2024 *Global Financial Stability Report*).[1] Cybercriminals can produce deepfakes, manipulating audio and video to impersonate key individuals in the financial sector, or spread other misinformation. Such deepfakes can lead to fraudulent transactions, manipulated stock prices, or an erosion of trust in financial institutions, triggering selloffs or deposit runs. Critical financial market or information technology infrastructure can be targeted, leading to significant disruptions in financial markets and beyond.

Although a dedicated AI cyberattack database does not currently exist, AI incidents are being tracked by multiple databases.[2] Despite better AI preparedness, most AI incidents have occurred in advanced economies, even when accounting for differences in GDP (Figure 3.2.1, panel 2). In many cases, AI incidents concern cases where AI was used with a legitimate objective, but where unanticipated consequences appeared. AI incident rates therefore

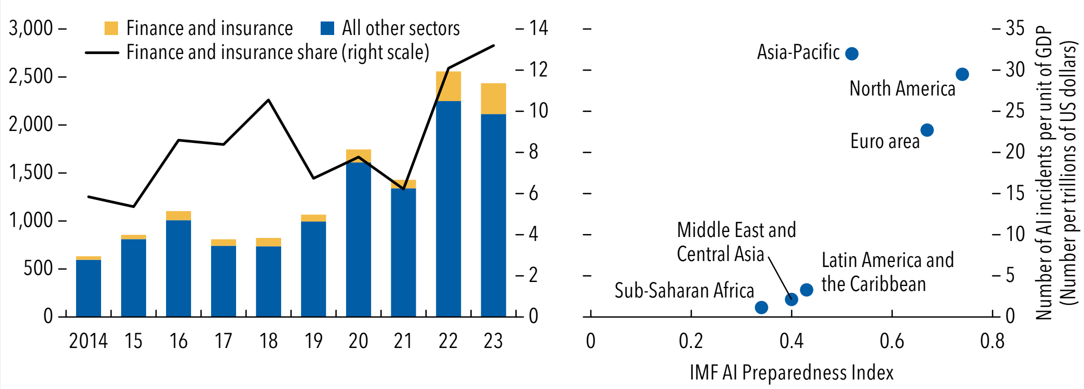
Figure 3.2.1. Cyberattacks and Artificial Intelligence Incidents

Cyberattacks have increased, with the financial sector share rising as well.

1. Cyberattacks
(Number per year; finance and insurance sector share in percent)

Despite higher AI preparedness, North America and Europe have higher rates of AI incidents.

2. AI Incidents per Unit of GDP and AI Preparedness
(Number per trillions of US dollars; index)



Sources: AI, Algorithmic, and Automation Incidents and Controversies (AIAAIC); University of Maryland Center for International and Security Studies; and IMF staff calculations.

Note: AIAAC defines an "incident" as a sudden known or unknown event (or "trigger") that becomes public and which takes the form of a disruption, loss, emergency, or crisis. In panel 2, the IMF AI Preparedness Index incorporates four macro-structural indicators that are relevant for AI adoption: digital infrastructure, innovation and economic integration, human capital and labor market policies, and regulation and ethics. AI = artificial intelligence.

[1]Chapter 3 of the April 2024 *Global Financial Stability Report* explains how the growing instances of cyberattacks post an acute threat to macrofinancial stability. Data cited comes from Figure 3.5, panel 4, of the report.

[2]There are three databases keeping track of so-called AI incidents: (1) the AI Incident Database (https://incidentdatabase.ai/apps/incidents/), (2) the Organisation for Economic Co-operation and Development's AI Incidents Monitor (https://oecd.ai/en/incidents), and (3) the AI, Algorithmic, and Automation Incidents and Controversies Repository (www.aiaaic.org).

Box 3.2 *(continued)*

largely reflect AI usage rates. This illustrates that the use of AI comes with risks when it behaves in ways that were not anticipated.

Recent incidents illustrate potential mechanisms through which an AI-triggered cybersecurity breach could lead to more significant ramifications. In a 2024 case, a finance worker at a multinational firm in Hong Kong SAR was reportedly tricked by AI-generated deepfake video and audio, allegedly leading to a $25 million payout to fraudsters.[3] This incident shows how generative AI can be used to exploit human or organizational vulnerabilities through personalization and social engineering. In the financial sector, bad actors could gain access to critical systems.

Cyberattacks can disrupt computer systems, with implications for key financial markets. Although a 2023 ransomware attack on the Industrial and Commercial Bank of China is not known to have been related to AI, it reportedly affected US Treasury market conditions.[4]

Finally, fake or genuine social media activity can amplify news and contribute to panic, possibly through manipulation. Reports suggest that First Republic Bank was targeted by an online manipulation campaign.[5]

[3]Chen, Heather, and Kathleen Magramo. 2024. “Finance Worker Pays Out $25 Million After Video Call with Deepfake ‘Chief Financial Officer.’” CNN, February 4. https://edition.cnn.com/2024/02/04/asia/deepfake-cfo-scam-hong-kong-intl-hnk/index.html

[4]*Financial Times.* 2023. “Ransomware Attack on ICBC Disrupts Trades in US Treasury Market.” November 10. https://www.ft.com/content/8dd2446b-c8da-4854-9edc-bf841069ccb8

[5]Khan, Amil, and Fergus McKenzie-Wilson. “The First ‘Safe’ Bank Brought Down by Disinformation Attacks.” Valent Projects, January 2024. https://www.valent-projects.com/news-and-insights/first-republic-bank-brought-down

Glossary

This glossary provides descriptions and, where possible, definitions of the most important AI-related concepts, as used in the chapter. It draws from definitions and descriptions used by international standard setting bodies.

Algorithmic trading (AT)	Trading in financial instruments whereby an algorithm independently executes trading decisions.[26] Algorithmic trading can be used for trade execution, market-making, or in other proprietary trading strategies. Algorithmic trading strategies vary in complexity and latency; in its simplest guise, algorithmic trading may involve the use of basic trading rules or instruction to feed portions of an order into the market at preset intervals to minimize market impact cost. More complex applications can involve multi-asset trading strategies based on advanced machine learning models. Reinforcement learning allows algorithms to learn dynamically from evolving trading patterns, as well as the actions of other algorithms.
Artificial intelligence (AI)[27]	The theory and development of computer systems able to perform tasks that traditionally have required human intelligence. The definition of AI is very broad and would include many simple applications that would generally not be described as AI in the public discourse. For example, simple linear regression would fall under this broad definition, even though most would not classify this as AI. The focus of this chapter is on more **sophisticated AI**, which includes not only generative AI but also more complex nongenerative applications such as clustering algorithms, neural networks, gradient-boosted decision trees, support vector machines, etc.
Deep learning	A form of machine learning that uses algorithms that work in “layers” inspired by the structure and function of the brain. Deep learning algorithms, whose structures are called artificial neural networks, can be used for supervised, unsupervised, or reinforcement learning (itself a form of machine learning).
FinTech[28]	Technology-enabled innovation in financial services that could result in new business models, applications, processes, or products with an associated material effect on the provision of financial services.
Foundation models[29]	An umbrella term referring to a diversity of models that are usually trained by applying deep learning to massive quantities of data, such as text and images. Because the expertise, time, and computing power involved in training foundation models from scratch are typically prohibitive for most nonspecialist firms, these models are usually pretrained and shared with end users for further refinement.
Generative AI	AI that generates new content, such as text, images, and videos, often based on user prompts. Generative AI is powered by foundation models, such as large language models.

[26]Financial Conduct Authority Handbook (2011).
[27]FSB (2017b).
[28]FSB (2017b).
[29]FSB (forthcoming).

High-frequency trading (HFT)	HFT is frequently equated to algorithmic trading. However, whereas HFT is a type of algorithmic trading, not all forms of algorithmic trading can be described as high frequency. Algorithmic trading predates HFT and has been extensively used as a tool to determine some or all aspects of trade execution like timing, price, quantity, and venue. Many intermediaries use algorithmic trading for their own proprietary trading or offer it to their clients. It has also become a standard feature in many buy-side firms, mainly with the purpose of devising execution strategies that minimize price impact or to rebalance large portfolios of securities as market conditions change. A number of common features and trading characteristics related to HFT are identified by IOSCO.[30]
Large language models (LLMs)	Large language models are AI systems designed to learn grammar, syntax, and semantics of one or more languages to generate coherent and context-relevant language.
Machine learning (ML)	A method of designing a sequence of actions to solve a problem that optimizes automatically through experience and with limited or no human intervention.
Market-making[31]	The provision of liquidity for clients in financial instruments, whereby a trader sets firm bid-offer quotes and thereby provides liquidity for a specific product or a particular product class. This is designed to avoid temporary imbalances between supply and demand for certain products.
Proprietary trading	Describes a trading unit which is separate from the rest of an organization's trading activities and is not involved in client business. It generates profits exclusively from taking positions. This trading unit has no client contact and is not involved in the broker market.
RegTech[32]	Any range of applications of FinTech for regulatory and compliance requirements and reporting by regulated financial institutions. This can also refer to firms that offer such applications.
Reinforcement learning (RL)	A type of machine learning paradigm where an agent learns to make decisions by taking actions in an environment to achieve some goal. The learning process is driven by the feedback the agent receives from the environment in the form of rewards or penalties.
Robo-advisors or automated advice	Applications that combine digital interfaces and algorithms, and can also include machine learning, to provide services ranging from automated financial recommendations to contract brokering to portfolio management to their clients, without or with very limited human intervention. Such advisors may be standalone firms and platforms or can be in-house applications of incumbent financial institutions.
SupTech	Any application of FinTech used by regulatory, supervisory, and oversight authorities.
Synthetic data	Artificially generated information that is designed to mimic real-world data in terms of statistical properties and structure. Unlike real data, which are directly collected from real-world events or interactions, synthetic data are created through algorithms and simulation models.

[30]IOSCO (2011, p. 22).
[31]CGFS (2014).
[32]FSB (2017a).

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