

Chapter 2 at a Glance

- Uncertainty regarding global economic outcomes and policies has been higher since the COVID-19 pandemic amid inflation shocks and rising geopolitical tensions.
- High macroeconomic uncertainty can profoundly affect macrofinancial stability by exacerbating downside market tail risks, delaying consumption and investment decisions, and reducing credit supply.
- As financial indicators may not fully capture macroeconomic uncertainty, particularly in economies with less-developed financial systems, there is merit in considering measures of macroeconomic uncertainty in systemic risk assessment frameworks such as the growth-at-risk framework.
- An increase in macroeconomic uncertainty equivalent to its rise during the global financial crisis reduces the downside outcome (the 10th percentile) of one-year-ahead real GDP growth by, on average, 1.2 percentage points in advanced and emerging market economies.
- Macroeconomic uncertainty also tends to amplify the effect of prevailing macrofinancial vulnerabilities, such as excessive leverage in the private and public sectors, on downside risks to future output growth.
- A significant easing of financial conditions amid high macroeconomic uncertainty can exacerbate downside risks to future output growth, particularly during periods of low financial market volatility (that is, during “macro-market disconnects”). An adequate macroprudential policy response can, however, mitigate this effect.
- The effects of macroeconomic uncertainty can spill over across borders through trade and financial inter-linkages, increasing the risk of contagion in the face of adverse shocks.

Policy Recommendations

- Reduce domestic macroeconomic uncertainty by strengthening the credibility and transparency of frameworks for monetary, fiscal, and financial sector policies and through effective communication strategies.
- Implement adequate fiscal and macroprudential policies to contain macrofinancial vulnerabilities and build resilience against adverse shocks, particularly when macroeconomic uncertainty is high.
- Build adequate international reserve buffers and allow exchange rate flexibility to help cushion the adverse spillover effects of an increase in foreign macroeconomic uncertainty.
- Devote resources to quantifying, managing, and mitigating the risks from rising geopolitical uncertainty on macrofinancial stability.

Introduction

A high level of uncertainty has characterized the global macroeconomic landscape since the COVID-19 pandemic. Uncertainty about economic outcomes and policies spiked during the COVID-19 pandemic and has remained high since then, compared with levels in

earlier years, amid inflation shocks, escalating geopolitical tensions, rapidly emerging new technologies, and increasing climate-related risks.¹ Different measures of macroeconomic uncertainty make this evident (Figure 2.1).²

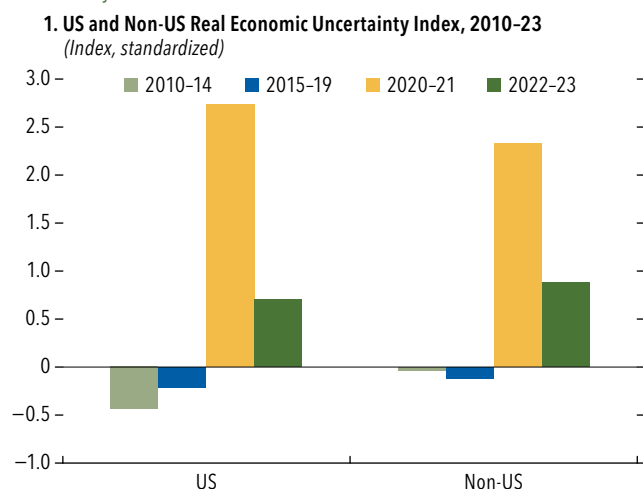
¹In economics, uncertainty refers to situations in which future outcomes are difficult to predict (Knight 1921).

²Measures of macroeconomic uncertainty tend to be volatile but on average have stayed elevated since the pandemic. Some measures, such as global economy policy uncertainty of Baker, Bloom, and Davis (2016), declined in the first quarter of 2024 but rose again in the second quarter amid electoral uncertainty in some major economies (Online Annex Figure 2.1.1).

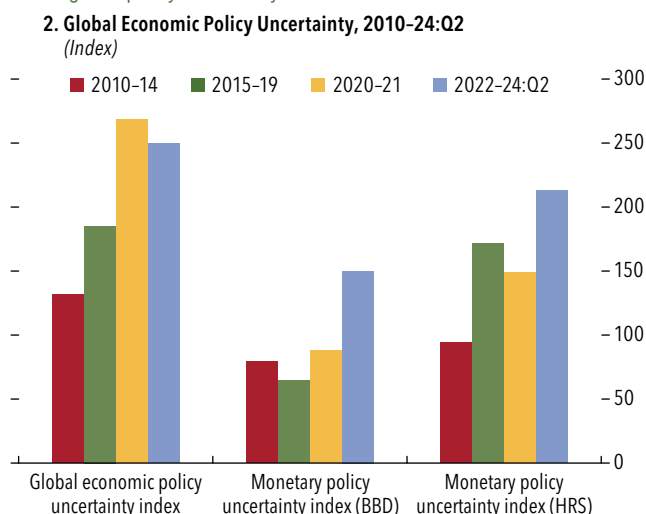
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Figure 2.1. Economic and Policy Uncertainty

Uncertainty around the macroeconomic outlook has increased ...



... along with policy uncertainty.



Sources: Baker, Bloom, and Davis 2016; Husted, Rogers, and Sun 2020; IMF, Global Data Source and International Financial Statistics databases; Organisation for Economic Cooperation and Development, Main Economic Indicators database; and IMF staff calculations.

Note: Panel 1 shows values on a real economic uncertainty index for the United States and other economies based on the approach in Ludvigson, Ma, and Ng (2021). The index is standardized over its historical mean (January 1990 through September 2023) and averaged across different periods. Non-US real economic uncertainty index is a GDP-weighted average across non-US economies. In panel 2, “Global economic policy uncertainty index” is a GDP-weighted index from Baker, Bloom, and Davis (2016) averaged over the indicated time period. For additional details on the data sources, see Online Annex 2.1. The monetary policy uncertainty indices pertain to the United States and are compiled by Baker, Bloom, and Davis (BBD, 2016) and Husted, Rogers, and Sun (HRS, 2020), respectively.

Increased macroeconomic uncertainty can profoundly affect macrofinancial stability. High macroeconomic uncertainty can potentially affect macrofinancial stability—or systemic risk—through three key channels.³ First, it can exacerbate downside market tail risks in the event of an adverse shock (the market channel). Second, it can delay private sector consumption and investment decisions, slowing economic activity and raising credit risks for financial institutions that can in turn trigger an adverse macrofinancial feedback loop (the real channel). And third, it can reduce the supply of domestic credit by financial institutions by exacerbating challenges in determining the creditworthiness of new borrowers (the credit channel). These three channels can interact and mutually reinforce each other, amplifying the effect of macroeconomic uncertainty on macrofinancial stability.⁴

³Macrofinancial stability is defined in terms of systemic risk, that is, the risk of disruption to the financial system that can have serious negative consequences for the real economy, and is measured by downside tail risks to future real GDP growth.

⁴While studies using well-known measures of macroeconomic uncertainty generally find it to be negatively associated with asset returns and volatility (Asgharian, Christiansen, and Hou 2015; Bali, Brown, and Tang 2017), the effect could also be positive. For example, high-tech revolutions promising future productivity gains can be a source of positive or “good” uncertainty, while geopolitical conflicts can be considered as a source of negative or “bad” uncertainty (Bloom 2014; Segal, Shaliastovich, and Yaron 2015; Dew-Becker and Giglio 2023).

Macroeconomic uncertainty can interact with potential vulnerabilities in the real and financial sectors to magnify the effects of adverse shocks. For example, in the presence of high levels of public debt relative to GDP, investors may react more strongly to an expansionary fiscal shock when uncertainty regarding the economic outlook is high instead of low, leading to a sharp increase in sovereign bond yields (see the October 2024 *Fiscal Monitor*). Periods of high macroeconomic uncertainty may also make the corporate debt market more vulnerable to adverse shocks, particularly when leverage in the corporate sector is high or credit spreads are perceived by investors to be overly compressed. Equity markets are also likely to experience larger price corrections in the face of adverse shocks when uncertainty about the macroeconomic outlook is high and valuations are stretched relative to fundamentals.⁵ These considerations may be particularly pertinent at the current juncture as, along with macroeconomic uncertainty, macrofinancial vulnerabilities remain elevated (Online Annex Figure 2.1.1).

The effect of macroeconomic uncertainty can spill over across borders. Global financial and real

⁵The set of shocks can include shocks to uncertainty itself that drive aggregate fluctuations (Bloom 2009; Bloom and others 2018).

interconnectedness implies that increased macroeconomic uncertainty can have cross-border implications through the aforementioned channels. For example, an increase in macroeconomic uncertainty that imposes losses on investors in a particular region may force them to sell assets in other countries, leading to large asset price declines and triggering international financial contagion.⁶ Similarly, by reducing domestic consumption and investment, macroeconomic uncertainty can weaken the demand for imports, raising downside risks to economic activity in trading partner countries.

Financial variables may not fully span macroeconomic uncertainty. Existing approaches to assess macrofinancial stability typically consider selected financial indicators, including those related to financial market uncertainty (for example, the Chicago Board Options Exchange Volatility Index [VIX]), as relevant variables in frameworks to assess systemic risk (Adrian, Boyarchenko, and Giannone 2019; Adrian and others 2019). However, financial indicators may not fully reflect macroeconomic uncertainty, making it useful to consider it in frameworks to assess systemic risk and predict tail risks to markets and economic activity.⁷ This may be particularly relevant for countries with less developed financial markets or during episodes of “macro-market disconnect”—that is, when macroeconomic uncertainty is high and financial market volatility (realized and implied) is low.⁸

Against this background, this chapter examines risks to macrofinancial stability posed by macroeconomic uncertainty. The chapter first lays out a simple conceptual framework for discussing the main

channels through which macroeconomic uncertainty can undermine macrofinancial stability, measured by downside risks to real GDP. It then uses panel data from a sample of 43 advanced and emerging market economies since 1990 (or the earliest year for which data are available) to empirically address three key questions.⁹ First, does macroeconomic uncertainty help predict downside risks to output? Second, how does macroeconomic uncertainty interact with macrofinancial vulnerabilities to affect downside risks to output? Third, does the effect of macroeconomic uncertainty spill over across borders to affect downside risks to economic activity in a country’s major financial and trading partners? The chapter then discusses policy options to mitigate the risks posed by high macroeconomic uncertainty.

To assess the downside risk to future economic activity from macroeconomic uncertainty, the chapter extends the growth-at-risk (GaR) framework. Since the global financial crisis, significant progress has been made in systemic risk analytics. The GaR framework (Adrian, Boyarchenko, and Giannone 2019) has become an operational cornerstone in this regard, providing a quantitative tool to assess the effect of financial conditions on downside tail risks to real GDP growth.¹⁰ The chapter builds on this framework in two dimensions. First, it augments the GaR model with measures of macroeconomic uncertainty to examine if these are associated with downside tail risks to real GDP growth. In this context, the chapter considers three types of commonly used macroeconomic uncertainty measures—those based on (1) the accuracy and dispersion of forecasts for key macroeconomic variables, (2) domestic policies, and (3) geopolitical tensions. Second, the chapter implements the augmented GaR framework using machine learning tools, in addition to the standard panel quantile regressions, to exploit their advantages in prediction and improve the forecasting of downside tail risks to future GDP growth.¹¹

⁶Bond and stock market volatility tend to be positively correlated across major economies, and this correlation seems to have increased since the pandemic (Online Annex 2.1), suggesting that stress in asset markets can spread quickly across the financial system.

⁷See, for example, Valkanov and Zhang (2018) and Dew-Becker and Giglio (2023). Online Annex 2.2 shows that financial variables explain about 80 percent of the variation in commonly used measures of macroeconomic uncertainty for advanced economies like the United States, and 40 to 50 percent of the variation in those for major emerging markets such as Brazil. This is because available financial instruments may not fully hedge important risks facing households and firms—for example, those related to housing markets (Shiller 2003, 2013; Benford, Ostry, and Shiller 2018).

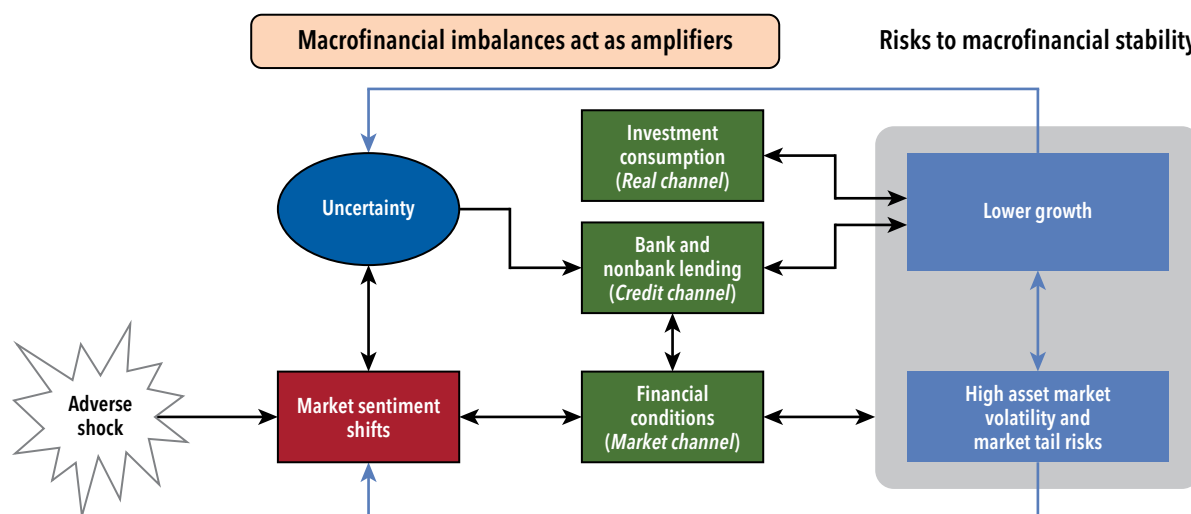
⁸Several factors can drive macro-market disconnects, including investor perception that future policy reactions will protect against downside market risks. Bialkowski, Dang, and Wei (2022) show that low-quality political signals, higher divergence in opinions among investors, and strong equity market performance drive disconnects between the VIX and US economic policy uncertainty. Todorov and Vilkov (2024) note the role played by hedging of covered calls in keeping the VIX at a low level in recent years.

⁹The cross-country sample coverage varies across exercises depending on data availability. See Online Annex 2.1 for information on countries included in the sample and the data sources.

¹⁰Downside risks to future GDP growth are typically captured by the 5th or 10th percentile of the distribution, while financial conditions are proxied by a composite indicator of risky asset prices (such as equity and corporate bond returns, real house price growth, etc.) and measures of financial uncertainty (such as the VIX).

¹¹Machine learning models have gained popularity for forecasting economic and financial variables as they can accommodate many predictors and complex, nonlinear relations between variables (Gu, Kelly, and Xiu 2020; Coulombe and others 2022; Lenza, Moutachaker, and Paredes 2023).

Figure 2.2. Macroeconomic Uncertainty and Macrofinancial Stability: Channels of Transmission



Source: IMF staff elaboration.

Macroeconomic Uncertainty and Financial Stability: A Conceptual Framework

Macroeconomic uncertainty can affect macrofinancial stability through three key channels. First, it can affect macrofinancial stability through a *market channel*, whereby macroeconomic uncertainty can amplify the impact of adverse shocks on investor sentiment, raising downside market tail risk—that is, the risk of large negative realized future asset returns (Figure 2.2) (Baker and Wurgler 2006; Birru and Young 2022). The realization of market tail risks could be transmitted to the broader economy through balance sheet and financial acceleration effects, raising downside risks to output (Adrian and others 2019). Second, macroeconomic uncertainty can affect macrofinancial stability through a *real channel*, whereby in response to higher macroeconomic uncertainty, firms and consumers may adopt a wait-and-see attitude and delay investment and consumption. This would slow economic activity, raising credit risks for financial institutions that could trigger an adverse macrofinancial feedback loop.¹² Third, macroeconomic uncertainty

¹²This channel originates from the “real options” literature, where the option value of deferring decisions rises with uncertainty (Bernanke 1983). Gilchrist, Sim, and Zakrajšek (2014), however, find that uncertainty mainly affects investment by causing financial distortions rather than through wait-and-see attitudes.

can affect macrofinancial stability through a *credit channel*. This channel may arise because of reduced credit supplied by financial intermediaries as they face greater challenges in determining the creditworthiness of new borrowers when the macroeconomic outlook is more uncertain.¹³ These three channels can potentially interact and mutually reinforce each other, amplifying the effect of macroeconomic uncertainty on macrofinancial stability.¹⁴

Recent technological innovations and social media could aggravate uncertainty as well as its effect on market tail risks. Over the past few years, investors and depositors have been more attentive to surprises in data and news disseminated through social media, affecting their relationship with financial institutions and intensifying stress episodes (see Online Annex Figure 2.1.3). At the same time, fintech has made

¹³See, for example, Valencia (2017); Buch, Buchholz, and Tonzer (2015); Wu and Suardi (2021); and Berger and others (2022).

¹⁴The literature has considered the effect of uncertainty both as a shock and as a type of vulnerability that can amplify the effects of other shocks. For example, Arellano, Bai, and Kehoe (2010); Christiano, Motto, and Rostagno (2014); and Gilchrist, Sim, and Zakrajšek (2014) analyze how increasing risk premiums can transmit uncertainty shocks to economic outcomes, while He and Krishnamurthy (2013) examine how high borrowing costs from higher uncertainty can undermine firms’ profitability and solvency, making them more vulnerable to financial shocks. Alfaro, Bloom, and Lin (2022) show that uncertainty shocks and financial shocks to firms can amplify each other.

conducting transactions faster and easier, exacerbating funding and market liquidity risks (see the April 2022 *Global Financial Stability Report*). In addition, artificial intelligence (AI) is penetrating deeply into the financial sector, with institutional investors' use of AI-based algorithmic trading strategies further raising market volatility risks because of a potential increase in herding behavior among investors using similar AI models (see Chapter 3). Although these innovations have benefits, they also create systemic complexities that can accelerate the transmission of shocks and amplify the effect of macroeconomic uncertainty on financial stability.

The Global Landscape of Macroeconomic Uncertainty

Macroeconomic uncertainty can stem from different sources. These include (1) innovations affecting the real sector of the economy such as output, product prices, factor costs, and firms' profitability; (2) monetary, fiscal, trade, and regulatory policies; and (3) geopolitical tensions, for example, conflicts or policy-driven decisions to impose barriers on cross-border trade and capital flows.¹⁵ To quantify macroeconomic uncertainty from these sources, the chapter considers different measures. For example, real sector uncertainty is proxied by two indicators: the real economic uncertainty index (REU) of Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2021), which reflects the accuracy of forecasts for a large set of key macroeconomic variables, and by the dispersion in real GDP forecasts based on Consensus Economics' survey of professional forecasters. Uncertainty pertaining to domestic macroeconomic and regulatory policies is captured by the text-based economic policy uncertainty index of Baker, Bloom, and Davis (2016), as well as by the world uncertainty index of Ahir, Bloom, and Furceri (2022). Finally, geopolitical uncertainty is measured

by the text-based geopolitical risk index of Caldara and Iacoviello (2022).¹⁶

The different measures of macroeconomic uncertainty tend to be positively but not strongly correlated. The degree to which the macroeconomic uncertainty measures correlate with each other varies considerably but is generally modest (Figure 2.3, panel 1). This suggests that the different measures capture some idiosyncratic phenomena in addition to common shocks, making it important to individually assess their association with tail risks to economic activity.¹⁷ The REU is of particular interest because it exhibits the strongest correlation with other measures of macroeconomic uncertainty, possibly because real sector outcomes may capture uncertainty from different sources including policies and geopolitics.

Measures of macroeconomic and financial uncertainty may contain complementary information but do not always fluctuate in tandem. The correlations of macroeconomic uncertainty measures with commonly used measures of financial uncertainty—such as that based on Ludvigson, Ma, and Ng (2021), which captures the precision of forecasts for different financial market variables, or the VIX—are generally positive but also modest (Figure 2.3, panel 1). Looking at the evolution of different measures of macroeconomic and financial uncertainty for the United States, for example, makes evident that in some major crises, such as the global financial crisis or the COVID-19 pandemic, all measures spiked in tandem (Figure 2.3, panel 2). However, for many economic and political events, only some of the measures have shown a significant response while other measures have remained muted. The US dot-com bubble of the late 1990s is one such case that is only captured by measures of financial uncertainty (VIX), while the intensification of trade tensions between China and the United States that started around 2018 is largely captured by an increase in the economic policy uncertainty index.

¹⁵Several other factors could also influence macroeconomic uncertainty such as climate change, climate policy, and technological innovation. These are not explicitly analyzed in the chapter because of limited data availability. However, some of the measures of macroeconomic uncertainty used in the chapter may at least partly capture the effects of these sources as well. There may also be some overlap between the different sources of macroeconomic uncertainty—for example, that stemming from geopolitical tensions could affect both real outcomes and policies.

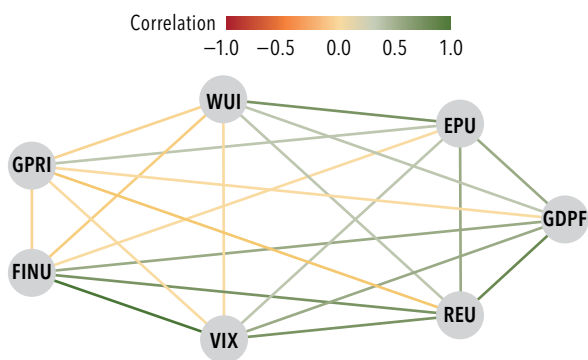
¹⁶See Online Annex 2.2 for further details on the various measures of uncertainty.

¹⁷Correlation among measures of uncertainty has increased over time (Online Annex Figure 2.1.4). Kozeniauskas, Orlik, and Veldkamp (2018) show that measures of economic uncertainty are statistically distinct and can covary positively or negatively depending on the type of shock. Nevertheless, these measures tend to have some common fluctuations beyond the business cycle effect, which is driven by changes to macroeconomic volatility.

Figure 2.3. Measures of Macroeconomic and Financial Uncertainty

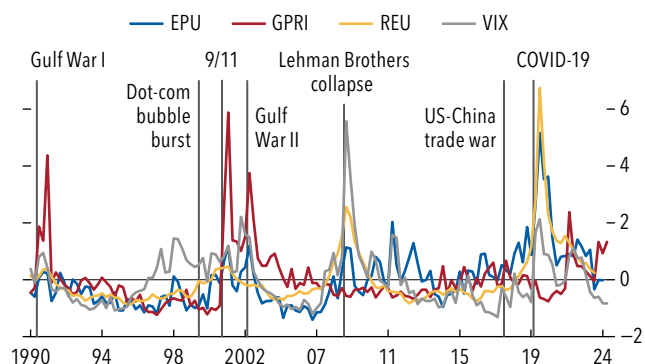
Measures of uncertainty are not perfectly correlated ...

1. Correlations between Selected Measures of Macroeconomic and Financial Uncertainty, 1990-2023 (Correlation coefficient)



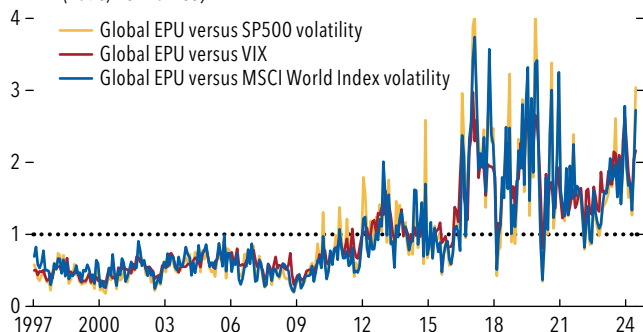
... and may increase idiosyncratically around certain events.

2. Selected Measures of Macroeconomic and Financial Uncertainty for the United States, 1990-2024 (Standardized values)



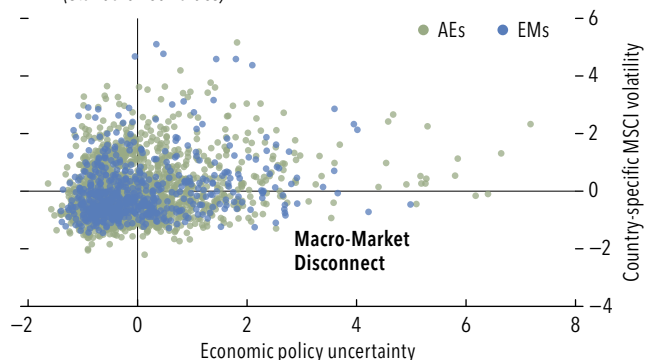
A disconnect between the level of macroeconomic and financial uncertainty can arise ...

3. Global Economic Policy Uncertainty Relative to Realized and Implied Stock Market Volatility, 1997-2024 (Ratio, normalized)



... and is often observed in both advanced and emerging market economies.

4. Realized Stock Market Volatility and Economic Policy Uncertainty across Economies, 1990-2024 (Standardized values)



Sources: See Online Annex 2.1; and IMF staff calculations.

Note: Panel 1 shows the correlation between several macroeconomic and financial uncertainty measures from 1990 to 2023. Panel 2 depicts standardized measures of uncertainty for the United States. Panel 3 shows the monthly ratios of the global economic policy uncertainty index to the realized S&P 500 volatility, to the VIX, and to the MSCI World Index volatility, with the ratios normalized to have a mean of one over 1997:M1-2024:M2. Panel 4 shows a scatterplot of standardized country-specific economic policy uncertainty against MSCI country-specific realized stock market volatility. Realized stock market volatility is computed as the within-quarter volatility of daily returns. The fourth quadrant of the panel (with above average macroeconomic uncertainty and below average stock market volatility) indicates observations of a macro-market disconnect across countries. AEs = advanced economies; EMs = emerging markets; EPU = economic policy uncertainty index; FINU = financial uncertainty measure; GDPF = real GDP forecast dispersion; GPRI = geopolitical risk index; REU = real economic uncertainty index; SP500 = S&P 500; VIX = Chicago Board Options Exchange Volatility Index; WUI = world uncertainty index.

Measures of macroeconomic and financial uncertainty can remain disconnected for a period of time. Commonly used measures of financial uncertainty are limited in scope and generally restricted to certain time horizons. For example, measures of option-implied market volatility, such as the VIX, capture risk related to stock market returns—that is, the performance of publicly traded firms as perceived by investors—at short time horizons. In contrast, the information embedded in measures of macroeconomic uncertainty

such as policy uncertainty can be relevant for assessing the outlook of an economy over much longer horizons, for example, when it pertains to geopolitical shocks or to electoral cycles.¹⁸ This may at least partly explain why at times financial market volatility (realized and

¹⁸Policy uncertainty can increase because of electoral uncertainty when candidates' policy proposals diverge significantly, or there is less clarity on the proposals. Goodell, McGee, and McGroarty (2020) show that changes in the incumbent party's probability of reelection drive key changes to policy uncertainty.

implied) may be low while macroeconomic uncertainty is high—that is, there is a “macro-market disconnect”—which may remain persistent (Figure 2.3, panels 3 and 4).¹⁹

Macroeconomic Uncertainty and Downside Risk to Output

To assess the association of macroeconomic uncertainty with downside risks to future output, the chapter estimates an augmented GaR model.²⁰ The analysis looks at the full distribution of future GDP growth at different horizons, with a focus on the left tail (the 10th percentile) as a measure of downside tail risk.

The results show that an increase in macroeconomic uncertainty is associated with a significant rise in downside risk to future GDP growth. A one-standard-deviation increase in measures of macroeconomic uncertainty reduces one-quarter-ahead real GDP growth (annualized) by 0.5 to 2.0 percentage points (Figure 2.4, panel 1).²¹ Measures of macroeconomic uncertainty based on real outcomes such as the REU and dispersion of GDP forecasts have quantitatively the largest effect, but the association of all measures with downside risks to future output is statistically significant. Moreover, the impact of macroeconomic uncertainty persists up to about seven quarters after the shock (Figure 2.4, panel 2). In cumulative terms,

¹⁹For example, while the 2016 US presidential election was associated with significant uncertainty about its effect on the country's long-term policies, volatility in stock markets remained low. Similarly, Brexit caused considerable uncertainty about UK trade, growth, and immigration policies, yet it had less of an impact on short-term stock market volatility. Ait-Sahalia and others (2024) show that macroeconomic uncertainty and stock return volatility could be disconnected. In particular, the relationship between macroeconomic uncertainty and volatility could vary over time depending on the precision of political signals, even though (a priori) they are expected to be positively correlated (Pástor and Veronesi 2013).

²⁰The analysis extends the baseline GaR model of Adrian, Boyarchenko, and Giannone (2019) to include measures of macroeconomic and financial uncertainty, while controlling for current GDP growth, financial conditions, and country fixed effects. Estimations are carried out using panel quantile regressions for different time horizons. While the focus of the analysis is on predicting downside risks to future output, and not on identifying the causal effects of uncertainty on future output, potential endogeneity concerns are addressed in robustness exercises. See Online Annex 2.3 for more details on the estimation methodology, results, and robustness analysis.

²¹These estimates are quantitatively significant, considering that the annual output decline in the bottom 10th percentile of the historical GDP growth distribution for the full sample, across advanced and emerging market economies, is 1.2 percent.

an increase in the REU equivalent to that observed on average across countries during the global financial crisis translates into a decline in one-year-ahead GaR of about 1.2 percentage points.²²

Increased uncertainty has an asymmetric association with the distribution of future GDP growth, affecting downside (“bad”) tail risks more strongly than upside (“good”) tail risks. Macroeconomic uncertainty has a negligible effect on the median of the distribution of future real GDP growth but a large and statistically significant effect on the lower and upper quantiles (Figure 2.4, panel 3).²³ Overall, however, an increase in uncertainty exerts a stronger effect on downside tail risks to future GDP growth (at the 5th or 10th percentiles) than on upside tail risks (at the 90th or 95th percentiles). Additional analysis presented in Online Annex 2.2 suggests that some technological revolutions (for example, the 1990s dot-com bubble in the United States and the mobile phone revolution in Finland), postcrisis reforms (for example, those in Korea after the Asian financial crisis), and major political shifts (for example, the reunification of East and West Germany in the late 1980s) could be considered as examples of “good” uncertainty that raised upside tail risks to future growth. By contrast, increased macroeconomic uncertainty at the onset of the global financial crisis or the COVID-19 pandemic are examples of “bad” uncertainty.²⁴

Machine learning models can improve predictions of downside risk to GDP growth, particularly when measures of macroeconomic uncertainty are added as predictors. Applying machine learning models—such as panel quantile random forest and panel quantile neural network—to the GaR framework (ML-GaR)

²²Note that an increase in the financial uncertainty measure also raises downside risks to real GDP growth beyond the effect of the financial conditions index included in the model. These estimates are based on panel data, capturing the cross-country average effects. The effects of macroeconomic and financial uncertainty variables for individual countries may be larger or smaller.

²³The macroeconomic uncertainty measures are significantly associated with the mean of one-quarter-ahead GDP growth when the financial conditions indicator is not included in the model, but they are not significant otherwise.

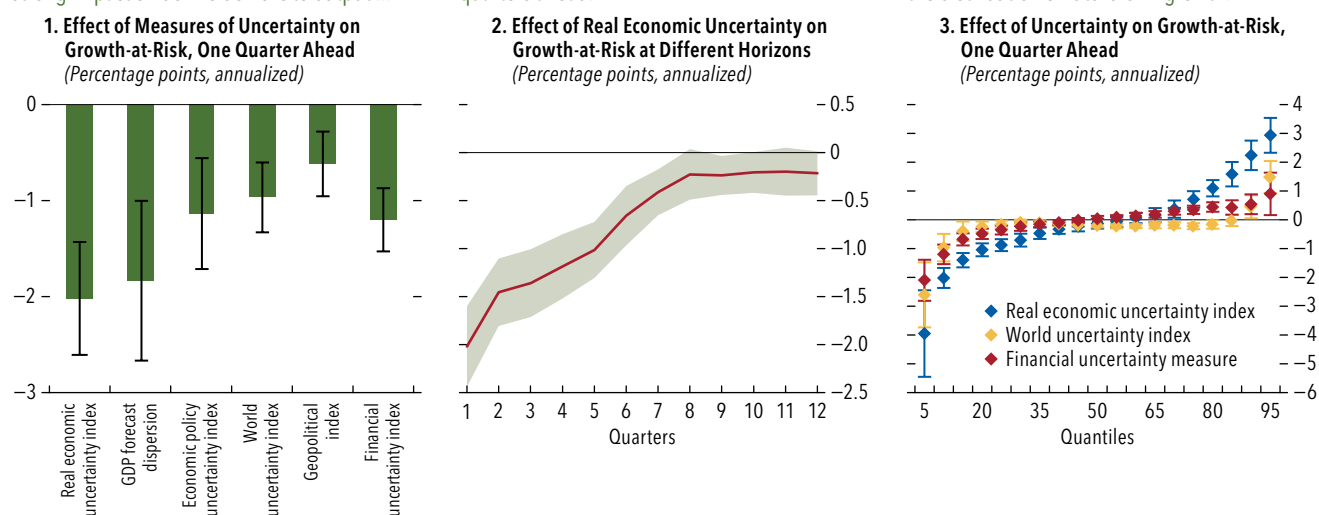
²⁴Episodes of “bad” and “good” uncertainty are distinguished by following the approach of Segal, Shaliastovich, and Yaron (2015) (see Online Annex 2.2 for details). Intuitively, uncertainty marked by positive shocks like technological advancements or unexpected market opportunities can potentially be “good” because businesses and investors, perceiving future gains, may increase investment and expand operations, driving economic growth and higher asset prices. By contrast, “bad” uncertainty, related to negative shocks to macroeconomic variables, would lower prices and reduce investment.

Figure 2.4. Uncertainty and Downside Risks to Output: Results from Panel Quantile GaR Model

Measures of macroeconomic uncertainty have a strong impact on downside risks to output ...

... and effects are persistent up to about seven quarters ahead.

A rise in uncertainty has asymmetric effects on the distribution of future GDP growth.



Sources: Ahir, Bloom, and Furceri 2022; Baker, Bloom, and Davis 2016; EUROPACE AG/Haver Analytics; IMF, Global Data Source and International Financial Statistics databases; LSEG Datastream; Organisation for Economic Co-operation and Development, Main Economic Indicators database; and IMF staff calculations.

Note: Panel 1 illustrates the impact of a one-standard-deviation increase in various measures of uncertainty individually on the 10th percentile of the one-quarter-ahead real GDP growth distribution, with current real GDP growth, financial conditions, and country fixed effects controlled for. Panel 2 shows the impact of a one-standard-deviation increase in the real economic uncertainty index used in the chapter, based on Ludvigson, Ma, and Ng (2021), on the 10th percentile of the average future real GDP growth distribution at different time horizons. The solid line shows estimated coefficients; shaded areas around estimated coefficients correspond to 90 percent confidence intervals. Panel 3 depicts the effect of various measures of uncertainty on the full distribution of one-quarter-ahead real GDP growth. All estimations are carried out using panel quantile regressions across the economies considered in the sample. Error bars indicate 90 percent confidence intervals. For more details on variables, estimations, and data sources, see Online Annexes 2.1, 2.2, and 2.3. GaR = growth-at-risk.

improves out-of-sample prediction accuracy compared to the standard benchmark GaR model based on linear quantile regressions. Specifically, out-of-sample prediction accuracy for advanced and emerging market economies improves by up to 7 percent at different horizons (Figure 2.5, panels 1 and 2, green bars).²⁵ Adding measures of macroeconomic uncertainty (such as the REU) as predictors further improves the out-of-sample forecast performance of ML-GaR models by 5 to 13 percent relative to the standard GaR models that exclude uncertainty (Figure 2.5, panels 1 and 2, red bars).²⁶

ML-GaR models also show that macroeconomic uncertainty contributes at least as much as the financial conditions index to predicting downside risk to

real GDP growth. For both one- and four-quarter-ahead forecasts of downside risks to output growth in advanced and emerging market economies, the REU on average contributes more to predictions than the financial conditions index typically included in GaR models (Figure 2.5, panels 3 and 4).²⁷

Market and credit channels play an important role in transmitting the effect of macroeconomic uncertainty on future output growth. An increase in macroeconomic uncertainty is associated with a greater likelihood of large negative realizations of stock market returns, as well as of spikes in sovereign bond spreads (Box 2.1). Furthermore, macroeconomic uncertainty influences tail risks to future bank lending, particularly in countries where banking exposure to sovereign debt is high.

²⁵The benchmark quantile regression GaR model and the machine learning models are estimated on the same panel of economies and predict the 10th percentile of the one- or four-quarter-ahead GDP growth distribution. See Online Annex 2.3 for further details.

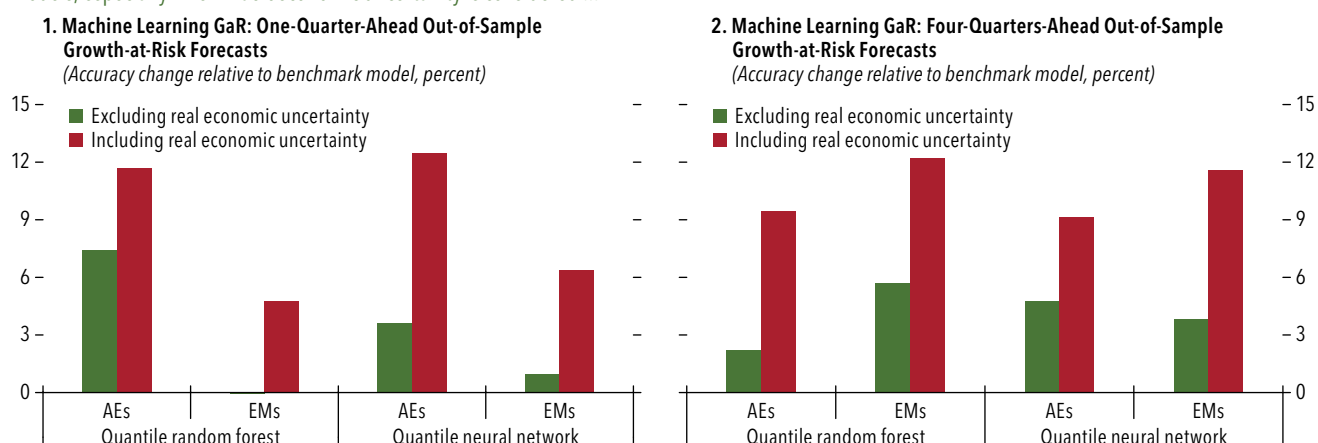
²⁶These results are qualitatively robust to the use of alternative measures of macroeconomic uncertainty and training samples that exclude major crises such as the global financial crisis and the COVID-19 pandemic (see Online Annex 2.3 for details).

²⁷Contributions for each variable to the forecast are calculated as average absolute Shapley values in panel quantile random forest and quantile neural network models. These contributions may vary across countries and over time. For example, the financial conditions index may play a more important role than the REU during periods of financial stress in advanced economies. On average, the contribution of the REU is higher when the quantile neural network models, which provide more flexibility to capture complex nonlinearities between uncertainty and other predictors, are used.

Figure 2.5. Improvement in Predictive Accuracy from Applying Machine Learning GaR Models

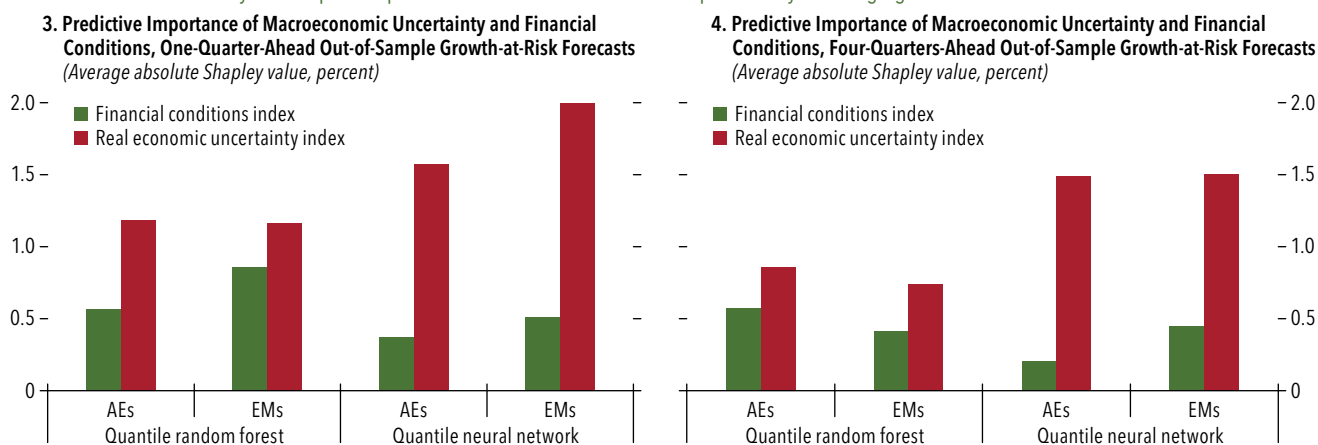
Machine learning tools increase the predictive power of growth-at-risk models, especially when macroeconomic uncertainty is considered ...

... and this holds for different time horizons.



Macroeconomic uncertainty is an important predictor ...

... particularly in emerging markets.



Sources: EUROPACE AG/Haver Analytics; IMF, Global Data Source and International Financial Statistics databases; Organisation for Economic Cooperation and Development, Main Economic Indicators database; LSEG Datastream; and IMF staff calculations.

Note: Panels 1 and 2 compare the predictive accuracy of alternative ML-GaR models (quantile random forest and quantile neural network) against a benchmark GaR model estimated using panel quantile regressions for one- and four-quarter-ahead output growth (at the 10th percentile), respectively, for a sample of advanced and emerging market economies. The benchmark GaR model includes current real GDP growth, the financial conditions index used in the chapter, and country fixed effects as predictors. The comparator ML models include the same variables for results presented in green bars and additionally include the real economic uncertainty index for results presented in red bars. The predictive accuracy improvement is defined as one minus the percentage change in realized quantile loss for the 10th percentile when moving from benchmark GaR to ML-GaR predictions for out-of-sample forecasts. Panels 3 and 4 display the average absolute Shapley values for the real economic uncertainty index and the financial conditions index to assess the importance of each variable for one- and four-quarter-ahead predictions of GaR (10th percentile of output growth). For additional details, see Online Annex 2.3. AEs = advanced economies; EMs = emerging markets; GaR = growth-at-risk; ML = machine learning.

Macroeconomic Uncertainty Amplifies the Impact of Macrofinancial Vulnerabilities

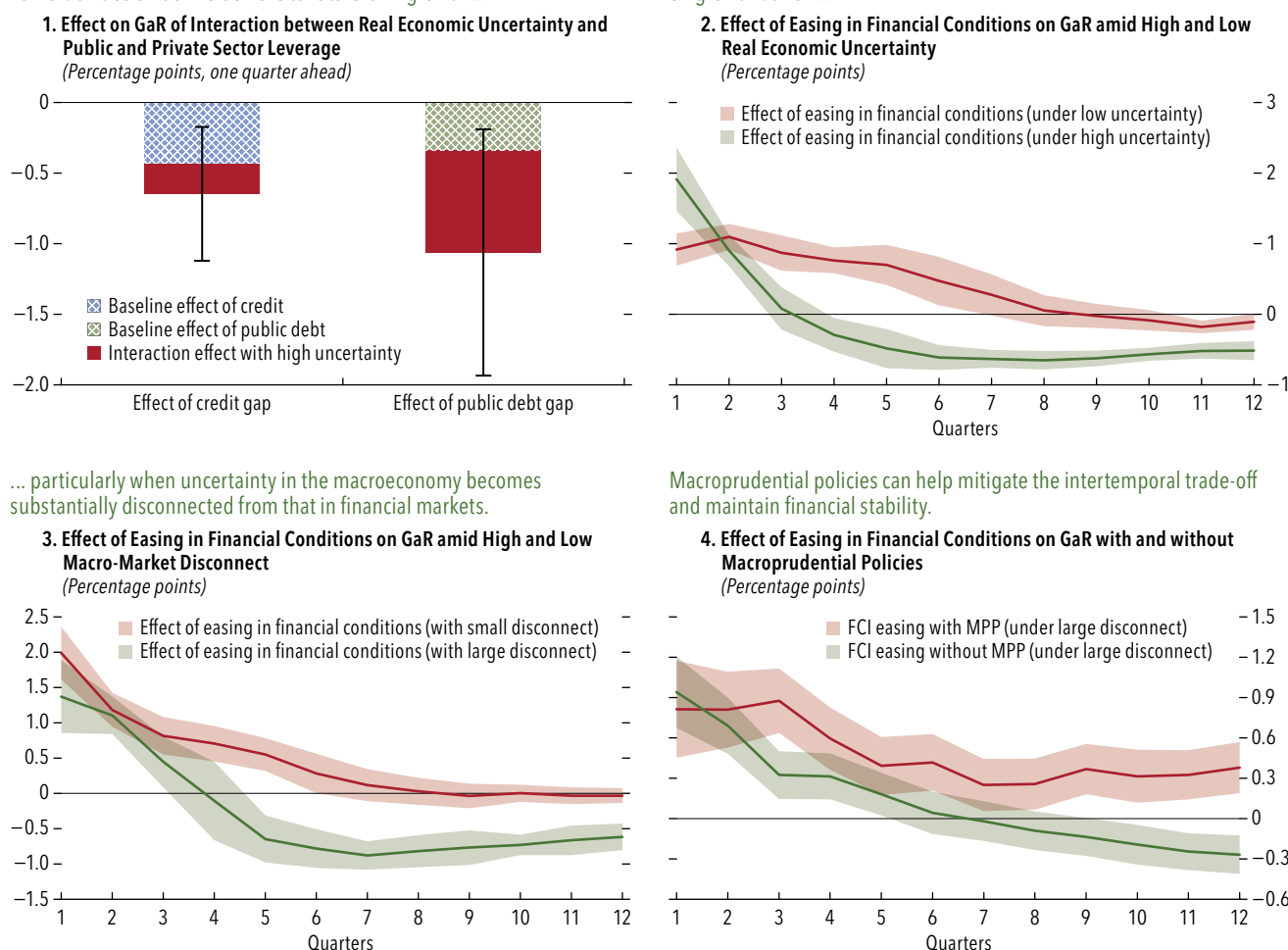
Macroeconomic uncertainty interacts with debt vulnerabilities to exacerbate downside tail risks to GDP growth. High real economic uncertainty combined with excessive domestic credit (measured as the deviation of the credit to the private-sector-to-GDP

ratio from its long-term trend) reduces one-quarter-ahead downside tail risk to GDP growth (that is, the 10th percentile of the distribution of future GDP growth) by 0.6 percentage points (Figure 2.6, panel 1). Similarly, high public debt levels (captured by the deviation of the public-debt-to-GDP ratio from its long-term trend) significantly increase downside risks to GDP growth, particularly when real economic

Figure 2.6. Macroeconomic Uncertainty and Macrofinancial Vulnerabilities

High macroeconomic uncertainty amplifies the effects of macrofinancial vulnerabilities on downside risks to future GDP growth ...

... as well as the intertemporal trade-off posed by easy financial conditions on growth-at-risk ...



Sources: EUROPACE AG/Haver Analytics; IMF, Global Data Source, Integrated Macroprudential Policy, and International Financial Statistics databases; LSEG Datastream; Organisation for Economic Co-operation and Development, Main Economic Indicators database; and IMF staff calculations.

Note: Panel 1 shows the impact of private credit-to-GDP gap and public debt-to-GDP gap on GaR (10th percentile of the distribution of one-quarter-ahead output, annualized) amid high real economic uncertainty. The analysis extends the baseline GaR model of Adrian, Boyarchenko, and Giannone (2019) by adding variables relating to the gaps in private credit and public debt, a dummy variable indicating periods of high uncertainty, and their respective interaction terms. Periods of high (low) uncertainty are defined as those with values above (below) the median. The credit-to-GDP gap and total public debt-to-GDP gap are measured by the deviations of the variables from a one-sided Hodrick-Prescott filter. Estimations are conducted using panel quantile regressions for the countries in the sample, depending on data availability. Error bars (solid color) indicate 90 percent confidence intervals for the sum of the coefficients on vulnerabilities and their interaction with the uncertainty dummy variable. Panels 2 and 3 present the impact of a one-standard-deviation easing in financial conditions on the term structure of GaR amid high (low) real economic uncertainty and amid high (low) macro-market disconnect, respectively. High (low) macro-market disconnect is defined as the ratio of real economic uncertainty to realized market volatility that is above (below) the mean. Panel 4 illustrates the impact of a one-standard-deviation easing in financial conditions during a period of macroprudential tightening, using a methodology similar to that in Chapter 2 of the April 2021 *Global Financial Stability Report*. The macroprudential tightening refers to quarters in the preceding year with net macroprudential tightening. See Online Annexes 2.1 and 2.4 for further details on estimations. Solid lines show estimated coefficients; shaded areas around estimated coefficients correspond to 90 percent confidence intervals. FCI = financial condition index; GaR = growth-at-risk; MPP = macroprudential policies.

uncertainty is high instead of low—possibly through the effects of increased public debt on borrowing costs, and thereby on investment and consumption.²⁸

More generally, high macroeconomic uncertainty can exacerbate macrofinancial stability risks associated with loose financial conditions. In the standard GaR framework, changes in financial conditions lead to intertemporal trade-offs. In the short term, an easing of financial conditions that is typically associated with rising asset valuations and a compression of credit spreads and stock market volatility reduces downside tail risks to GDP growth. Easy financial conditions, however, also encourage a buildup of debt vulnerabilities which exacerbate downside tail risks to GDP growth in the medium term. This intertemporal trade-off has relevance for monetary and macroprudential policy making because tighter policies can help weaken it (Adrian and Liang 2018). An increase in macroeconomic uncertainty can, however, amplify the trade-off, particularly when it is not synced with financial market volatility—that is, when there is a macro-market disconnect. This is because such a disconnect increases the possibility of sudden jumps in financial market volatility and market crashes in the face of adverse shocks as investors realign their expectations, with broader implications for financial stability.²⁹

The analysis suggests that macroeconomic uncertainty significantly influences the intertemporal trade-off. Estimates of the GaR model augmented with the REU show that under high macroeconomic uncertainty, looser financial conditions exacerbate downside tail risks to GDP growth in the medium term (Figure 2.6, panel 2). The impact of looser financial conditions is even more pronounced when there is a large macro-market disconnect, confirming that compressed market volatility may reverse quickly in the

face of a shock when real economic uncertainty is high (Figure 2.6, panel 3).

Macroprudential policies can help mitigate the intertemporal trade-off. Further analysis suggests that a net tightening of macroprudential policies can help offset the rise in medium-term downside risks that accompany easy financial conditions, especially when there is a macro-market disconnect.³⁰ Specifically, when the macro-market disconnect is large, a loosening of financial conditions coupled with a net tightening of macroprudential policies is associated with a reduction in downside risks to GDP growth of 0.3 to 0.6 percentage points in the medium to long terms, compared with a scenario in which no macroprudential measures are put in place (Figure 2.6, panel 4). These findings suggest that policymakers may need to be more proactive in deploying policies aimed at preserving financial stability in periods when macroeconomic uncertainty is high relative to market volatility. More generally, credible policy frameworks may also help reduce macroeconomic uncertainty and its impact on downside risks to output (Box 2.2).

The Downside Risks of Macroeconomic Uncertainty and Cross-Border Spillovers

The downside risks from macroeconomic uncertainty can spill over across borders through trade and financial linkages. An increase in macroeconomic uncertainty in a country's major trading and financial partners can raise domestic downside risks through the real channel (as the demand for the country's exports dwindles) as well as through the market and credit channels (by limiting foreign capital flows).³¹ To investigate these possible cross-border spillover

²⁸For example, uncertainty about future economic policies can prompt investors to demand higher risk premiums, thereby increasing government borrowing costs and making debt servicing more expensive. Machine learning models further expose the nonlinear relationship between public and private debt and downside risks to GDP growth, conditional on the level of real economic uncertainty (Online Annex Figure 2.4.1).

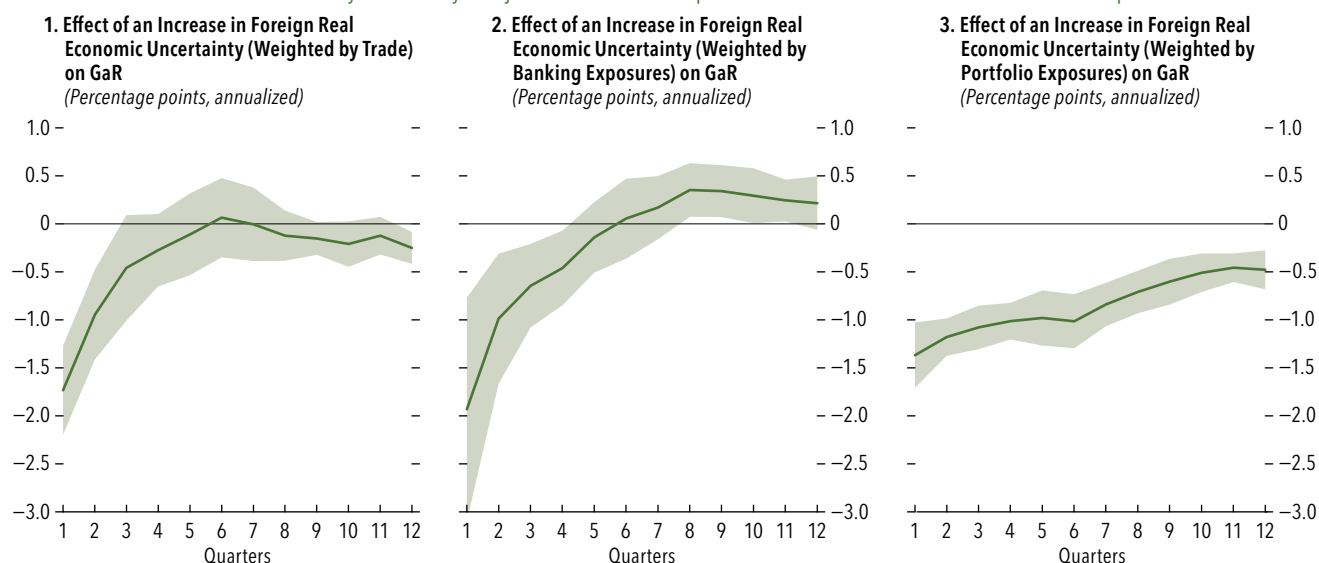
²⁹Periods of compressed risk premiums may be associated with overexuberant sentiment and are often followed by a reversal in valuations (Greenwood and Hanson 2013). Extending the GaR model with a variable for a large macro-market disconnect—defined as the ratio of real economic uncertainty to realized stock market volatility that is above its mean level—confirms that such a disconnect is associated with an increase in downside tail risks to future output growth (see Online Annex 2.4).

³⁰This result complements the findings in Chapter 2 of the April 2021 *Global Financial Stability Report*, which show that macroprudential policy can temper buildups in private sector leverage, reducing downside risks to growth in the medium term. The analysis here considers the presence of all types of macroprudential measures, focusing on the frequency of tightening episodes rather than on their intensity (for details, see Online Annex 2.5).

³¹A large body of literature examines the cross-border spillover effects of global financial uncertainty (proxied by the VIX) on asset prices, capital flows, domestic credit growth, and output, documenting strong effects (for example, Rey 2013; Obstfeld, Ostry, and Qureshi 2019; Bhattarai, Chatterjee, and Park 2020). Biljanovska, Grigoli, and Hengge (2021) show that an increase in economic policy uncertainty in China, Europe, and the United States reduces economic activity in the rest of the world, and Londono, Ma, and Wilson (2024) find that foreign uncertainty negatively affects domestic economic outcomes. These studies, however, mostly focus on the mean spillover effects of uncertainty and not on tail risks to output.

Figure 2.7. Cross-Border Spillover Effects of Foreign Uncertainty

An increase in real economic uncertainty in a country’s major trade and financial partners can raise downside risks to domestic output.



Sources: EUROPACE AG/Haver Analytics; IMF, Global Data Source and International Financial Statistics databases; LSEG Datastream; Organisation for Economic Co-operation and Development, Main Economic Indicators database; and IMF staff calculations.

Note: The figure shows the effect of a one-standard-deviation increase in various measures of foreign uncertainty on the 10th percentile of future quarterly domestic real GDP growth (annualized) over time. In panel 1, the measure of foreign uncertainty is calculated as a weighted average of the chapter’s real economic uncertainty index in a country’s trading partners, with weights computed as the sum of the ratios of bilateral exports and imports to domestic GDP. In panel 2 (3), the measure of foreign uncertainty is calculated as a weighted average of the chapter’s real economic uncertainty index in a country’s financial partners, with weights computed as the sum of the ratios of bilateral banking (portfolio) assets and liabilities to domestic GDP. The model controls for current GDP growth, the domestic financial conditions index, measures of domestic real economic and financial uncertainty (based on Ludvigson, Ma, and Ng 2021), global real GDP growth, the global financial conditions index, a dummy variable for the global financial crisis and country fixed effects. Estimations are conducted using a panel quantile regression framework for the full sample of advanced and emerging market economies. For more details on computations and data sources, see Online Annex 2.6. Graph lines represent estimated coefficients; shaded areas around estimated coefficients correspond to 90 percent confidence intervals. GaR = growth-at-risk.

effects, the chapter constructs measures of “foreign uncertainty” as a weighted average of measures of macroeconomic uncertainty in each country’s major trading and financial partners—with weights based on the intensity of trade (export and import) or banking and portfolio investment exposures between the domestic and partner economy. The foreign uncertainty measures are included in the GaR model, along with measures of domestic uncertainty and other relevant control variables, and the model is estimated for the full sample of advanced and emerging market economies.³²

The findings show that foreign macroeconomic uncertainty can exacerbate downside tail risks to domestic GDP growth through both trade and financial linkages. The 10th percentile of the one-quarter-ahead distribution of GDP growth declines

by 1.7 percentage points following a one-standard-deviation increase in the trade-weighted foreign macroeconomic uncertainty measures (based on the REU) (Figure 2.7, panel 1). The effect is, however, less persistent than that resulting from a similar increase in domestic macroeconomic uncertainty (Figure 2.3, panel 2) and peters out in about three quarters. Similar results are obtained for an increase in the REU in partner countries with which a country has strong banking relationships (Figure 2.7, panel 2) or cross-border portfolio investment exposures (Figure 2.7, panel 3).³³ In the latter case, the effect is notably more persistent, suggesting that nonbank financial intermediaries can potentially play an important role in transmitting

³³These results are robust to other measures of macroeconomic uncertainty. For uncertainty related to foreign economic policy, the impact on domestic downside risks to output is found to be more persistent, lasting up to six quarters.

macroeconomic uncertainty across borders through the market channel.³⁴

International reserve buffers and exchange rate flexibility can help mitigate the adverse implications of foreign uncertainty. While macroeconomic uncertainty can be a potential source of international financial contagion, additional analysis shows that downside risks arising from a rise in foreign macroeconomic uncertainty could be mitigated by building adequate international reserve buffers, or through greater exchange rate flexibility (Online Annex 2.6).

Conclusion and Policy Recommendations

Macroeconomic uncertainty remains elevated globally since the COVID-19 pandemic. This chapter shows that high uncertainty about economic fundamentals and policies increases downside risks to future real GDP growth, stock and bond market returns, and bank lending. Macrofinancial vulnerabilities, such as high ratios of public and private sector debt to GDP, can interact with high macroeconomic uncertainty to amplify the effects of adverse shocks on future output growth. Moreover, high macroeconomic uncertainty worsens the intertemporal trade-off posed by an easing of financial conditions for downside risk to medium-term output growth, particularly when accompanied by low financial market volatility (a macro-market disconnect). The impact of macroeconomic uncertainty tends to spill over across borders through trade and financial linkages, raising the risk of international contagion in the face of large adverse shocks. The chapter also presents evidence that macroprudential policies, larger buffers of international reserves, and enhanced exchange rate flexibility can help mitigate the domestic and cross-border effects of macroeconomic uncertainty.

The findings also show that machine learning models can improve the forecasting capacity of systemic risk assessment frameworks such as the GaR framework. Regulatory and policy institutions can enhance their systemic risk monitoring frameworks by explicitly considering the role of macroeconomic uncertainty as a key determinant of systemic risk while also exploiting the advantages of AI tools such as machine learning models for predicting downside tail risks to output and financial markets. Other AI tools (such as natural language models) can be

³⁴Studies note that nonbank financial intermediaries are more sensitive to changes in drivers of global liquidity flows than banks (Buch and Goldberg 2024) and that nonbanks' large-scale selling during uncertain times can amplify global market disruptions (Ma, Xiao, and Zeng 2022).

used to extract useful and high-frequency information from a range of text-based sources (including firms' earnings call reports, social media, and local and global news) to enhance real-time monitoring of systemic risk.³⁵

Policy actions should focus on reducing macroeconomic uncertainty as well as on mitigating its adverse effects by strengthening resilience and containing macrofinancial vulnerabilities.

Reducing Policy Uncertainty

Credible monetary and fiscal policy frameworks and improved communication can reduce macroeconomic uncertainty and its adverse effects on the economy. Enhancing the credibility of policy frameworks through, for example, the adoption of fiscal and monetary policy rules supported by strong institutions can reduce policy uncertainty (Box 2.2). Credible policy frameworks can also offer policymakers more room to cope with large adverse shocks, thereby mitigating the effects of increases in macroeconomic uncertainty on downside risks to output growth. In addition, improved transparency and well-designed policy communication frameworks can steer market expectations and make policy decisions more predictable and less uncertain.³⁶

A stable financial regulatory framework is important to help mitigate policy uncertainty. In the financial sector, constant innovations open new loopholes and sources of complexity, which can threaten financial stability and require a regulatory response without delay. To prevent these reforms from generating unnecessary policy uncertainty among market participants and financial institutions, they should be announced and implemented with clear communication strategies, robust calibration, phase-in periods as necessary, and clear and practical use of supervisory discretion and enforcement.

³⁵Although machine learning methods are well suited for improving systemic risk surveillance, their application entails conceptual and practical challenges. First, data requirements and technological know-how for applying machine learning tools are significant, which may pose challenges for many emerging market and developing economies with data, skill, and technological constraints. Second, weak signal-to-noise ratios of financial variables can lead large and sophisticated models to perform poorly out of sample. Finally, machine learning methods often suffer from poor transparency and interpretability. Online Annexes 2.3 and 2.4 discuss how these shortcomings have been addressed in the chapter using cross-validation methods for model selection and overfit mitigation, as well as by numerical simulations and analysis of variable importance.

³⁶For example, Blinder and others (2008) show that increased transparency and improved policy communication among central banks in major economies has increased the predictability of central banks' interest rate decisions, reducing their impact on market volatility.

Mitigating the Financial Stability Risks Associated with Macroeconomic Uncertainty

Policymakers should deploy adequate macroprudential and fiscal policies to contain financial stability risks arising from elevated macrofinancial vulnerabilities amid high macroeconomic uncertainty. As high uncertainty can exacerbate the adverse effects of macrofinancial vulnerabilities such as excessive private sector leverage on the real economy, policymakers should remain vigilant and proactively deploy macroprudential policies to limit these vulnerabilities. This is particularly relevant when financial conditions are loose and seemingly disconnected from the elevated uncertainty prevailing in the broader economy.³⁷ In such cases, the response could include not only tighter macroprudential policies but also a tighter monetary policy stance by the central bank if that is aligned with its goal of maintaining price stability (Adrian 2020).³⁸

³⁷The specific type of macroprudential policy to be deployed would depend on prevailing circumstances and vulnerabilities. Policies to build resilience against turns in the financial and credit cycle, such as countercyclical capital buffers, could be relevant. Borrower-based measures could also be activated, for example, if lax financial conditions amid high uncertainty (a macro-market disconnect) encourage excessive borrowing for investment in real estate.

³⁸Higher uncertainty tends to shorten the horizons at which the intertemporal trade-off becomes unfavorable for financial stability (that is, the horizons at which downside risks to future growth rise in response to an easing of current financial conditions), as Figure 2.6 illustrates. Because monetary and macroprudential policies can have very different implementation and transmission lags, the level of macroeconomic uncertainty and its disconnect from financial market volatility can inform policymakers' decisions regarding policy instruments and the magnitude of the response.

In addition, fiscal policies should prioritize debt sustainability to contain the adverse effects of elevated public debt levels on borrowing costs that risk undermining macrofinancial stability (see the October 2024 *Fiscal Monitor*).

Prudential regulators and supervisors should ensure that bank and nonbank financial institutions assess their vulnerabilities to cross-border spillovers of spikes in foreign macroeconomic uncertainty. At the country level, given the cross-border spillovers of macroeconomic uncertainty, adequate reserve buffers and greater exchange rate flexibility can help countries cushion the potential adverse impacts of foreign uncertainty shocks.

Amid rising geopolitical uncertainty, governments should build adequate safety nets to mitigate macrofinancial stability risks. As uncertainty related to geopolitical developments can exacerbate tail risks to domestic markets, credit, and output, governments should make utmost efforts to reduce geopolitical tensions through diplomacy and multilateral cooperation. To the extent that such cooperation remains elusive, policymakers should devote resources to identifying, quantifying, managing, and mitigating financial stability risks associated with increases in geopolitical tensions and uncertainty (see Chapter 3 of the April 2023 *Global Financial Stability Report*). In this context, policymakers should ensure an adequate level of international reserves as well as of capital and liquidity buffers at financial institutions to mitigate the adverse consequences of increasing geopolitical risks.

Box 2.1. Market and Credit Channels Are Important in Transmitting the Effect of Macroeconomic Uncertainty on Output

Dynamics originating in the financial sector amid high macroeconomic uncertainty can play a crucial role in generating risks to macrofinancial stability through the market and credit channels (Figure 2.2). This box examines whether different measures of macroeconomic uncertainty can help explain downside tail risks to future asset (stock and sovereign bond) returns as well as to bank lending by using a panel quantile regression framework.¹

Market Channel

The results indicate that macroeconomic uncertainty raises the likelihood of future spikes in sovereign bond yields. A one-standard-deviation increase in the real economic uncertainty index (REU) is, on average, associated with an increase of 150 basis points in upside tail risks to sovereign bond spreads (defined as the 90th percentile of the distribution of sovereign bond spreads) in emerging market economies at a six-month horizon (Figure 2.1.1, panel 1). By contrast, for the average advanced economy, a shock of a similar magnitude to the REU increases upside tail risks by about 25 basis points.²

In addition, the impact of macroeconomic uncertainty on sovereign bond spreads is more pronounced when fiscal vulnerabilities such as public debt service and banks' exposure to public debt are high rather than low in emerging market economies (Figure 2.1.1, panel 2).³ In turn, a widening of sovereign bond spreads is more likely to have an adverse impact on public debt dynamics and macrofinancial stability (through the sovereign–financial sector nexus) when public debt or debt service as a share of GDP is already high (see Chapter 2 of the April 2022 *Global Financial Stability Report*). Thus, amid elevated public debt vulnerabilities

and macroeconomic uncertainty, a sharp widening of spreads becomes more likely as well as more damaging to the economy (Figure 2.6, panel 1).

Analysis for stock market returns suggests that increased macroeconomic uncertainty can also exacerbate the risk of stock market crashes. A one-standard-deviation increase in the REU can raise downside tail risks to stock market returns (the 10th percentile of the distribution of stock market returns) by about 30 percentage points, one year after the shock in advanced and emerging market economies (Figure 2.1.1, panel 3).

Credit Channel

To examine the relevance of the bank lending channel, the analysis estimates the effect of macroeconomic uncertainty on tail risks to bank lending, defined as the 10th percentile of future bank lending distribution. Macroeconomic uncertainty is measured using the various indicators discussed earlier as well as a new text-based measure developed from transcripts of individual banks' earnings calls.⁴ The bank-level measure is intended to capture more directly the level of uncertainty banks perceive, which can influence their lending decisions.

The results indicate a strong relationship between macroeconomic uncertainty and tail risks to future bank lending. For example, a one-standard-deviation increase in the REU is associated with a decline of about 1 percentage point (annualized) in the 10th percentile of the distribution of one-quarter-ahead real credit growth (Figure 2.1.2, panel 1).⁵ This effect persists through about seven quarters, although it becomes smaller over time. These findings are qualitatively robust across the

¹See Online Annex 2.5 for methodological details and regression results for the analysis presented in this box.

²These findings complement the analysis in Chapter 1 of the October 2024 *Fiscal Monitor*, which shows that higher global policy uncertainty and geopolitical risk raise sovereign yield volatility across countries.

³For advanced economies, fiscal vulnerabilities do not appear to play a statistically significant role in amplifying the effect of macroeconomic uncertainty on sovereign bond spreads (Box Figure 2.1.1, panel 2). This could be because spikes in macroeconomic uncertainty may trigger flight to quality effects, whereby investors reallocate investments from equity or corporate bonds with low credit ratings to sovereign bonds. In addition, in response to increased macroeconomic uncertainty, central banks in advanced economies are more likely to intervene in sovereign bond markets (purchasing bonds to lower yields) when fiscal vulnerabilities and yields are already elevated—reinforcing the role of such bonds as a “safe haven” for investors.

⁴Following the approach of Soto (2021), the bank-level uncertainty measure is constructed by calculating the percentage of sentences including words related to uncertainty in the earnings call transcripts of specific banks, using definitions from the February 2024 update of the Loughran-McDonald Master Dictionary (<https://sraf.nd.edu/loughranmcdonald-master-dictionary/>). These percentages are then averaged across banks in a specific country to arrive at a country-level indicator. As Online Annex 2.5 shows, the bank-level text-based measure generally exhibits a low degree of correlation with the other measures of uncertainty.

⁵The estimates are based on panel quantile regressions for a sample of 18 advanced and 13 emerging market economies using data from 2001 to 2023. The model controls for lagged credit growth dynamics, output growth, financial conditions, and financial vulnerabilities. The last of these are measured by the position in the credit cycle and banking sector fundamentals such as capital adequacy, asset quality, profitability, and exposure to sovereign risk. The model also includes country and time fixed effects. See Online Annex 2.5 for more details on the methodology and estimation results.

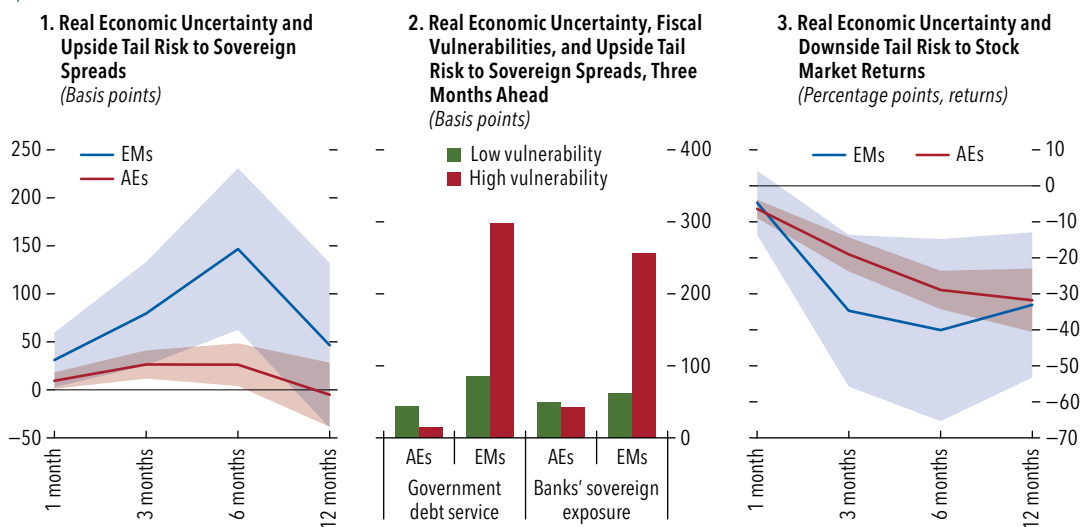
Box 2.1 (continued)

Figure 2.1.1. Macroeconomic Uncertainty and Tail Risks in Financial Markets

Macroeconomic uncertainty raises upside tail risks of sovereign bond spreads ...

... particularly amid elevated fiscal vulnerabilities ...

... while raising downside tail risks to stock market returns.



Sources: EUROPACE AG/Haver Analytics; Federal Reserve Bank of St. Louis, Federal Reserve Economic Data; ICE Bank of America; IMF, Global Data Source and International Financial Statistics databases; LSEG Datastream; Organisation for Economic Co-operation and Development, Main Economic Indicators database; and IMF staff calculations.

Note: Panel 1 shows the effects of a one-standard-deviation increase in the real economic uncertainty index at time t on upside tail risks to sovereign bond spreads (that is, the 90th percentile of the distribution of changes to sovereign bond spreads between time t and time $t + h$) at different horizons ($h = 1, 3, 6,$ and 12 months), estimated using panel quantile regressions with country fixed effects. The sample consists of monthly data for 20 advanced and 9 emerging market economies from 1990:M1 to 2023:M12. The underlying regressions include relevant controls for the sovereign bond market at the country and global levels, following Gilchrist and others (2022), as well as the lagged dependent variable. Spreads for each country are calculated relative to a benchmark economy (Germany for Euro area countries and the United States for all others) using only debt denominated in the same currency as that of the benchmark economy. Panel 2 illustrates the effect of a one-standard-deviation increase in the real economic uncertainty index on upside tail risks to sovereign bond spreads at a three-month horizon conditional on high and low levels of government debt service (as a percentage of GDP) and domestic banks' exposure to sovereign risk (measured by domestic banks' holdings of sovereign bonds as a share of their total assets). Low and high levels of government debt service and banks' sovereign exposure are defined as the 25th percentile (green bars) and the 75th percentile (red bars) of the respective distributions. Note that the difference between green and red bars (that is, low and high fiscal vulnerabilities) is not statistically significant for advanced economies in the analysis. Panel 3 presents the effect of a one-standard-deviation increase in the real economic uncertainty index in month t on the 10th percentile of the distribution of the overall stock market return at different horizons ($t + 1, 3, 6,$ and 12 months), estimated using panel quantile regressions with country fixed effects. The sample consists of monthly data for 21 advanced economies and 19 emerging markets from 1990:M1 to 2023:M12. The panel quantile regressions include as explanatory variables country fixed effects, lagged returns, and relevant controls at the country level, following Schmeling (2009) and Goyal and Welch (2008). Solid lines show estimated effects; shaded areas represent 95 percent confidence intervals. See Online Annex 2.5 for further details. AEs = advanced economies; EMs = emerging markets.

various measures of uncertainty, including the bank-level text-based measure (Figure 2.1.2, panel 2), and also hold for the subsamples of advanced and emerging market economies.⁶

⁶Although the bank-level text-based measure of uncertainty has a somewhat smaller impact on future tail risks to bank lending than the REU, it remains statistically significant when all other measures of uncertainty are included in the regression. This suggests that the measure captures aspects of uncertainty that may not be captured by other broad-based indicators.

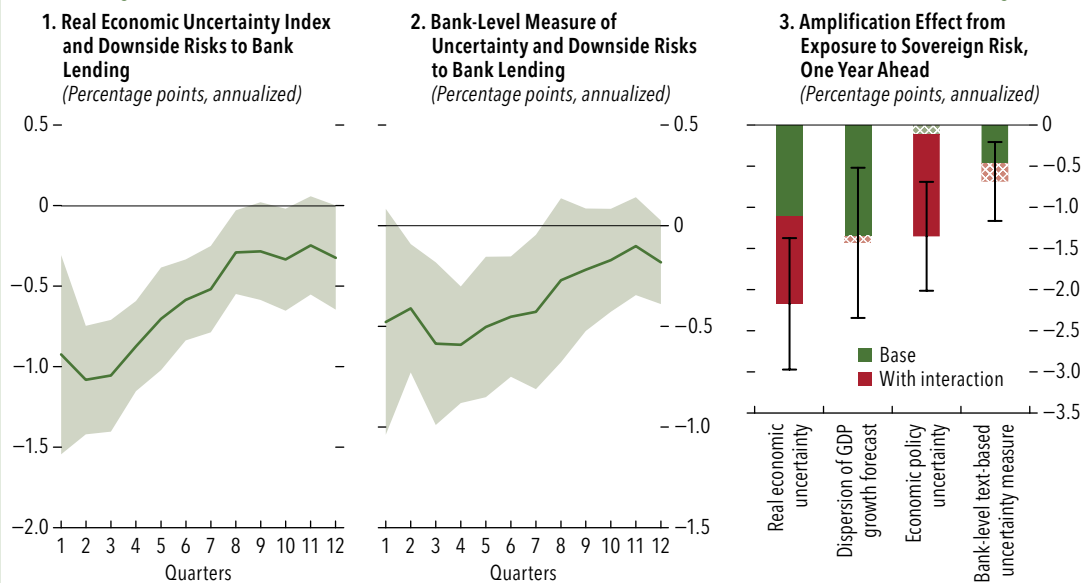
Existing financial vulnerabilities can amplify the effects of higher uncertainty on downside risks to bank lending. Extending the model to include interaction terms of the macroeconomic uncertainty measure with financial vulnerabilities such as banks' exposure to sovereign debt shows that countries with a higher bank exposure to sovereign risk exhibit a greater likelihood of a sharp decline in future bank loan growth when macroeconomic uncertainty rises (Figure 2.1.2, panel 3). For instance, a one-standard-deviation

Box 2.1 (continued)

Figure 2.1.2. Macroeconomic Uncertainty and Tail Risks to Bank Loan Growth

Higher macroeconomic uncertainty is associated with larger downside risks to future credit growth ...

... and its impact increases when financial vulnerabilities are high.



Sources: Bank for International Settlements; Fitch Analytics; IMF, Global Data Source and International Financial Statistics databases; Organisation for Economic Co-operation and Development, Main Economic Indicators database; and IMF staff calculations.

Note: Panels 1 and 2 show the effects of a one-standard-deviation increase in the real economic uncertainty index and the bank-level text-based uncertainty measure, respectively, on the 10th percentile of the distribution of future aggregate real credit growth at different time horizons. For each horizon, the growth rate indicates the average quarterly rate (annualized). Results are obtained from a panel quantile regression using country-level data for both advanced and emerging market economies. Graph lines show estimated effects; shaded areas represent 90 percent confidence interval. Panel 3 shows the effect of a one-standard-deviation increase in four types of measures of uncertainty on the 10th percentile of the distribution of one-year-ahead real credit growth interacted with banks' exposure to sovereign debt (defined as the share of banks' holdings of sovereign debt in an economy as a share of banks' total assets). The "Base" effect (green bars) shows the coefficient for the measure of uncertainty, and "With interaction" (red bar) shows the effect of uncertainty when banks' exposure to sovereign debt is one standard deviation above the mean. The measures of uncertainty and sovereign exposure variable are standardized. Estimated coefficients (solid bars) are statistically significant at the 10 percent level. The error bars represent the 90 percent confidence intervals for the sum of the coefficients, including both the base effect and the interaction effect. See Online Annex 2.5 for further details.

increase in the REU is associated with an increase in the one-year-ahead downside risk to lending (10th percentile of the real credit growth distribution) of about

1 percentage point when domestic banks' exposure to sovereign risk is high (one standard deviation above the mean) compared to at the mean level.

Box 2.2. Macroeconomic Uncertainty and Policy Credibility

Many factors, including policy uncertainty, can drive macroeconomic uncertainty (Bloom 2009). Several studies document that monetary and fiscal policy uncertainty can have contractionary effects (Fernández-Villaverde and others 2015; Husted, Rogers, and Sun 2020; Beckmann and Czudaj 2021; Mumtaz and Ruch 2023). This box examines whether rules-based frameworks, or strengthening of policy frameworks more generally, can reduce policy uncertainty.

Monetary Policy

Early proponents of monetary policy rules (Henry Simons, Lloyd Mints, Milton Friedman) argued that reducing policy uncertainty and its adverse effects on the real economy (inefficiencies) was the main benefit of such rules. In their view, inflation expectations were stabilized through reduced policy uncertainty (Dellas and Tavlas 2022).¹ Empirical evidence shows that enhanced monetary policy credibility can help stabilize an economy by more firmly anchoring inflation expectations to target levels (Park 2023; Beckmann and Czudaj 2024) and that policy rules can play an important role in reducing uncertainty (Cochrane, Taylor, and Wieland 2020, and references therein).²

More generally, the degree of soundness of monetary policy frameworks (regardless of whether they are strictly rules based) may reduce monetary policy

uncertainty and its effect on downside risk to GDP growth. Figure 2.2.1, panel 1, shows that countries where inflation expectations deviate more from the policy (inflation) targets experience higher levels of economic policy uncertainty. This result suggests that a weaker policy framework or impaired policy credibility can amplify economic policy uncertainty. In addition, in the context of the growth-at-risk framework, Figure 2.2.1, panel 2, shows that increased macroeconomic uncertainty (real or policy related) has a larger effect on downside risk to one-quarter-ahead GDP growth when policy targets were missed by wider margins over the preceding three years (that is, when monetary policy frameworks were weaker). These results support the view that enhanced credibility and reliance on stronger monetary policy frameworks can mitigate the adverse implications of increased uncertainty for macrofinancial stability.

Fiscal Policy

Similar arguments in favor of fiscal rules and their impact on macroeconomic uncertainty apply to fiscal policy. Several studies have analyzed the effects of fiscal policy rules on policy variables (such as budget balances or debt levels), market variables (interest rates and sovereign risk premiums), and output cyclicality, concluding that fiscal rules can reduce fiscal policy uncertainty, fiscal procyclicality, and market volatility and enhance fiscal sustainability (Reuter 2015). Fatas and Mihov (2006), Badinger and Reuter (2017), and Arroyo Marioli, Fatas, and Vasishtha (2024) document that more stringent fiscal rules can reduce overall macroeconomic volatility (and hence real economic uncertainty).^{3,4}

³Discretionary fiscal policy is prone to deficit bias due to political incentives to delay austerity, leading to excessive deficits and debt (Alesina and Drazen 1991). Fiscal rules can help offset this bias by acting as a commitment device to limiting the government's incentives to exert discretion (Alesina and Tabellini 1990).

⁴There is also evidence that increased uncertainty can impair the effectiveness of fiscal policy (Jerow and Wolff 2022; Liu 2023), suggesting that policy responses themselves could become more uncertain, potentially magnifying macroeconomic uncertainty.

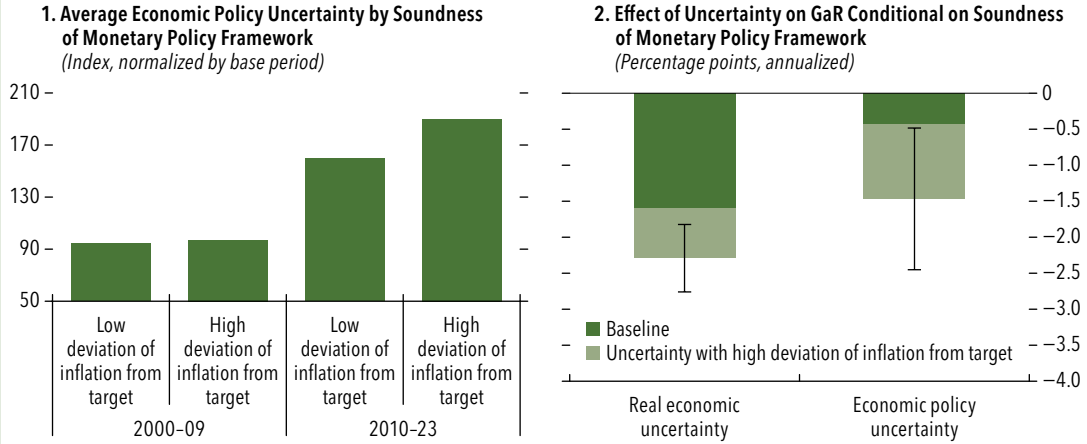
¹The modern (that is, since the late 1970s) literature on rules versus discretion proves theoretically that discretion can generate inefficiencies even if it does not increase policy uncertainty. Although this literature places less emphasis on uncertainty, it does not provide evidence regarding, or argue against, the connection between policy rules and uncertainty; it establishes that weaker theoretical conditions are needed to favor rules over discretion (Dellas and Tavlas 2022).

²Policy uncertainty can also increase when the effectiveness of policies comes into question (Carney 2016). Available evidence indicates that high uncertainty can weaken monetary policy transmission (Castelnuovo and Pellegrino 2018; Lakdawala and Moreland 2024). A more uncertain response of the economy to policy stimulus, in turn, exacerbates policy uncertainty, increasing uncertainty surrounding the extent to which policy instruments will need to be adjusted to achieve policy goals.

Box 2.2 (continued)

Figure 2.2.1. Soundness of Monetary Policy Framework and Effect of Uncertainty on Future GDP

Credible policy frameworks tend to help reduce economic policy uncertainty and its impact on downside risks to output.



Sources: Online Annex 2.1; and IMF staff calculations.

Note: In panel 1, high deviation is based on the sample median of the deviation of inflation expectations from the policy inflation target (absolute value summed over preceding three years). The “high deviation” regime acts as a proxy for the effectiveness of monetary policy framework across countries, indicating less effective frameworks. Panel 2 shows the effect of a one-standard-deviation increase in measures of real and economic policy uncertainty on the 10th percentile of the distribution of one-quarter-ahead real GDP growth without (baseline, dark green bar) and with (interaction term, light green bar) sound monetary policy frameworks. Whiskers (solid bars) indicate 90 percent confidence intervals (significance). GaR = growth-at-risk.

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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.

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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 GenAI¹ 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,

¹For 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 more 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.

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

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.

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 <ul style="list-style-type: none"> 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 <ul style="list-style-type: none"> 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 <ul style="list-style-type: none"> Feature extraction (beta, momentum, and so on) Network/multidimension analysis for relative value analysis and identify price dislocation 	Minimize market impact <ul style="list-style-type: none"> Structured trade execution algorithms to minimize market impact Analyzing unstructured data and cross-market indicators to identify prevailing liquidity conditions 	Assist price discovery <ul style="list-style-type: none"> Modelling executable prices for illiquid securities through multiple market indicators 	Dynamic risk sensing <ul style="list-style-type: none"> Generate risk hypothesis To identify performance drivers and anomalies through multidimensional analysis 	Customize insights <ul style="list-style-type: none"> Customized content generation, reports, and dashboards Chatbot
		Derive signals from unstructured and alternative data <ul style="list-style-type: none"> Natural language processing models for sentiment analysis to identify thematic opportunities Polarity detection, microtext analysis, aspect extraction, or sarcasm detection to improve signal quality 		Assist price discovery <ul style="list-style-type: none"> Modelling executable prices for illiquid securities through multiple market indicators 	Improve liquidity management efficiency <ul style="list-style-type: none"> Forecast liquidity needs (margin management, collateral, etc.) through clustering/network analysis 	Generate risk scenario <ul style="list-style-type: none"> Value-at-risk estimation through generative adversarial networks to capture temporal dynamics in time-series data 	Ease compliance monitoring <ul style="list-style-type: none"> Screening, flagging, and reporting of anomalies

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.

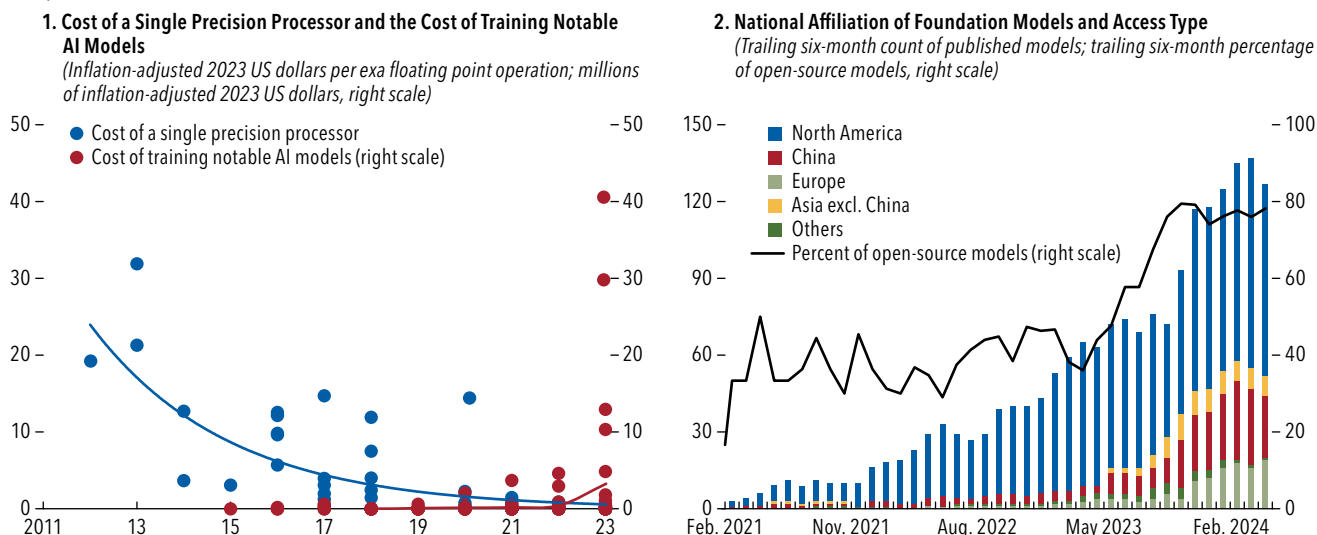
As adoption is still at a relatively early stage, this chapter gives a forward-looking assessment of the

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 ...

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



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

³Notable 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).

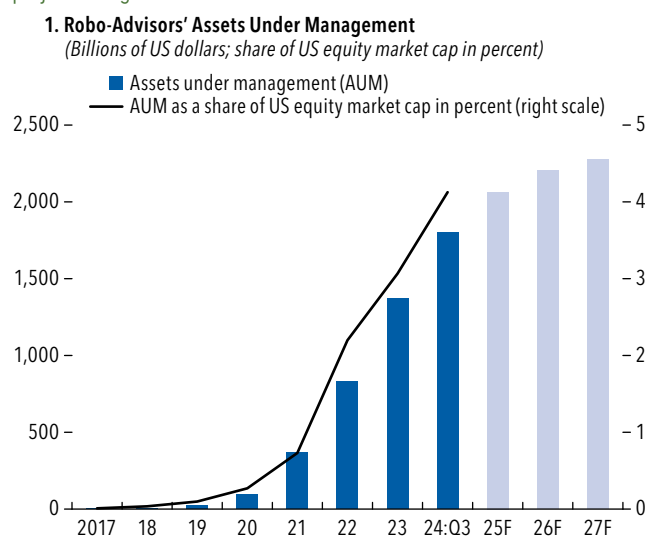
talent enabling development and distribution of sophisticated AI systems may exacerbate market concentration, whereby the few private sector developers with existing commercialization channels could continue to dominate the space (noting that the growing number of open source models may challenge this 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

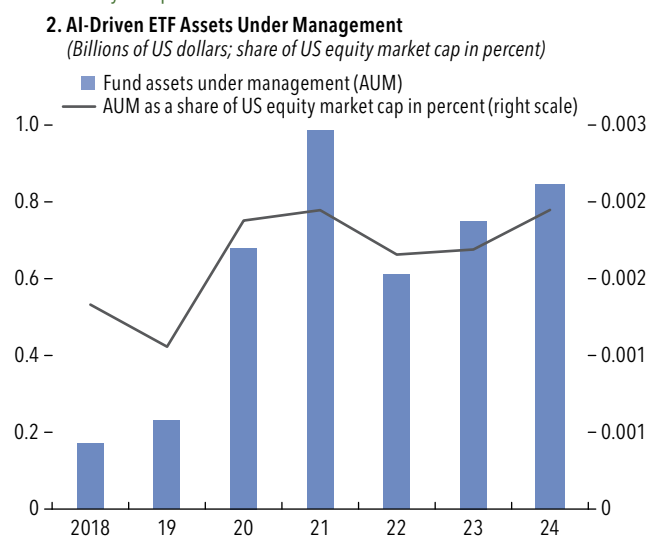
From a capital market perspective, the expansion and considerable scale of robo-advising highlights a move toward automation by the investment industry (Figure 3.3, panel 1). However, genuinely AI-driven strategies are still in their early stages. For instance, AI-powered ETFs—where AI is used to construct 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

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

⁴For 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).

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

⁵Alternative 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.

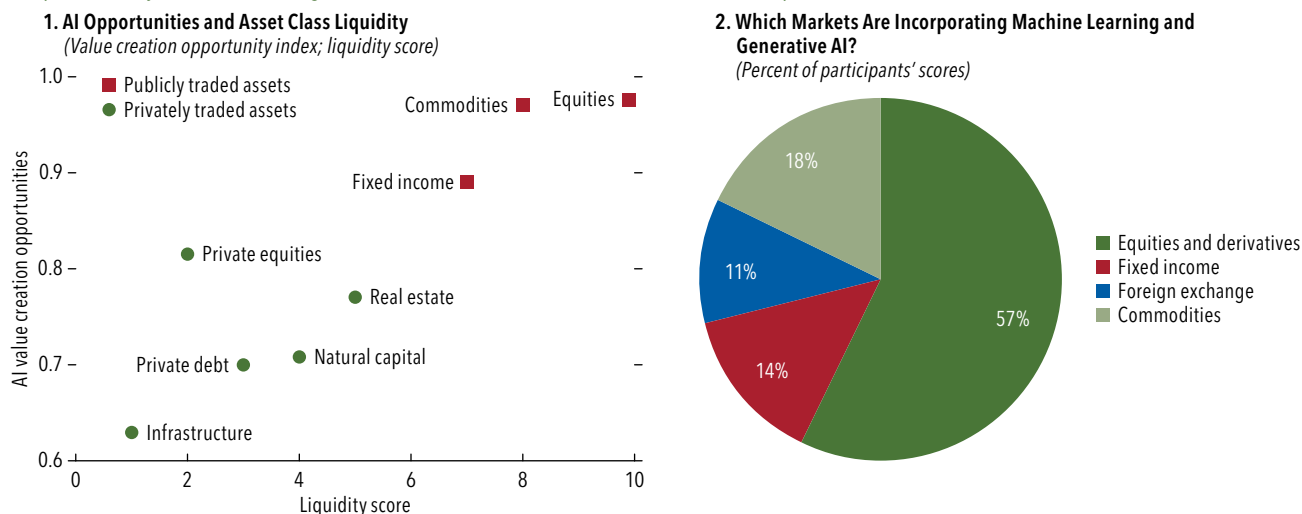
⁶Some market participants also employ AI techniques on price movements from other asset classes or instruments to estimate valuation and executable prices for some illiquid instruments.

⁷AI 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.

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



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

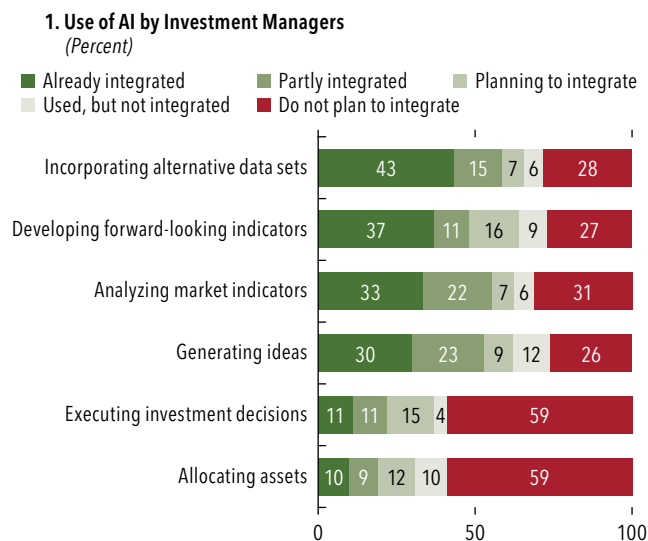
of investment decisions is still nascent (Figure 3.5, panel 1). Concentrating on the more specialized area of algorithmic trading, evidence is mixed. Survey data among participants of a major energy market (The Netherlands) suggest that more autonomous algorithms may still be based on simpler methods (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

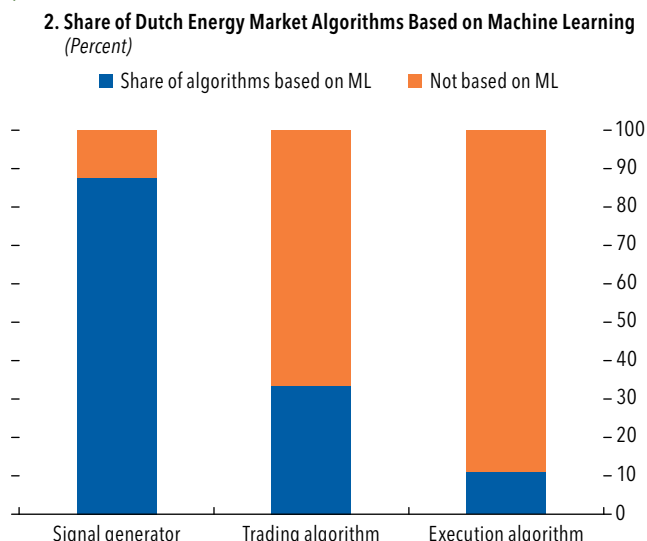
⁸The Dutch Authority for the Financial Markets found that on the Euronext exchange, “trading firms tell the Authority for the Financial Markets that machine learning is implicitly or explicitly used in 80 to 100 percent of their trading algorithms.” It should be noted however, that “explicit” use cases 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

Adoption of AI in trading and investment decision making is still nascent.



Adoption of machine learning has not yet penetrated autonomous trading 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.

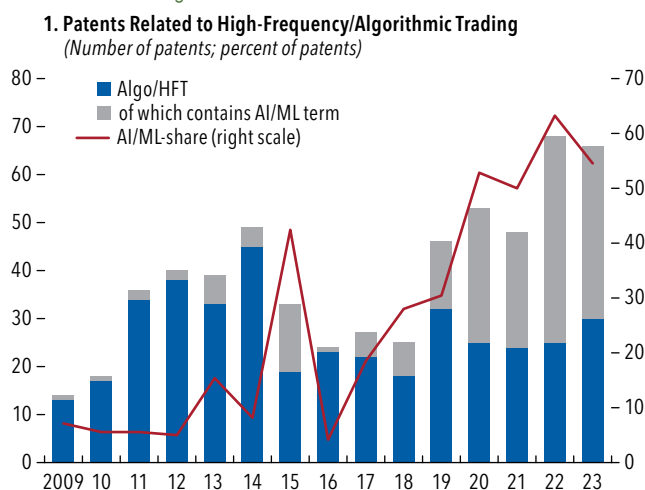
Future Adoption: Evidence from Patent Filings and Labor Markets

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.

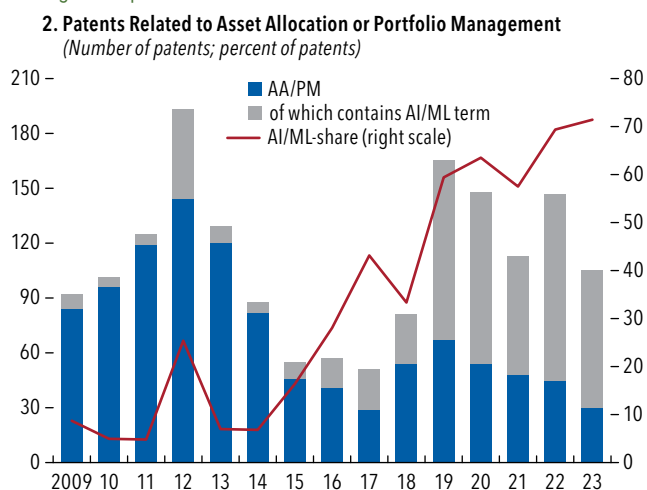
The number of filings that reference AI/ML terminologies in the context of high-frequency or algorithmic trading has increased (Figure 3.6, panel 1). Over the past year, filings lean toward improving operational efficiency of brokerage or trading platforms and on developing systems that compute trading 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 ...



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



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 out-

⁹Ranking 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.

reach, 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 concentration¹¹ 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

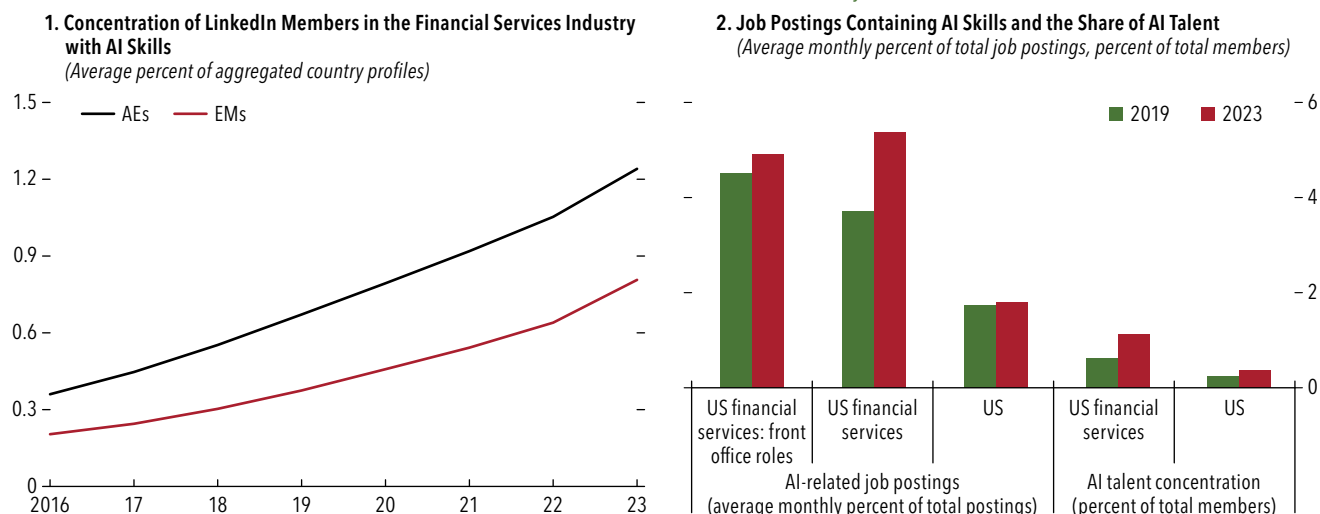
¹⁰Also known as "front office" roles, including traders, portfolio managers, portfolio strategist, asset allocation analysts, and programmatic traders. Job postings containing AI terminology for these roles rose from a monthly average of 4.5 percent of front office roles in 2019 to 4.9 percent in 2023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

¹¹A 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.



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

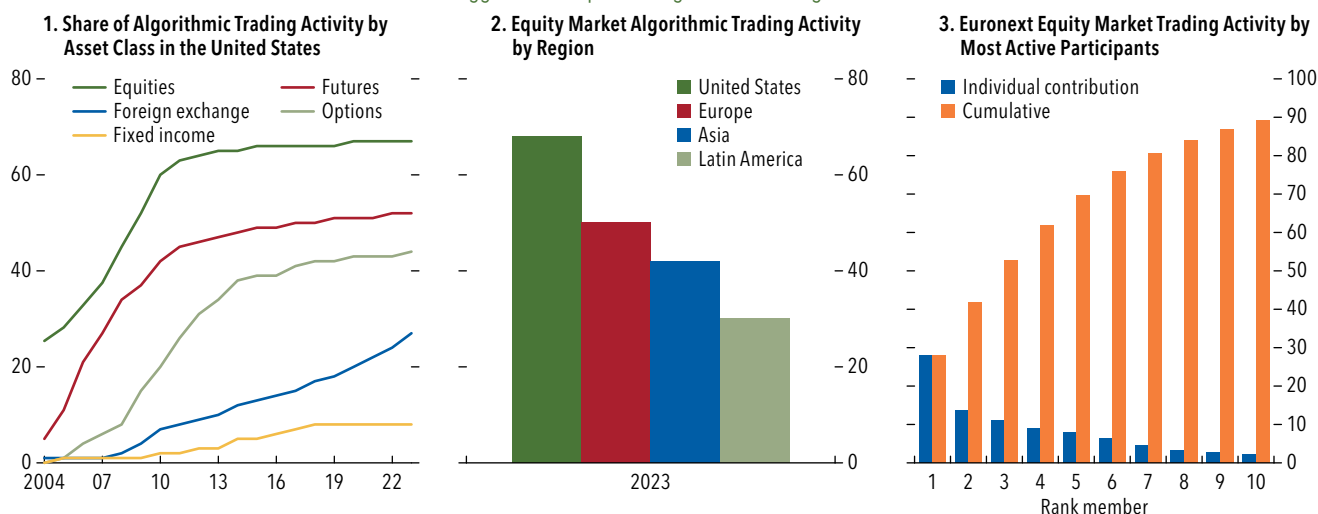
The adoption of AI in capital market activities has the potential to change the structure and dynamics of markets. Some of these changes are more evolutionary, whereby existing trends may be amplified. Other impacts could be more revolutionary: For example, the

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

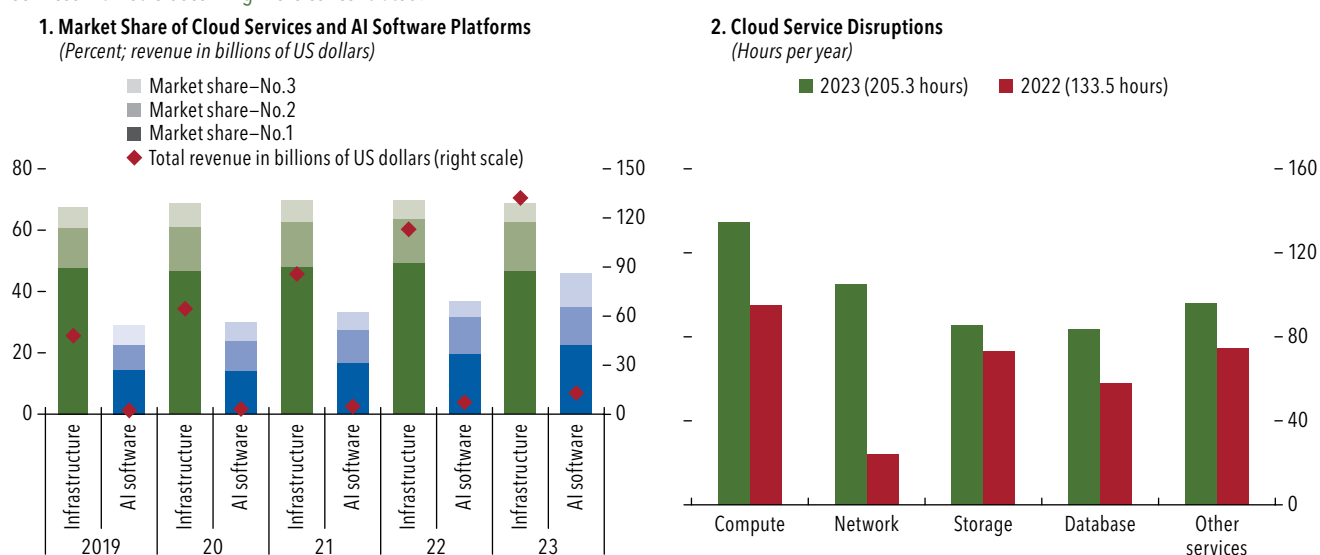
are lagging behind in the share of algorithmic equities trading, but they could catch up briskly (Figure 3.8, panel 2). Increasing returns to scale seem to have resulted in those markets with a relatively high share of algorithmic trading activity also tending to see a concentration of activity among 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.

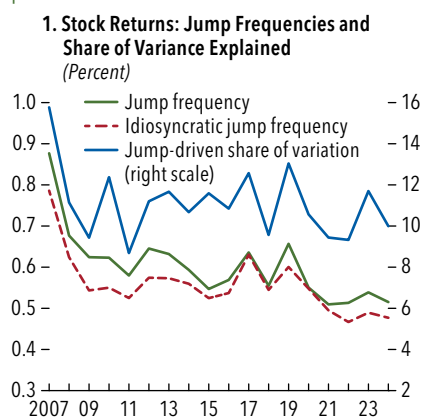
This is relevant from a systemic perspective because most bonds are traded over the counter rather than on centralized exchanges where banks and securities dealers facilitate transactions.

- 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

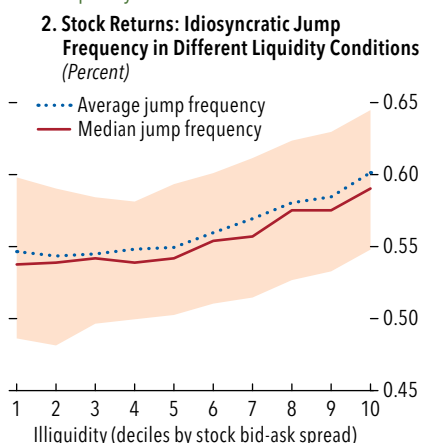
¹²See Box 1.4 in the October 2018 *Global Financial Stability Report*. Idiosyncratic jumps are identified by considering jumps in individual stocks that do not coincide with jumps in large and liquid passive ETFs that track the S&P 500 index (SPDR S&P 500 ETF Trust—SPY). The robustness of this identification 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

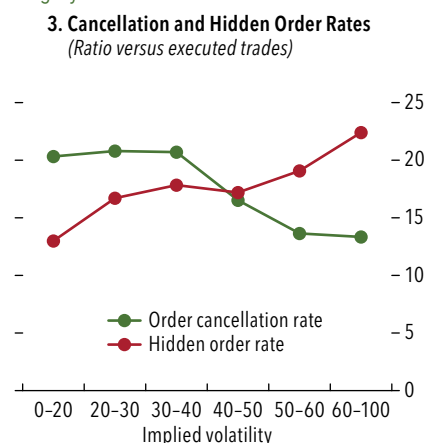
Markets have become less “jumpy” over the past two decades ...



... whereby idiosyncratic jumps are associated with illiquidity.



Liquidity and algorithmic trading may be “flighty” under stress.



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.

¹³These 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).

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

¹⁴See, 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 multitraded 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 ETFs¹⁶ 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

¹⁷Bonelli 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.

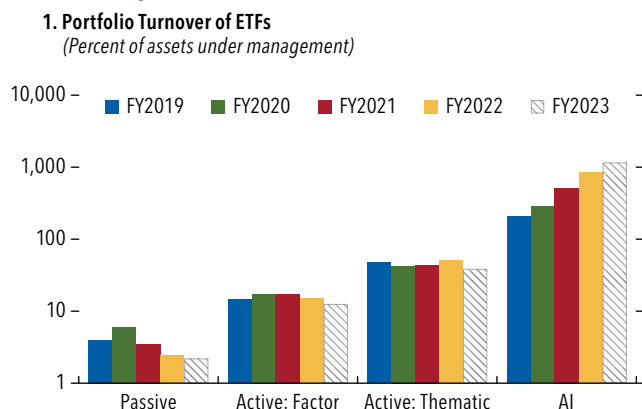
¹⁸Chen and Ren (2022) find that AI-powered mutual funds do not outperform the market but that they do significantly outperform their human-managed peers through superior stock selection capability and lower turnover ratios.

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

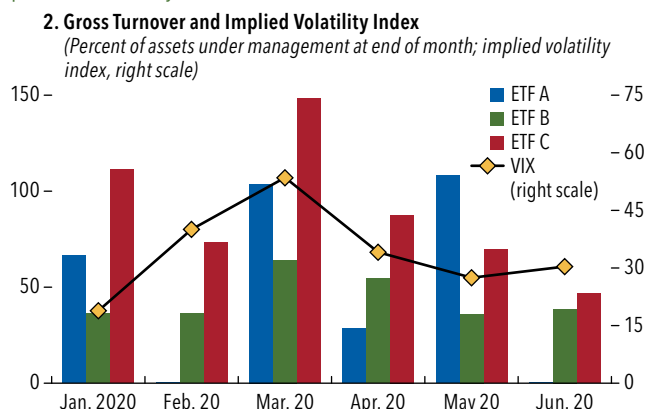
¹⁶AI-powered ETFs are ETFs whose security selection and weights are optimized and periodically rebalanced using AI techniques with the objective to outperform their respective benchmarks.

Figure 3.11. New Artificial Intelligence Trading Dynamics

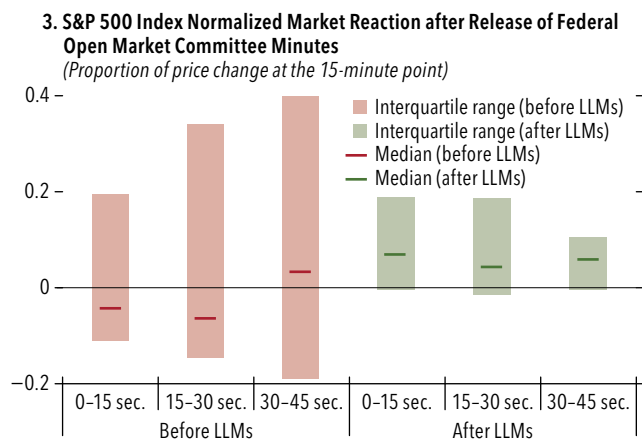
The annual turnover of AI ETFs outstrips that of other active ETFs and has been increasing.



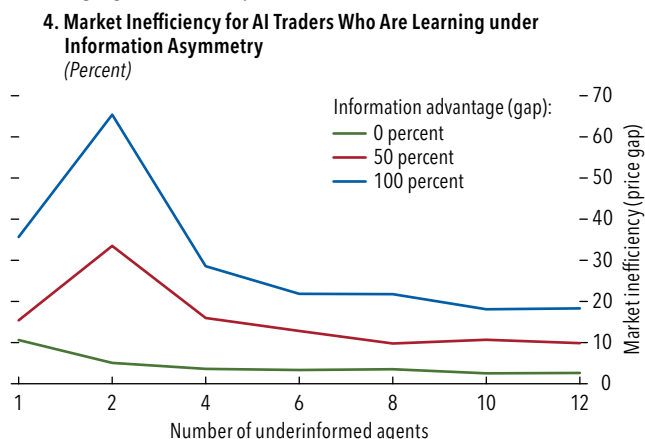
AI-driven trading could drive higher trading volumes, especially during periods of volatility.



Some theoretical frameworks point to the possibility of tacit algorithmic conclusions.



Theoretical models point to various possible market structure outcomes, including algorithmic manipulation.



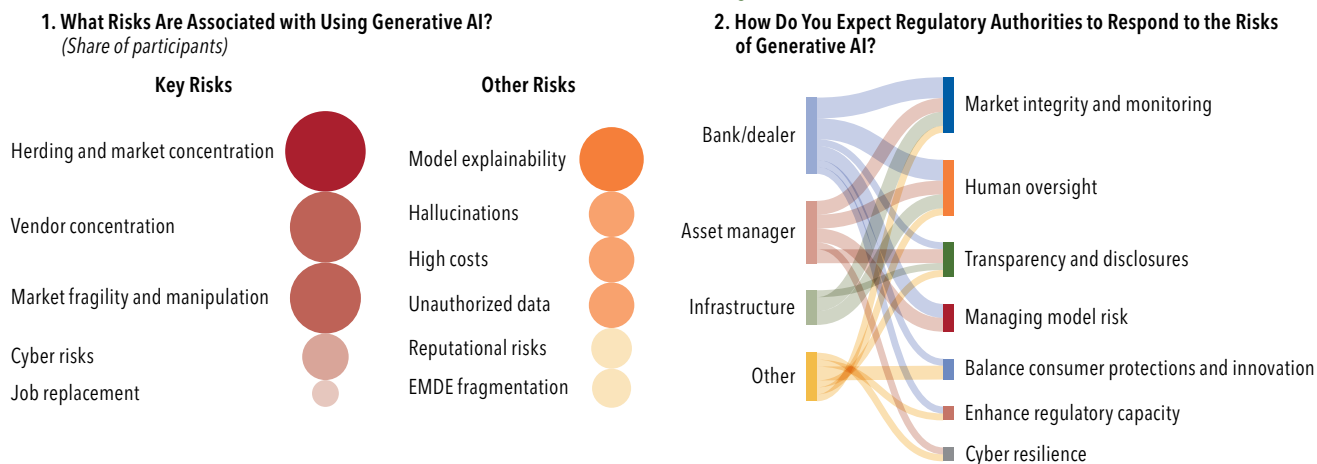
Sources: Bloomberg Finance L.P.; US Securities and Exchange Commission filings; and IMF staff calculations.

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.

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



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

¹⁹Figure 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 hallucination²¹ 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.

²⁰Guardrails 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).

²¹See 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.’”

²²A 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

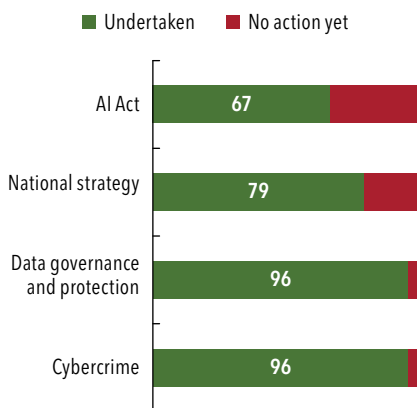
Standard-setting bodies are designing frameworks by building on accepted practices, while considering their application to AI.

1. Standard-Setting Body Response



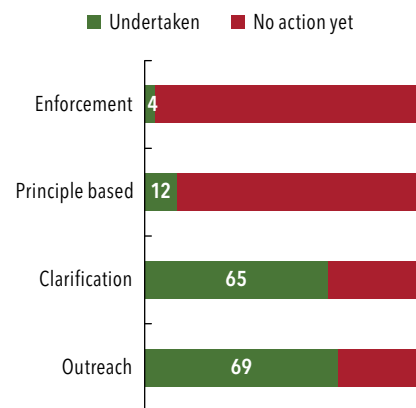
Governments with large capital markets are leveraging cyber and data frameworks to pivot to AI strategies ...

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

²³While 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 mis-

leading 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 NBFIs 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.

²⁴In 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

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

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

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 non-bank dealers by easing market funding conditions (CGFS 2014).

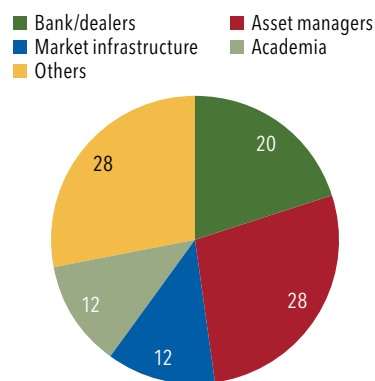
Box 3.1. IMF Staff Market Outreach: Qualitative Assessment of Advances in Artificial Intelligence and Its Implications for Capital Markets

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 sophisticated 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

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.

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.

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,

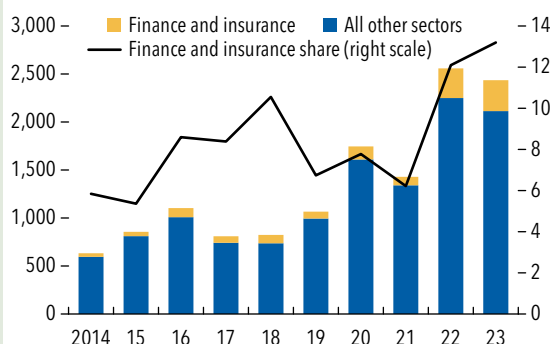
manipulated stock prices, or an erosion of trust in financial institutions, triggering selloffs or deposit runs. Critical financial market or information technology infrastructure can be targeted, leading to significant disruptions in financial markets and beyond.

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

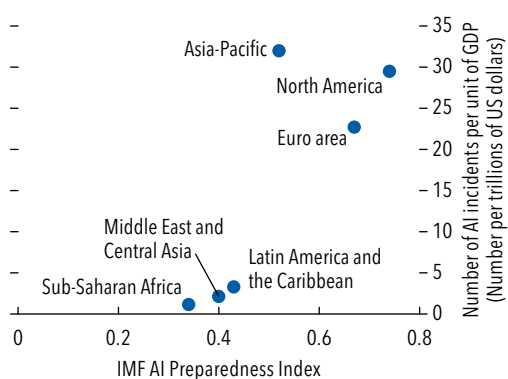
Cyberattacks have increased, with the financial sector share rising as well.

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: AIAAIC 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.

¹Chapter 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.

²There 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

³Chen, 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>

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

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>

⁵Khan, 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.

²⁶Financial Conduct Authority Handbook (2011).

²⁷FSB (2017b).

²⁸FSB (2017b).

²⁹FSB (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.

³⁰IOSCO (2011, p. 22).

³¹CGFS (2014).

³²FSB (2017a).

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