European Commission

European Financial Stability and Integration Review 2025

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European Financial Stability and Integration Review 2025

European Commission

Directorate-General for Financial Stability, Financial Services and Capital Markets Union

European Commission

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European Financial Stability and Integration Review (EFSIR)

Economic Paper 01 – 12 June 2025

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The European Financial Stability and Integration Review (EFSIR) is informed by the international discussion on financial integration and stability. It presents these topics in a non-technical format that remains accessible to a non-specialist audience.

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ACKNOWLEDGEMENTS

This document has been prepared by the European Commission's Directorate-General for Financial Stability, Financial Services and Capital Markets Union (DG FISMA) under the direction of John Berrigan (Director-General), Alexandra Jour-Schroeder (Deputy Director-General), Nathalie De Basaldua (Director, general affairs) and Klaus Wiedner (Director, financial system surveillance and crisis management).

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LIST OF ABBREVIATIONS

Countries (in alphabetical order)

AL	Albania	IS	Iceland
AT	Austria	IT	Italy
BE	Belgium	JP	Japan
BA	Bosnia and Herzegovina	LT	Lithuania
BG	Bulgaria	LU	Luxembourg
BM	Bermuda	LV	Latvia
CA	Canada	MC	Monaco
CH	Switzerland	MK	Republic of North Macedonia
CN	China	ME	Montenegro
CY	Cyprus	MT	Malta
CZ	Czechia	NL	Netherlands
DE	Germany	NO	Norway
DK	Denmark	PL	Poland
EE	Estonia	PT	Portugal
EL	Greece	RO	Romania
ES	Spain	SE	Sweden
FI	Finland	SG	Singapore
FR	France	SI	Slovenia
HR	Croatia	SK	Slovakia
HU	Hungary	UK	United Kingdom
IE	Ireland	US	United States

Others

AI	Artificial intelligence	GDP	Gross domestic product
AMECO	Annual macroeconomic database	GPAI	General Purpose AI system
AML	Anti-money laundering	HFT	High-frequency trading
ASI	Artificial superintelligence	HICP	Harmonised index of consumer prices
ATMs	Automated teller machines	IMF	International Monetary Fund
BIS	Bank for International Settlements	INFE	International Network on Financial Education
BU	Banking Union	IOSCO	International Organization of Securities Commissions
CDS	Credit default swaps	KYC	Know-your-customer
CFT	Countering the financing of terrorism	LAM	Large action model
CISS	Composite indicator of systemic stress	LLMs	Large language models
CMU	Capital Markets Union	MPT	Modern Portfolio Theory
CRE	Commercial real estate	ML	Machine learning
DORA	Digital Operational Resilience Act	MWh	Megawatt hours
EA	Euro area	NFC	Non-financial corporation
EBA	European Banking Authority	NLP	Natural Language Processing
ECB	European Central Bank	NPLs	Non-performing loans
EFAMA	European Fund and Asset Management Association	OECD	Organisation for Economic Cooperation and Development
EIOPA	European Insurance and Occupational Pensions Authority	PEPP	Pandemic emergency purchase programme
ESAs	European supervisory authorities	RRE	Residential real estate
ESMA	European Securities and Markets Authority	SIU	Savings and Investments Union
ETF	Exchange-traded fund		
EU	European Union	SME	Small and medium-sized enterprise
FCA	Financial Conduct Authority	UCITS	Undertakings for collective investment in transferable securities
FSB	Financial Stability Board	WEF	World Economic Forum
GenAI	Generative AI systems		

EXECUTIVE SUMMARY

The European Financial Stability and Integration Review (EFSIR) is published annually. It looks at recent economic and financial developments; and discusses specific topics pertaining to the financial sector that might pose challenges to financial integration and stability, and raise policy issues.

Chapter 1 reports on recent economic and financial developments in the EU from the beginning of 2024 to the beginning of the second quarter of 2025, but it does not examine in detail the most recent developments after the cutoff date [1]. Economic activity gradually improved in 2024, driven by the services sector, declining inflation and a strong labour market. Eased credit conditions and the Next Generation EU initiative supported investment. However, economic growth stalled in Q4 2024 due to significant political and policy uncertainty, mainly stemming from the US elections. In Q1 2025, growth was primarily driven by the services sector but remained modest because of substantial domestic and trade policy uncertainty.

Throughout 2024, systemic financial stability stress remained contained. However, short-lived disruptions during the summer exposed market vulnerabilities while the risk of economic and financial adversities also significantly increased due to policy uncertainty stemming from the new US administration. Key stability concerns in the period under review included potential asset repricing, debt sustainability in the sovereign and non-financial sectors, and sovereign financing risks.

Financial integration in the EU recovered during 2024 due to stabilising economic conditions, reduced inflationary pressures and the normalisation of monetary policies (as measured by the convergence of financial prices and increased cross-border financial activities). Geopolitical events in late 2024 affected financial integration, with clear positive and negative effects visible across different subindices of financial integration. Continuing efforts to foster integration (such as the measures proposed in the European Commission's Savings and Investments Union Communication [2]) are needed to reduce the remaining barriers and fragmentation in EU financial markets.

Chapter 2 provides an analysis of household savings and financial asset holdings in the EU. Households in the EU hold financial assets exceeding 200% of GDP, mostly managed by domestic financial intermediaries. Almost one third of these assets are in the form of cash and bank deposits. Over the past 15 years, the purchasing power of these deposits has generally declined because the average interest rates on deposits in the EU were lower than average annual consumer price inflation. By contrast, major stock markets have grown significantly, albeit unevenly. Historical data suggest that EU households could earn higher gross returns by diversifying their savings portfolios. Bond and equity prices are volatile, however, so investors should consider their risk tolerance and investment horizon before purchasing these assets.

Long-term savings can be supported in various ways, including via national tax incentives. In addition, there is evidence to suggest that automatic enrolment in pension savings plans, which exists in some EU Member States, mitigates the risk of low participation in voluntary schemes, leading to higher overall household savings. Most Member States have implemented or are

[1] The report in general covers the period up to the end of April 2025 and does not report on more recent developments, unless explicitly stated otherwise.

[2] Communication from the Commission to the European Parliament, the Council, the European Central Bank, the European Economic and Social Committee and the Committee of the Regions: savings and investments union, a strategy to foster citizens' wealth and economic competitiveness in the EU, COM(2025) 124 final of 19 March 2025.

developing national financial literacy strategies to empower citizens to take informed personal finance decisions. Savings and investments decisions are also influenced by the ease of accessing financial markets (such as via online platforms) and the impact of social media. Incentivising households to hold more of their savings in capital market instruments is one of the main pillars of the savings and investments union strategy.

Chapter 3 reviews the uses and risks of artificial intelligence (AI) in the financial services sector. AI has the potential to radically transform our economies. It not only automates mundane repetitive tasks but also outperforms humans in certain areas and can replace certain human interactions and thinking. This capability can lead to significant productivity gains. The financial services sector has rapidly adopted AI technology in recent years and most market participants now use it in some capacity. Typical applications include customer support, profiling tasks, detecting fraud, anti-money laundering (AML) and countering the financing of terrorism (CFT). In addition, AI is also increasingly affecting core business operations such as pricing, risk management and the processing of deposits, loans and trades. Supervisors are also building up their capabilities and will increasingly rely on AI to monitor the financial services sector.

Like all technologies, AI is not without limitations and risks. The EU Artificial Intelligence Act already addresses some of these risks, including in financial services. Current AI systems still lack the inherent 'true' intelligence that would prevent clearly incorrect, incoherent or ethically questionable outputs. In financial services, such flawed AI output could have significant negative effects, which could even, in adverse circumstances, lead to systemic impacts. AI also raises consumer protection concerns. Besides concerns about the use of (personal) data in AI systems, AI applications could discriminate against or exclude consumers of certain services. The technology also comes with external risks – including new types of fraud and cyber vulnerabilities. It is therefore essential for supervisors to closely monitor AI and its use in financial services. As supervised entities deploy AI in business sensitive areas and compliance functions, new forms of structured monitoring and supervision may be necessary.

In conclusion, AI is set to become a key technology with many benefits. However, certain risks that arise from its use need to be monitored and managed appropriately. Any potential future changes to the current framework(s) which aim to address risk-related issues need to strike a delicate balance between a prudent treatment of risks and maintaining sufficient flexibility to avoid creating barriers to innovation.

Chapter 1 THE MACROECONOMY, MARKET DEVELOPMENTS, FINANCIAL STABILITY AND FINANCIAL INTEGRATION

By Chris Bosma and Lars Linz

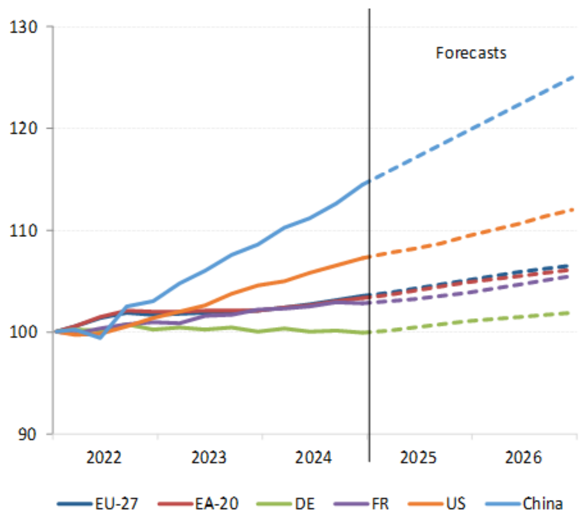
1.1 Macroeconomic developments

GDP is estimated to have grown by 1% in the EU and by 0.9% in the euro area (EA) in 2024 (see Chart 1.1). Growth was led by the services sector, while manufacturing remained weak due to subdued demand for goods, the diminishing effects of previous monetary policy tightening and significant trade policy uncertainty (see Chart 1.2).

In Q1 2024, the economy experienced stronger-than-expected growth, with GDP increasing by 0.3% quarter-on-quarter (q-o-q) in the EU and the EA. Consumer spending emerged as the main driver of economic expansion, supported by slowing inflation and a robust labour market. Easing credit conditions and the continued rollout of Next Generation EU funds have increased investment activity, but at a slower pace than expected.

Economic growth continued through Q2 and Q3 2024, recording q-o-q increases of 0.3% and 0.4% in the EU, respectively (0.2% and 0.4% in the EA). Supported by a rise in real private consumption and strong income growth, the economy grew by a further 0.4% in the EU and by 0.2% in the EA in Q4 2024. The outlook for 2025 as a whole (as foreseen in the Commission's spring 2025 economic forecast – published after the general cut-off date of analysis for this report [3]) is for further moderate growth of 1.1% in the EU and 0.9% in the EA, amid global economic uncertainty.

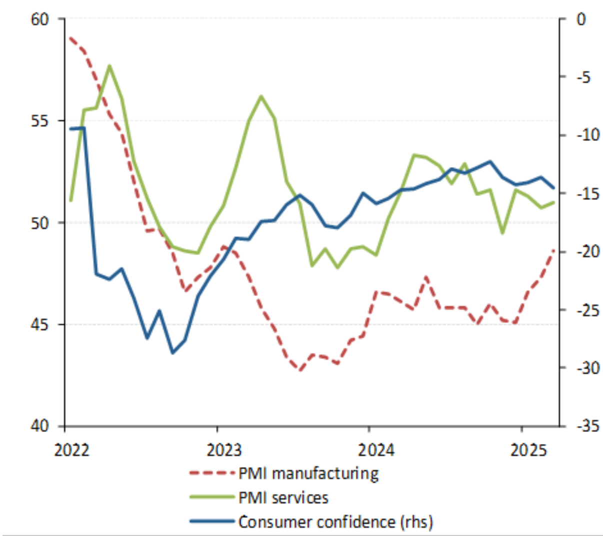
Chart 1.1: GDP growth



Source: OECD; European Commission, *European economic forecast autumn 2024*, Institutional Paper 296, November 2024.

Note: indexed data (Q4 2021 = 100). Q-o-q growth of quarterly GDP (except that forecasts for China are based on y-o-y GDP growth of yearly data).

Chart 1.2: Euro area business and consumer sentiment indicators



Source: S&P Global; European Commission (DG ECFIN) (2024), *Business and consumer survey results*, 4 April 2025.

Note: monthly data, index points.

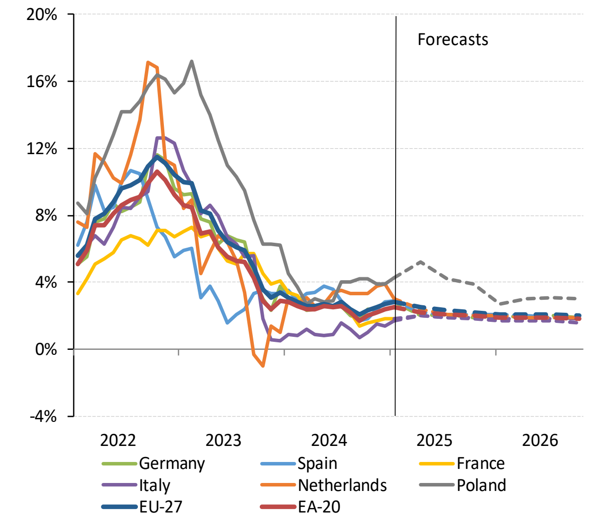
Over 2024, headline inflation in the euro area (as measured by the harmonised index of consumer prices – HICP) continued to moderate but not steadily (see Chart 1.3). In Q1 2024, HICP inflation

[3] European Commission (DG ECFIN), '[European economic forecast autumn 2024](#)', *Institutional Paper*, No 318, May 2025.

decreased further following a sharp decline in 2023. It remained stable in Q2 2024 before decreasing again in Q3. However, it rose again in Q4, reaching 2.4% in December 2024 (see Chart 1.4). Throughout 2024, services inflation remained at a high level, driven by a tight labour market. Price pressures in services remained significant, but they were projected to decrease from early 2025, driven by slowing wage growth and an expected increase in productivity. Headline inflation in the EA (EU) was anticipated to gradually decline to 2.1% (2.4%) in 2025.

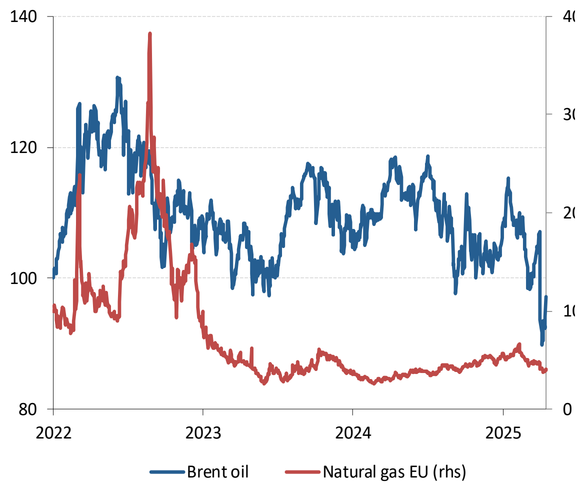
With inflation continuing to moderate in 2024, the ECB started to cut its policy rates, thereby rewinding the monetary policy rates hiking-cycle it had finished in September 2023. The ECB lowered its rates four times during 2024 and three times in the first months of 2025 [4]. Central banks in EU Member States outside the euro area also initiated or had already initiated monetary policy easing cycles [5].

Chart 1.3: HICP inflation – EU Member States



Source: Eurostat and European Commission, *European economic forecast autumn 2024*, Institutional Paper 296, November 2024.
Note: headline data, y-o-y % change. Monthly data (except forecasts which are based on quarterly data). HICP stands for harmonised index of consumer prices.

Chart 1.4: Oil and natural gas



Source: Bloomberg Finance L.P.
Note: daily data, indexed (Jan 2022 = 100). Brent oil in USD/barrel and natural gas in EUR/MWh.

1.1 Financial market developments

Entering 2024, an improving macroeconomic outlook and expectations of monetary policy easing sparked a rally in financial markets. Despite substantial uncertainty in the macrofinancial environment (including the effects of financing costs that are now structurally higher than a few years ago) as well as in the geopolitical environment, volatility in risk asset markets (stock markets) remained low, while volatility in interest rate markets remained high. Volatility in stock markets and interest rates picked up in June following unexpected EU and national election outcomes, but this volatility abated soon afterwards. In August, several factors (including stretched positions in a less active equity market, market expectations of faster US monetary policy easing amid disappointing labour data and unexpected monetary tightening in Japan) led to the unwinding of Japanese yen-funded carry trades. This caused global jitters, but the market

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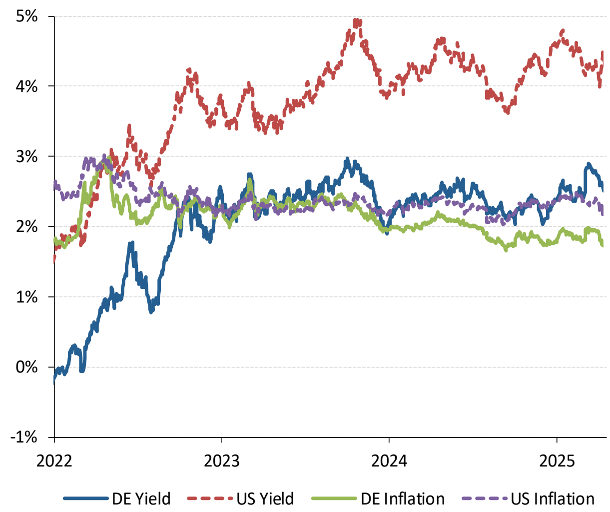
[4] This report covers the period up to 23 April 2025 and does not report on more recent developments.
[5] For instance, Hungary started monetary easing in October 2023, Czechia in December 2023, Sweden in May 2024, Denmark in June 2024 and Romania in July 2024.

correction was brief and a recovery ensued shortly afterwards. However, risk sentiment in EU markets remained cautious for the rest of 2024. At the beginning of 2025, markets regained strength but then weakened again amid global trade policy uncertainty. Asset prices dropped sharply in early April when the US announced a larger-than-expected tariff package. The announcement of retaliatory measures by trading partners added to concerns about a potential global trade war, leading to further market sell-offs. However, the US later announced a 90-day suspension of many tariffs, which alleviated these concerns. Asset prices therefore recovered a large part of their earlier losses.

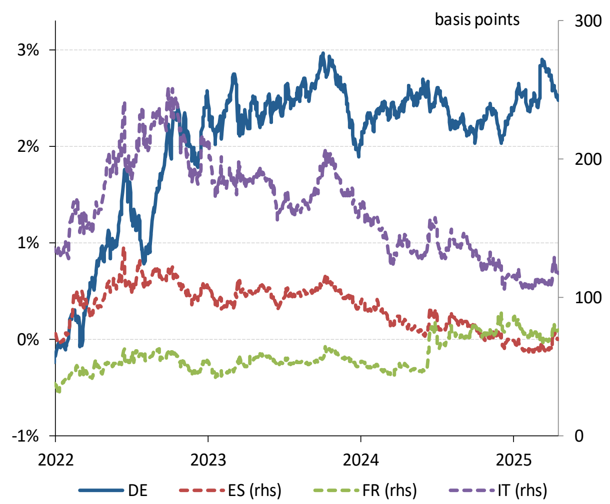
EA sovereign benchmark yields rose in the first half of 2024 supported by the improving economic growth outlook. Over the summer of 2024, benchmark sovereign bond yields declined across all maturities due to increased global political and policy risk, lower-than-expected macroeconomic activity indicators in the EU and the US, and more pronounced monetary loosening. In line with US yields, benchmark sovereign bond yields reversed course in October. At the end of the year, benchmark yields rose again due to an upward revision of inflation expectations driven by rising energy prices and other factors. In early March, EU benchmark sovereign yields jumped strongly higher on the prospects of increased (defence) spending by Germany but gradually declined afterwards (see Chart 1.5).

Chart 1.5: 10-year sovereign bonds yields and expected inflation



Source: Bloomberg Finance L.P.
Note: 10-year maturity bond daily data. 10-year inflation expectations based on the break-even inflation rate on inflation-linked bonds.

Chart 1.6: 10-year sovereign bond spreads



Source: Bloomberg Finance L.P.; DG FISMA calculations.
Note: spreads are calculated against the 10-year German Bund.

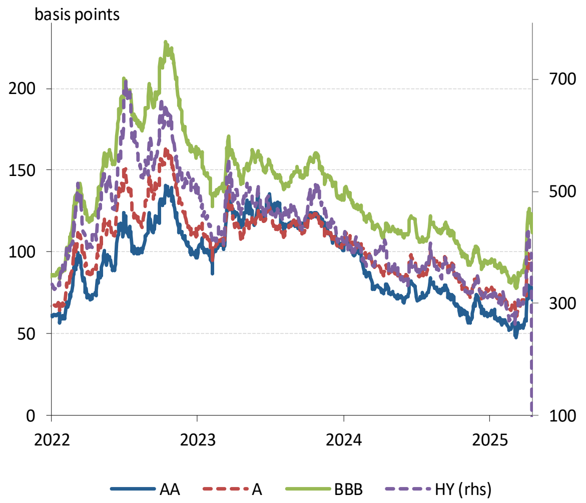
Most sovereign bond spreads tightened further over 2024 and approached very low pre-COVID levels. Sovereign bond yields and spreads were unaffected by reinvestment of maturing principal payments from securities purchased under the Pandemic Emergency Purchase Programme (PEPP) [6]. After the EU elections, EA government bond spreads to the Bund widened somewhat but tightened substantially afterwards. The more positive sentiment of rating agencies regarding the fiscal outlook of some Member States had a positive impact on spreads. However, French spreads rose above those of Spanish bonds due to increased uncertainty over the fiscal outlook in France following the dissolution of the French parliament and the snap election that was then

[6] The ECB initiated the PEPP in March 2020 following the COVID-19 outbreak. The PEPP was a temporary asset purchase programme that covered private and public sector securities. Its purpose was to counter the significant risks to the monetary policy transmission mechanism and negative effects for the outlook for the euro area.

called. In April 2025, EA sovereign bond spreads widened from narrow levels amid the increased risk aversion in markets. Spreads remained broadly stable over the year in other non-EA Member States (including Hungary, Poland and Romania).

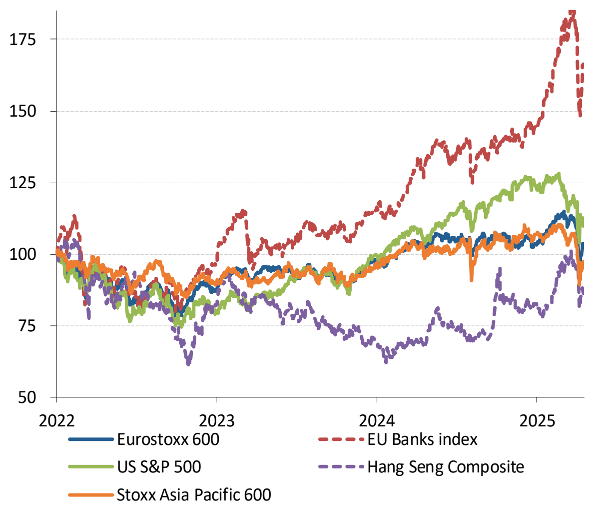
Increased issuance activity by sovereigns and continued selling of bonds by the European System of Central Banks (ESCB) amid quantitative tightening have been supported by strong demand as investors were attracted by higher real yields and sought to lock in yields in anticipation of an expected cycle of policy rate cuts.

Chart 1.7: Euro-area corporate bond spreads



Source: Bloomberg Finance L.P.; DG FISMA calculations.
Note: Five-year maturity bond data. Daily data. Spreads are calculated against the five-year German sovereign bond yield. HY stands for high yield.

Chart 1.8: Stock market performance



Source: Bloomberg Finance L.P.
Note: daily data, indexed (Jan 2022 = 100).

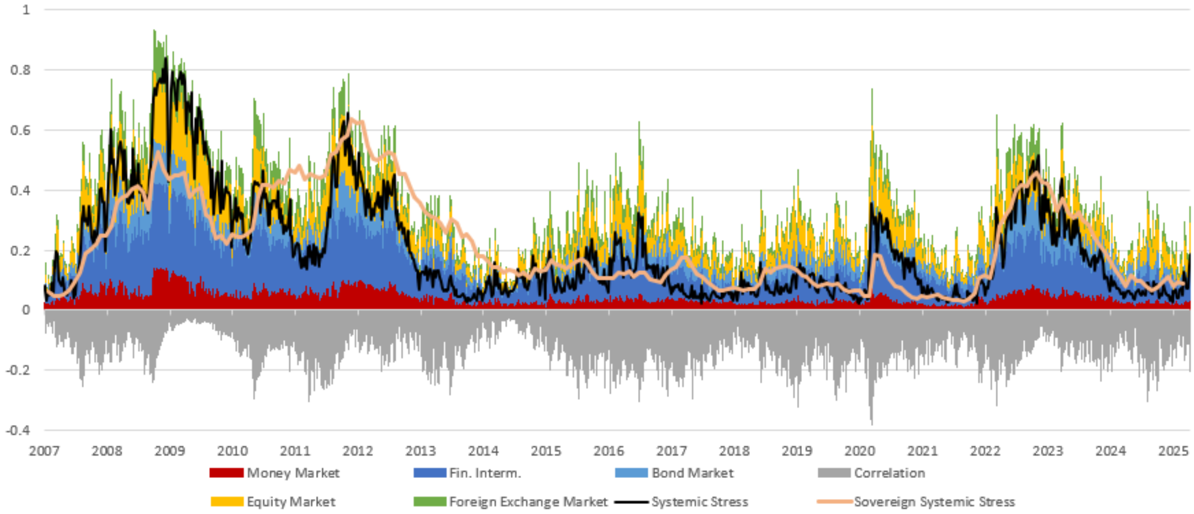
Apart from a brief increase over the summer, corporate bond spreads in 2024 narrowed to near-historical lows for both investment-grade and higher-risk bonds. In particular, high-risk spreads remain narrow by historical standards despite an anticipated rise in default frequencies. The real cost of borrowing (measured by inflation-adjusted interest rates) continued to normalise. However, in April 2025, the spreads widened to the levels seen in early 2024 but decreased slightly towards the review's cut-off date.

Equity markets rallied in Q1 2024, driven by investors' optimism about an economic rebound in the EU and anticipated lower financing costs. EU bank shares benefited and outperformed the market. However, markets remained broadly range-bound for the rest of the year, as improved earnings expectations were offset by increases in the equity risk premium. Interest-sensitive sectors like real estate sector underperformed. In early 2025, EU stock markets rallied significantly and outperformed their US counterparts, but these gains were cancelled out during the market correction of April 2025.

1.2 Financial stability

The level of systemic financial stability stress remained well contained throughout 2024. In H1 2024, financial stability conditions improved as the immediate risk of a severe economic downturn faded away. In addition, inflation decreased faster than anticipated, easing financial stability concerns. However, short-lived events over the summer highlighted the fact that financial markets were still susceptible to sudden changes in sentiment. The risk of economic and financial difficulties significantly increased in H2 2024, largely due to considerable policy uncertainty stemming from the new US administration. This uncertainty negatively affected the EU's financial stability outlook. By the end of 2024 and in early 2025, concerns were focussed more on growth fears than on worries about inflation, although achieving the ECB 2% inflation target remained challenging.

Chart 1.9: Composite indicator of systemic stress (CISS)



Source: European Systemic Risk Board.

Note: the composite indicator of systemic stress (CISS) measures either the current state of instability, which is defined as the current level of frictions, stresses and strains (or their absence) in the financial system as a whole; or, as an equivalent, the level of 'systemic stress'. The CISS comprises the following five financial system segments: bank intermediaries; non-bank financial intermediaries; money markets; securities (equities and bonds) markets; and foreign exchange markets.

The risk of a disorderly market correction remained a top concern for financial stability. This risk persisted due to consistently low risk premiums and valuations that were susceptible to a sudden shift in market expectations. Meanwhile, worries about debt sustainability in the non-financial corporate sector increased. Corporate insolvencies continued to rise, reaching their highest level since 2018. Small and medium-sized enterprises (SMEs) appeared particularly vulnerable due to the current economic conditions and higher borrowing costs impaired their ability to service debt. In addition, high public debt remained an important issue in several EU Member States. This challenge was exacerbated by the need for increased social spending and investment to achieve the green and digital transitions, which strained future government budgets amid a sluggish economic performance. These major financial stability risks are explored in further detail below.

1.2.1 Risk of a disorderly repricing in major financial market asset classes

Amidst political and policy developments and despite the stress experienced over the summer, EU financial markets demonstrated resilience in 2024 (see Section 1.2). However, the risk of a significant repricing of financial assets has increased, especially in the US. This risk partly materialised early in 2025 amid the mounting global trade policy tensions.

Financial conditions in the US were characterised by record-high stock market valuations, narrow credit spreads and strong profit margins. President Trump's second term has seen inflation risks skew upwards, amid trade tariffs and a more stringent immigration policy. Concerns about US debt sustainability (given the substantial US budget deficits, increasing government debt and increased interest rates) could increase volatility in global financial markets. Meanwhile, US equity markets still appear overvalued and show a significant degree of complacency (as indicated by the VIX index, which measures projected equity volatility and has remained low).

A repricing of financial assets in the US is likely to spill over significantly into EU markets, as highlighted by the market turbulence in August 2024.

Concerns remain regarding vulnerabilities in the non-bank financial sector. These could trigger adverse market dynamics due to forced asset sales, low market liquidity and procyclical selling, thereby increasing the risk of disorderly financial market conditions. This risk is particularly significant for specific investment funds, such as hedge funds, which operate with high leverage, significant liquidity mismatches and possibly a substantial market footprint.

1.2.2 Debt sustainability concerns in the non-financial private sector

Moderate macroeconomic growth, increased debt-servicing costs and rising labour costs have weighed on the profitability of the non-financial corporate sector. By Q2 2024, gross disposable income was 7.5% below its peak in Q2 2023 due to increasing labour cost factors and rising interest expenses that had doubled since Q2 2022. Higher refinancing costs for maturing debt threaten to further strain profitability.

A substantial portion of corporate bond debt (amounting to 34% of all outstanding debt) is set to mature over the next three years and will need to be refinanced at higher interest rates. This will make debt-servicing more challenging as the dynamics of bank lending to corporates remain weak.

However, the large proportion of fixed-rate debt issued by non-financial corporations (NFCs) has delayed this impact and has been softening the immediate effects of significant policy rate increases since early 2022. These developments require monitoring, but they are less concerning when viewed historically.

Corporate vulnerabilities were higher for NFCs with weak credit profiles. The number of corporate insolvencies in the EU continued to rise, increasing by 3.1% in Q2 2024 compared with Q1 2024, with significant differences across sectors.

Household vulnerabilities were generally contained, as households benefited from a strong labour market and passive deleveraging (due to the higher inflation of recent years). Real incomes were still recovering from a loss of purchasing power, but the situation improved thanks to slowing inflation and real wage adjustments. The cost of mortgages and new borrowing began to decrease in 2024, but some households (particularly low-income households or those with floating-rate mortgages) still faced challenges due to higher interest rates. Households in Member States where floating-rate mortgages are common (e.g. Estonia, Cyprus, Latvia, Lithuania, Portugal, and Finland) experienced significant increases in debt-servicing costs. To a lesser extent, this was also true for households in Ireland, Greece, Spain, Italy, Luxembourg, Malta, Austria and Slovenia. Residential real estate (RRE) markets have adjusted in an orderly manner and have even stabilised in some Member States, but other Member States still have high mortgage debt levels and overvalued property markets.

1.2.3 Sovereign financing risks and debt sustainability concerns

In late summer 2024, the Member States' governments released their medium-term fiscal and structural plans for the first time under the EU's revised economic governance framework. The comprehensive reform of the Stability and Growth Pact has helped to reduce some uncertainties around future fiscal adjustments and concerns about debt sustainability. The growth-friendly focus on reforms and investments is expected to boost the Member States' medium-term economic growth potential and foster debt sustainability. Fully and transparently implementing the revised framework without delay should assist governments in consistently reducing budget deficits and debt ratios.

At the end of 2024, the seasonally-adjusted general government-deficit-to-GDP ratio was 3.2% in the EU and 3.1% in the EA (compared with 3.5% in both regions at the end of 2023). These budget deficits are expected to decline further in the coming years. The tightening fiscal stance so far mostly reflects the phasing-out of a large part of energy-related and inflation-related support measures. More structural measures will be needed in the next two years to lower the deficit to offset the effect of gradually increasing interest expenditure and other structurally-rising expenditure (e.g. expenditure related to ageing). In both the EU and EA, the sovereign-debt-to-GDP ratio bottomed out at the end of 2023 (at 80.8% and 87.3% respectively in Q4 2023) and increased slightly in 2024 (81.0% and 87.4% respectively in Q4 2024), driven by higher interest payments.

Fiscal slippage nevertheless remains a risk in some Member States. Elections and the resulting challenges of implementing fiscal reforms have demonstrated the difficulties of fiscal consolidation in some Member States. These challenges are quickly mirrored in the pricing dynamics of sovereign bonds, as indicated by widening bond and credit default swaps (CDS) spreads. According to the European Commission's debt sustainability monitor published in March 2025, nine Member States (Belgium, Greece, Spain, France, Italy, Portugal, Romania, Slovakia and Finland) are at risk of experiencing high fiscal sustainability issues in the medium term. High public debt reduces Member States' resilience to potential future shocks.

The sovereign-bank nexus remains a concern. However, the share of sovereign exposures linked to their own 'home sovereign' is less than 50% of the total sovereign exposure for most Member States. Czech, Polish and Romanian banks continue to have very high exposures to their home sovereigns, exceeding 90%. Hungarian banks reduced their share from nearly 100% in 2018 to 70% in 2024, although banks' domestic government bond holdings as a share of total assets increased in 2024. Larger issuers like Germany, Spain, France and Italy also exhibit significant 'home bias' in the sovereign exposures of their banks. These shares are roughly 50% to 60% for French and Spanish banks and have remained stable over the past five years. Italian banks have a slightly higher share. German banks had around a 50% share in 2018, which declined to 40% in 2024.

1.2.4 Other risks

Besides the three above-mentioned major financial stability risks, other risks are still being closely monitored. These include risks stemming from the banking sector and the non-bank financial sector, as well as risks related to commercial real estate (CRE) developments and to technological developments.

In the EU banking sector, banks' balance sheets have demonstrated robustness, with capital ratios that are generally well above regulatory requirements, and strong liquidity ratios. Profitability has remained high, supported by still sizeable interest rate income and relatively low loan-loss provisions. However, there is significant variation in profitability across Member States. Interest margins are likely to narrow as interest rates decline and this may put downward pressure on interest income, even though lending volumes could increase. The subdued economic growth in the EU is expected to further challenge banks by reducing asset quality and probably triggering loan-loss provisions. Non-performing loans (NPLs) have slightly increased from a low base (particularly in specific sectors such as SMEs, CRE and, to a lesser extent, consumer financing).

Non-bank financial intermediaries (mainly investment funds, insurers and pension funds) are facing increased risks of disorderly market corrections and deteriorating credit quality. For operators with high leverage and liquidity mismatches, adverse market developments could lead to forced assets sales, potentially speeding up price corrections.

Risks to financial stability related to real estate developments in some Member States also remained a matter of concern, particularly as regards CRE. Conditions in euro-area CRE markets have shown signs of stabilising. Investor demand has recovered somewhat, in line with less restrictive monetary policy. However, structural factors related to the post-pandemic shift to remote working and e-commerce, as well as environmental considerations, have continued to make the outlook for some real estate firms challenging, particularly in the office building segment. CRE firms and developers' outlook is also closely tied to changes in long-term interest rates for refinancing.

Financial stability risks related to technological change (including cyber risks, data integrity and AI) remain substantial. The increased speed and interconnectedness of markets and systems facilitated by these technologies can have a significant systemic impact. However, when managed properly, these technologies can offer substantial benefits, such as in risk management and monitoring by supervisors.

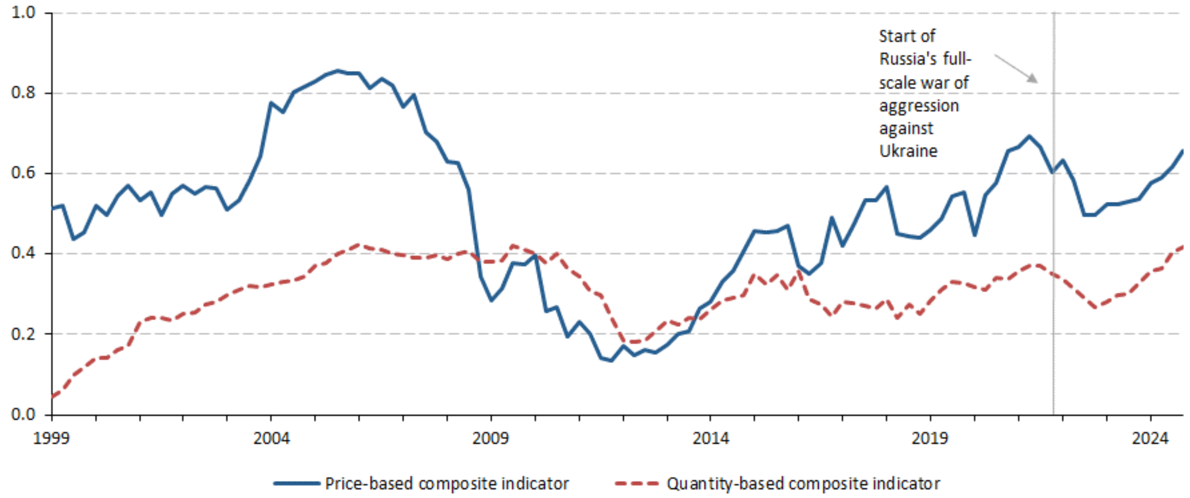
All in all, while systemic financial stability stress remained well contained, several vulnerabilities remain to be monitored.

1.3 Financial integration

Financial integration stabilised in the euro area during 2024. Both the price-based and quantity-based composite indicators of financial integration grew throughout the year (after dropping to their lowest values since the COVID-19 pandemic, shortly after the start of Russia's full-scale war of aggression against Ukraine in February 2022). The more volatile price-based index, which rises with reduced cross-border dispersion in asset prices or returns, has passed its level from Q1 2022 (0.63). The index jumped from 0.54 in Q4 2023 to 0.66 in Q4 2024, indicating that financial markets are pricing assets more uniformly across the euro area. In the meantime, the quantity-based indicator, which shows increased cross-border holdings of financial assets, is approaching an all-time high value (0.42 - Q1 2006). The indicator's improvement from 0.33 in Q4 2023 to 0.42 in Q4 2024 points to greater capital mobility and reduced home bias in the euro area.

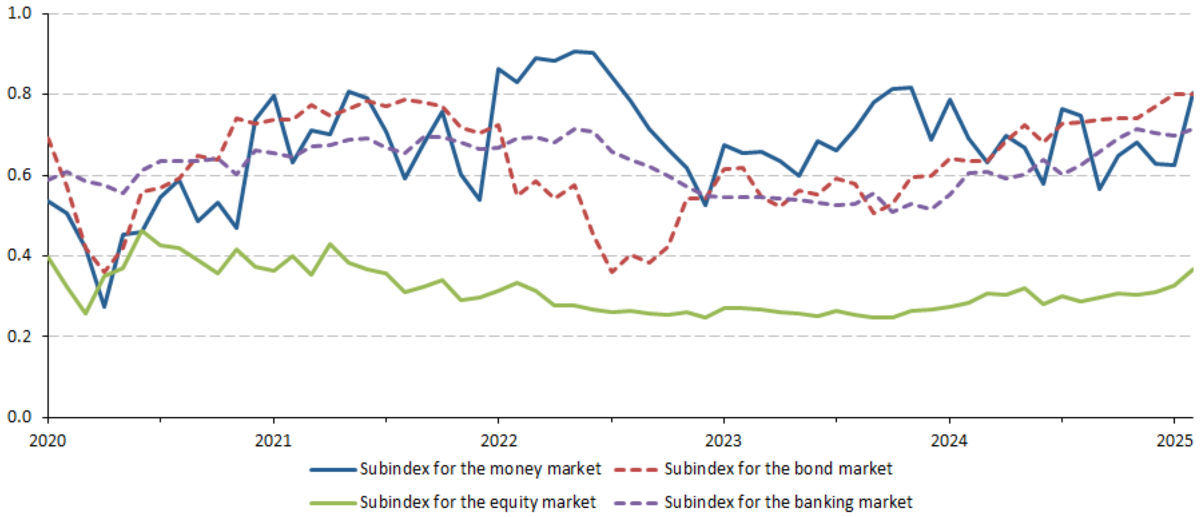
Trends in price-based financial integration were mainly positive throughout 2024, partly due to decreasing inflationary pressure along with normalising monetary and financing conditions. The money market index (the most sensitive to short term factors, such as monetary policy decisions) fluctuated the most in 2024. By the close of 2024, this index had marginally declined compared with its position at the close of 2023. The subindices for the equity, bond and banking markets all rose during most of 2024, driving the overall increase in the price-based composite indicator. In addition, the outcome of the US presidential election caused several subindices to deviate from their long-term trajectory. In particular, the increase in bond market integration strengthened while the positive trends in banking and money market integration reversed. These shifts underscore the significant influence of geopolitical events on financial integration dynamics in the euro area.

Chart 1.10: Price-based and quantity-based composite indicators of euro area financial integration



Source: ECB.
Note: the price-based composite indicator aggregates 10 indicators. The quantity-based composite indicator aggregates 5 indicators. A value of 1 corresponds to the highest degree of integration. The quantity-based indicator uses quarterly data between Q1 1999 and Q4 2024. The price-based indicator uses monthly data (converted into quarterly values) between Q1 1999 and Q4 2024.

Chart 1.11: Subindices of the price-based composite indicator of financial integration



Source: ECB.
Note: monthly data for the period from January 2020 to February 2025 inclusive.

During 2024, EU financial integration improved due to stabilising economic conditions. However, persistent fragmentation is continuing to hinder efforts to fully integrate the financial system, and this is in turn preventing the EU from fully realising the advantages of the single market. In March 2025, the Commission adopted its strategy on the savings and investments union [7], aiming to create a more cohesive and efficient financial ecosystem across the EU. This initiative seeks to reduce market fragmentation and improve the EU financial system's ability to channel savings toward productive investments [8].

[7] Communication from the Commission to the European Parliament, the Council, the European Central Bank, the European Economic and Social Committee and the Committee of the Regions: Savings and investments union, a strategy to foster citizens' wealth and economic competitiveness in the EU, COM(2025) 124 final of 19 March 2025.
[8] The European Commission publishes an annual set of indicators monitoring progress in building integrated capital markets. For further details, see the list of indicators to monitor progress towards the capital markets union objectives.

Chapter 2 HOUSEHOLD SAVING PATTERNS IN THE EU

By Anton Jevčák

2.1 Household saving rates and financial asset holdings

2.1.1 Gross saving rates

Household savings are the main domestic source of funding. Households save for various reasons, such as: (i) to cover unexpected expenses or potential income loss (this is known as 'precautionary saving'); (ii) to finance planned major expenses, like buying a car or a house; (iii) to maintain a consistent standard of living over time, especially during retirement; and (iv) to accumulate wealth or leave a bequest. The household saving rate is the portion of disposable income not spent on consumption [9] and is affected by many factors. These include economic conditions (e.g. employment opportunities, inflation, interest rates and government policies) as well as demographic factors (e.g. age, education level, family size and marital status). Personal and psychological factors (e.g. risk tolerance, time preference and financial literacy) also influence saving decisions.

Moreover, the level of control over saving decisions varies. Residual saving occurs involuntarily and without planning when some income remains unspent. Discretionary saving involves a conscious decision to set aside a portion of income for future use. Contractual saving entails a formal agreement with a financial institution to regularly transfer a specific amount into a financial product, such as a bank savings account, investment fund, pension fund or life insurance policy.

Since 2010, the average gross household saving rate in the EU has been 12.9% of disposable income. It fluctuated around 12% throughout the 2010s. It then spiked to over 18% in 2020 as lockdowns related to the COVID-19 pandemic hindered spending while fiscal transfers supported disposable incomes. After the pandemic restrictions were lifted, the saving rate initially fell to below 13% in 2022 (partly due to high inflation which required increased spending on private consumption). It then rose again somewhat during 2023-24. According to an ECB study [10], rising real incomes, high real interest rates and negative real wealth effects have driven household savings higher over the past two years.

Before the pandemic, the average household saving rate in the EU was consistently higher than in the UK and Japan, and hovered close to the US rate. After the drop from the pandemic-related surge, the saving rate in the EU remained at higher levels than in the US, Japan and the UK in 2022 and 2023. However, household saving rates vary significantly across EU Member States. In 2023, the saving rate exceeded 19% in Czechia and Germany but was less than 10% in Denmark, Estonia, Greece, Croatia, Cyprus, Latvia, Lithuania, Poland, Portugal, Romania and Slovakia.

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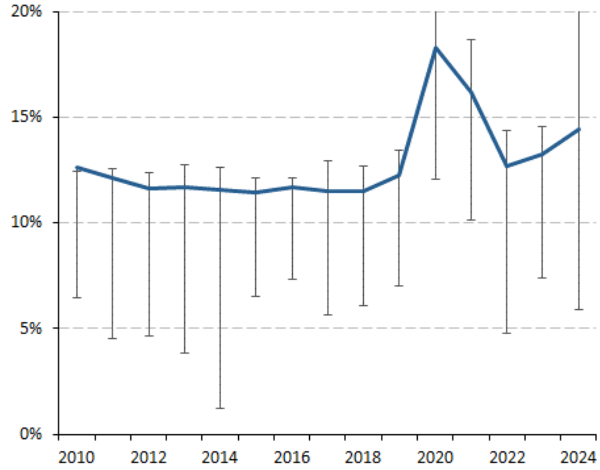
[9] Saving rates can be measured on either a gross or net basis. Net saving rates are measured after deducting consumption of fixed capital (depreciation).

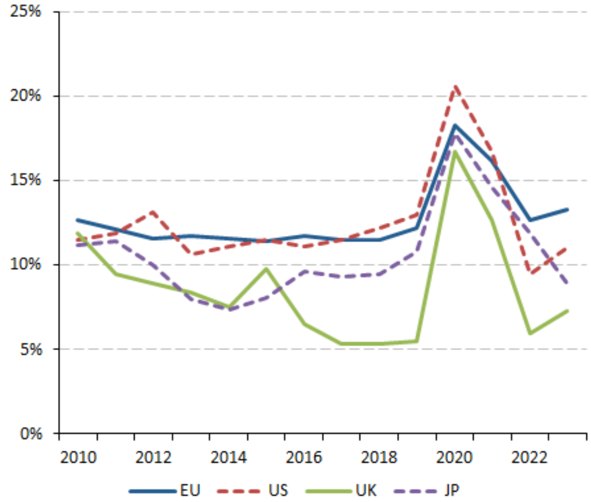
[10] Bobasu, A., Gareis, J. and Stoevsky, G., 'What explains the high household saving rate in the euro area?', *ECB Economic Bulletin*, No 8/2024, 9 January 2025.

Chart 2.1: Gross household saving rates in the EU



Source: Eurostat; DG FISMA calculations.
Note: the household gross saving rate is defined as gross household saving divided by gross disposable income, with the latter being adjusted for the change in households' pension entitlements. Annual data from 2010 to 2024. The vertical bars represent the range between the first quartile (the value below which 25% of the data lies) and the third quartile (the value below which 75% of the data lies) of observations at Member State level.

Chart 2.2: Gross household saving rates in the EU, Japan, UK and US



Source: AMECO.
Note: the household gross saving rate is defined as gross household saving divided by gross disposable income, with the latter being adjusted for the change in households' pension entitlements. Annual data from 2010 to 2023.

In the EU, saving rates are generally lower for individuals under 35 who are at the start of their careers. They then increase and stay relatively stable until the age of 64, before declining again during retirement. This pattern is consistent with the life-cycle hypothesis [11] which postulates that people try to maintain a consistent level of consumption across their overall lifespan. They do this by incurring debt or liquidating assets during periods of low income (such as early or late in life) and saving during their prime earning years when their income is higher. In addition, median saving rates in the EU rise with income levels. For instance, research indicates that households at the top of the income distribution range accounted for most of the excess savings accumulated during the COVID-19 pandemic [12]. Individuals with tertiary education also save more than those with lower education levels.

2.1.2 Financial asset holdings

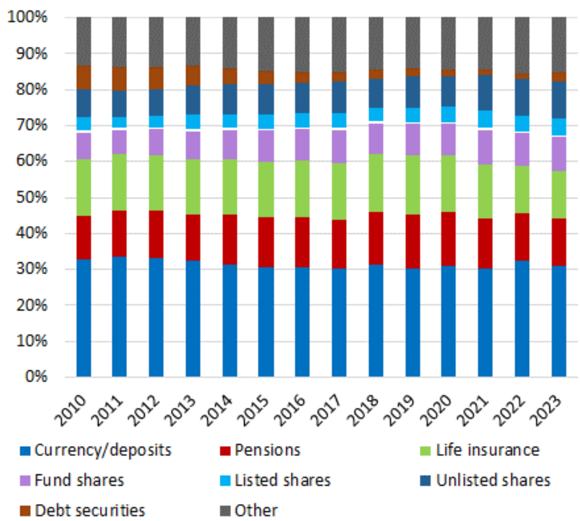
Modern Portfolio Theory (MPT) [13] provides a systematic approach to constructing and managing portfolios. According to MPT, the risk-return trade-off is crucial for determining the optimal portfolio composition. The optimal portfolio should maximise the expected return for the level of risk a household is willing to accept. Diversification, which involves spreading investments across a range of different assets, is a key strategy for achieving this outcome. Holding a well-diversified portfolio allows households to benefit from a more favourable risk-return trade-off than by concentrating their savings in a single asset or asset class. While methods for identifying optimal portfolio allocations continue to evolve, diversification remains a fundamental principle. At the same time, there is evidence that very few people properly understand the benefits of diversification [14].

[11] See Modigliani and Brumberg (1954).
[12] Battistini, N. and Gareis, J., 'Excess savings: To spend or not to spend', *The ECB Blog*, 2 November 2023.
[13] See Markowitz (1952).
[14] See e.g., Florentsen et al. (2019) or Reinholtz (2021).

Overall, households in the EU mainly hold financial assets through financial institutions (see Chart 2.3). In 2023, currency and deposits accounted for 31% of their financial assets; pension and life insurance entitlements accounted for 26%; and investment fund shares accounted for 10%. By contrast, direct holdings of listed shares were below 5% and debt securities were under 3%, while unlisted shares accounted for 10% of their holdings. The savings pattern of EU households has remained relatively stable. However, the share of life insurance entitlements has declined by nearly 3 percentage points (pps) since 2010 and the share of direct debt holdings by about 4 pps. This trend probably reflected the low-interest environment throughout the 2010s (see Section 2.2.1 for more details), resulting in relatively low-interest income from debt securities. Meanwhile, holdings of investment fund shares and unlisted shares have increased by approximately 2 and 3 pps respectively.

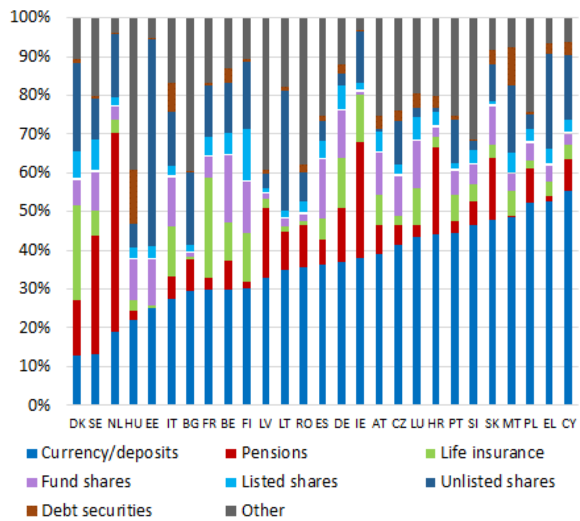
There are notable differences in saving patterns and portfolio choices among EU Member States (see Chart 2.4). In 2023, currency holdings and deposits accounted for more than 50% of households' financial asset holdings in Poland, Greece and Cyprus, but less than 20% in Denmark, Sweden and the Netherlands. In the Netherlands, households held more than 50% of their financial assets in pension entitlements and more than 30% in Ireland and Sweden. Households in Denmark and France allocated more than 20% to life insurance. Investment fund shares made up at least 10% of households' financial asset holdings in 11 Member States but less than 5% in another 11. Only Hungarian households allocated more than 10% of their holdings to debt securities.

Chart 2.3: Composition of financial assets held by households in the EU



Source: Eurostat; DG FISMA calculations.
Note: assets of EU households (and non-profit institutions serving households) as a share of total financial assets. Annual data. The white line in the middle of each bar segregates assets intermediated by financial institutions from directedly held financial instruments and other assets. The 'other' category contains other equity, non-life insurance technical reserves, provisions for calls under standardised guarantees, financial derivatives and employee stock options, other accounts receivable/payable and loans. Download date 16 May 2025.

Chart 2.4: Composition of financial assets held by households in EU Member States



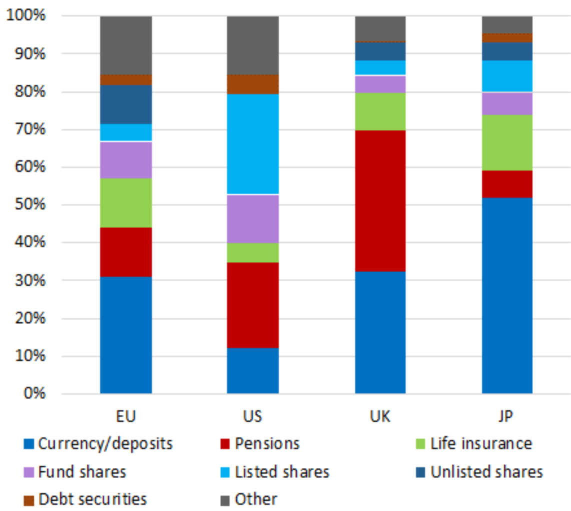
Source: Eurostat; DG FISMA calculations.
Note: assets of EU households (and non-profit institutions serving households) at the end of 2023 as a share of total per Member State. Member States are ranked from lowest to highest share of currency/deposits. The white line in the middle of each bar segregates assets intermediated by financial institutions from directedly held financial instruments and other assets. The 'other' category contains other equity, non-life insurance technical reserves, provisions for calls under standardised guarantees, financial derivatives and employee stock options, other accounts receivable/payable and loans. Download date 16 May 2025.

By the end of 2023, EU households' financial asset holdings stood at 222% of GDP. This was lower than the holdings of US, UK and Japanese households, which stood at 423%, 245%, and

369% of GDP respectively. Notably, holdings of listed shares corresponded to about 10% of GDP in both the EU and the UK. US and Japanese households held more listed shares (111% and 29% of GDP respectively) and could therefore directly benefit from increasing stock market valuations.

When considering the relative shares of different asset classes, assets intermediated by financial institutions constituted 67% of households' financial assets in the EU, 53% in the US, 84% in the UK and 79% in Japan. EU households held a higher proportion as cash and deposits (31%) than US households (12%), a similar share to the UK (33%) but less than Japanese households (52%). UK households held a larger share of financial assets in pension entitlements (37%) than those in the US (23%), the EU (13%) and Japan (7%). Life insurance accounted for the largest share in Japan (15%), followed by the EU (13%), the UK (10%) and the US (5%). Investment fund shares made up 13% of financial asset holdings in the US, 10% in the EU, 6% in Japan and 4% in the UK. Except for listed shares, which account for 26% of US households' financial asset holdings, no other distinct asset class (except residual other assets) accounts for more than 10% of households' financial asset holdings in these four economies.

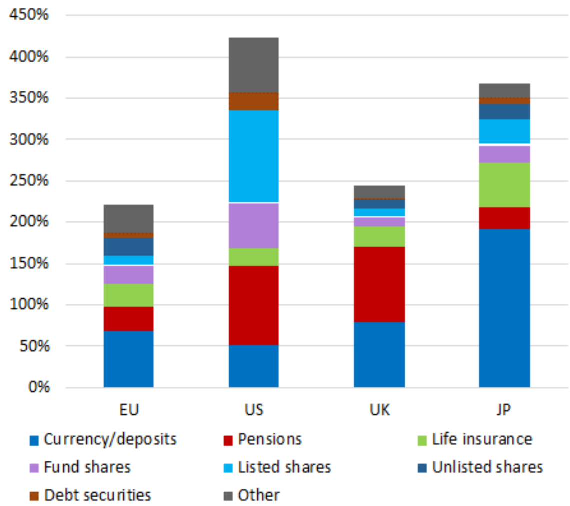
Chart 2.5: Household financial assets holdings in the EU, US, UK and Japan



Source: Eurostat, Bank of Japan, OECD; DG FISMA calculations.

Note: assets of EU households (and non-profit institutions serving households) as a share of the total in the EU, US, UK and Japan at the end of 2023. The white line in the middle of each bar segregates assets intermediated by financial institutions from directely held financial instruments and other assets. The 'other' category contains other equity, non-life insurance technical reserves, provisions for calls under standardised guarantees, financial derivatives and employee stock options, other accounts receivable/payable and loans. Download date 16 May 2025.

Chart 2.6: Household financial assets holdings in the EU, US, UK and Japan



Source: Eurostat, Bank of Japan, OECD; DG FISMA calculations.

Note: assets of EU households (and non-profit institutions serving households) as a share of domestic GDP in the EU, US, UK and Japan at the end of 2023. The white line in the middle of each bar segregates assets intermediated by financial institutions from directly held financial instruments and other assets. The 'other' category contains other equity, non-life insurance technical reserves, provisions for calls under standardised guarantees, financial derivatives and employee stock options, other accounts receivable/payable and loans. Download date 16 May 2025.

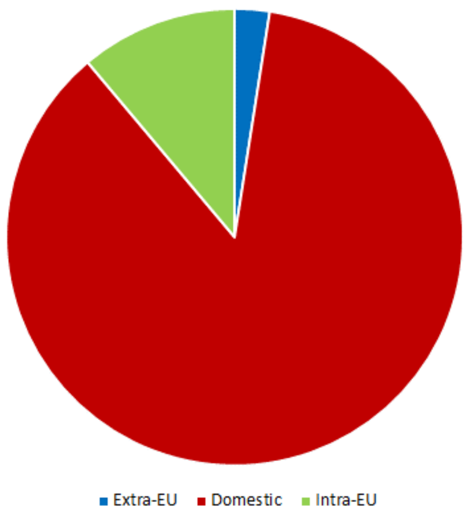
Various factors are often cited to explain differences in saving patterns and portfolio choices. These factors can be broadly divided into individual characteristics (e.g. age, marital status, risk tolerance, financial literacy, income and wealth levels, and job security), institutional factors (e.g. financial education, auto-enrolment in pension saving plans, tax policies, and other financial incentives to save) and broader socio-economic factors (e.g. the macroeconomic environment, access to financial markets as well as cultural and social norms) [15].

2.1.3 The role of foreign financial assets

Modern Portfolio Theory suggests that diversifying asset holdings, including internationally, can maximise risk-adjusted returns. Consolidated sectoral data for the EU on the geographic location of counterparties to financial flows is not readily available. The Commission services' calculations show that EU households hold a relatively small portion (13.6% at the end of 2023) of their financial asset portfolios in the form of direct claims on foreign entities. Most of these claims are estimated to be against counterparties in other EU Member States (11.1%) with the share of direct claims on non-EU counterparties standing at about 2.5% by the end of 2023. These shares have been gradually increasing in recent years.

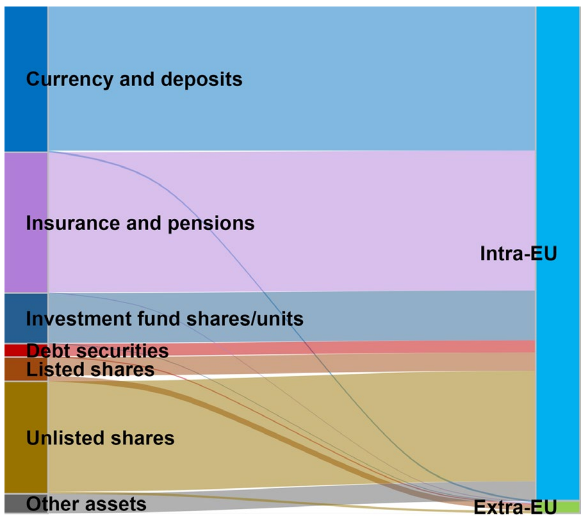
The shares of direct claims on non-EU entities vary per financial instrument. In the case of claims on financial intermediaries (i.e. bank deposits, investment fund shares, insurance and pension funds), non-EU shares remain below 2%. However, as further discussed below, EU financial intermediaries also finance non-EU counterparties. In addition, around 24% of listed shares and 8% of debt securities held by EU households were issued by non-EU counterparties.

Chart 2.7: Household financial assets by counterparty location at the end of 2023



Source: JRC and DG ECFIN calculations.
Note: Claims on domestic counterparties, counterparties in other EU Member States (intra-EU) and non-EU counterparties (extra-EU) as a share of total financial assets.

Chart 2.8: Intra-EU and extra-EU financial assets at the end of 2023



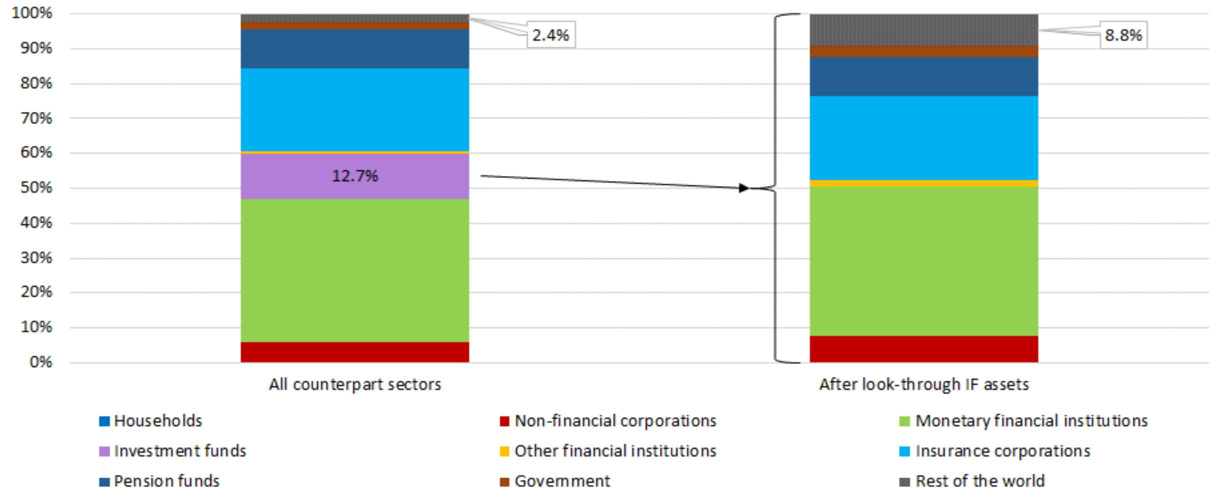
Source: JRC and DG ECFIN calculations.
Note: Claims on EU and non-EU counterparties per financial asset class.

Focusing on the euro area, for which some consolidated data on the holdings intermediated by investment funds (i.e. look-through data) are also available, only 2.4% of domestic households' financial holdings was directly in the form of assets issued by non-euro-area residents at the end of Q1 2024 [16]. However, the share of foreign assets was almost 9% if foreign assets held indirectly through investment funds were also counted [17]. The share would probably increase

[15] See Section 2.2 for a more detailed discussion of these factors.
[16] Arampatzi, A., Christie, R., Evrard, J., Parisi, L., Rouveyrol, C. and Overbeek, F.V., 'Capital markets union: a deep dive – five measures to foster a single market for capital', *ECB Occasional Paper Series*, No 2025/369.
[17] Anacki, M., Aragonés, A., Calussi, G. and Olsson, H., 'Exploring the investment funds households own', *ECB Blog Posts*, 17 September 2024.

further if look-through data were also available for other financial institutions. This shows that financial intermediaries play a crucial role in channelling cross-border financial flows.

Chart 2.9: Euro-area household financial assets by counterparty sector



Source: ECB.
Note: financial assets held by euro-area households directedly and indirectly through investment funds.

2.2 Determinants of household portfolio choices

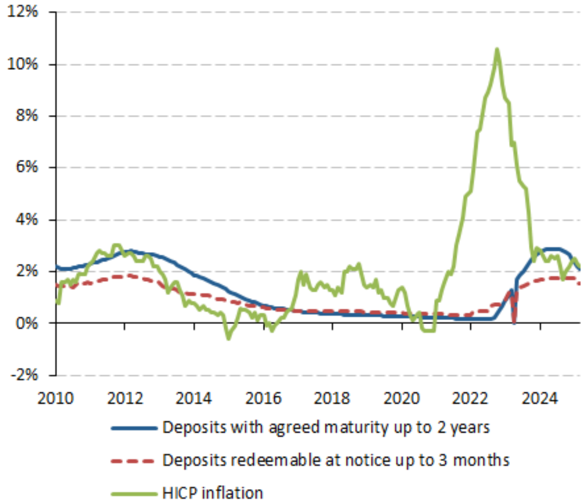
2.2.1 Risk-return optimisation

Bank deposits (especially savings accounts) are highly liquid and generate consistent and stable nominal returns. They are therefore a simple and secure way to store and grow savings in nominal (non-inflation-adjusted) terms. All segments of society can access banking services through branches, automated teller machines (ATMs) and digital platforms, and banking services are often supported by long-term client relationships. They are therefore a significant element in households' financial asset portfolios.

However, holders of bank deposits often incur substantial opportunity costs because these deposits offer relatively low returns. Interest rates on bank deposits are generally lower than the average long-term returns of other financial assets such as bonds, stocks or investment fund shares, and often result in a loss of purchasing power (see Charts 2.8 and 2.9). For example, in the euro area, the interest rate on deposits with an agreed maturity of up to two years has been 1.3% on average since 2010 and the interest rate on deposits redeemable at notice of up to three months has been only 1.0%. This was less than the average annual consumer price inflation of 2.2% during this period. Similar trends were observed in the EU's non-euro-area Member States. To the extent that households' risk aversion and time horizons make it possible to take up more risky financial assets, it is essential that households complement their deposits with holdings of other financial assets in order to preserve or increase the real value of savings [18].

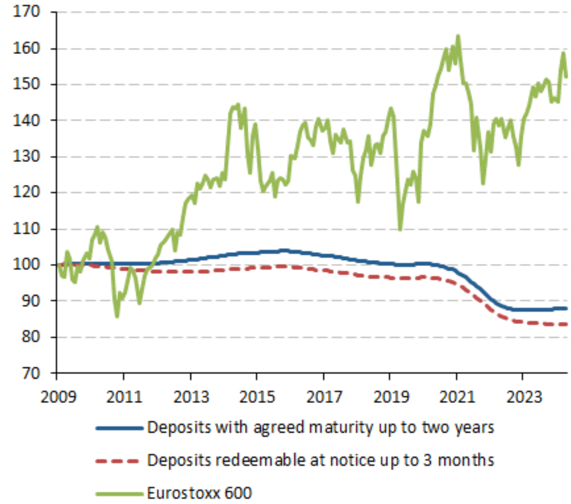
[18] See e.g., Arampatzi, A.S., Christie, R., Evrard, J., Parisi, L., Rouveyrol, C. and Overbeek, F.V., 'Capital markets union: a deep dive – five measures to foster a single market for capital', *ECB Occasional Paper Series*, No 2025/369.

Chart 2.10: Household deposit rates and inflation in the euro area



Source: ECB, Eurostat.
Note: annual interest rate on deposits with agreed maturity up to two years and redeemable at notice up to three months. Inflation is measured by the year-on-year HICP inflation rate. Monthly data between January 2010 and March 2025.

Chart 2.11: Gross real growth of savings in deposits and EU stock market index



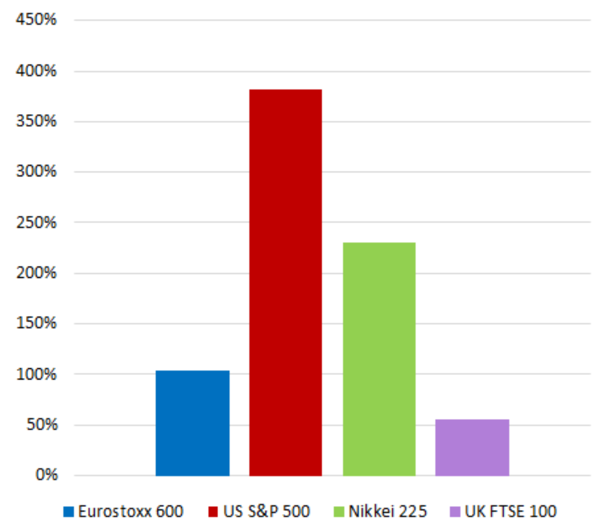
Source: ECB, Eurostat; DG FISMA calculations.
Note: gross real growth of savings in deposit and EU stock market index, as measured by the Eurostoxx 600. Monthly data from December 2009 to March 2025.

Despite the clear academic consensus on the long-term benefits of risk-return optimisation through portfolio diversification, holding financial assets other than bank deposits typically involves higher nominal return volatility. There have been notable cases of significant capital misallocation and asset mispricing. One example is the dot-com bubble in the late 1990s when the US Nasdaq Composite index [19] rose by over 400% between 1995 and early 2000 [20]. After peaking in March 2000, it fell by nearly 80% over the following two and a half years, wiping out almost all its gains as the bubble burst. It took the Nasdaq index 15 years to recover and reach a new all-time high in 2015 [21]. However, the volatility [22] of major stock markets has been broadly similar since the global financial crisis.

Over the past 15 years, major stock markets have grown significantly but unevenly. The US S&P 500 index increased by more than 350%, the Asia Nikkei 225 by more than 200%, the Eurostoxx 600 by about 100% and the UK FTSE 100 by more than 50%. The US share of global free-float market capitalisation therefore rose from about 40% after the global financial crisis to over 60% by early 2025 [23]. This situation has raised concerns about stock valuations, particularly for US tech companies, which seem to have been driven by excessive optimism about their future earnings. By the end of August 2024, tech firms accounted for 49% of S&P 500 market capitalisation, compared with 47% at the peak of the dot-com bubble [24]. In this context, it should be noted that in terms of assets held more than half of the 100 largest exchange-traded funds (ETFs) domiciled in the EU are linked to US benchmarks, according to Morningstar data [25].

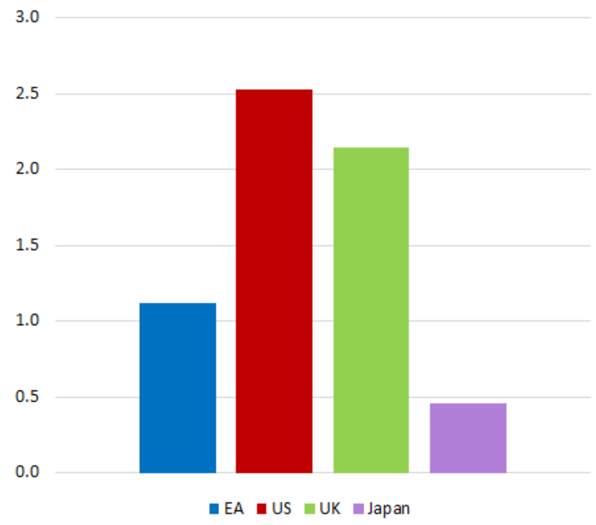
[19] The Nasdaq Composite Index is heavily weighted towards companies in the information technology sector.
[20] This period was marked by massive investments and souring valuations of internet-based companies. However, many of these start-ups went out of business by early 2000 because they had used up their capital before they could become profitable.
[21] Goldman Sachs,'The late 1990s Dot-Com bubble implodes in 2000'.
[22] Daily volatility is measured as standard deviation of logarithmic returns.
[23] Stacey, S. and Novik, M., 'How big is the stock market's America bubble?', *Financial Times*, 3 March 2025.
[24] See e.g., Lombardi, M.J. and Pinter, G., 'The valuations of tech stocks: dotcom redux?', *BIS Quarterly Review*, 16 September 2024.
[25] See Box 2.1 on the broader implications of the rise in passively-managed index funds.

Chart 2.12: Stock market index growth since 2010



Source: Bloomberg Finance L.P.; DG FISMA calculations.
Note: equity index growth between 1 January 2010 and 23 April 2025.

Chart 2.13: Average benchmark bond yields since 2010



Source: Bloomberg Finance L.P.; DG FISMA calculations.
Note: average benchmark bond yields based on daily data between 1 January 2010 and 23 April 2025.

Looking at debt markets, since 2010, the yield on 10-year benchmark bonds has averaged 2.5% in the US, 2.1% in the UK, 1.1% in the euro area and 0.5% in Japan. These relatively low yields reflect accommodative monetary policies within a low-inflation environment across major global economies during the 2010s. These conditions encouraged leverage build-up and supported asset valuations. However, the major central banks tightened their monetary policies after inflation spiked following the COVID-19 pandemic. Recent disinflation trends have led to some easing of monetary conditions in most developed economies, but it remains unclear whether a longer-lasting return to a low-interest environment can be expected.

Box 2.1: Impact of structural changes in asset management on risk-return optimisation

In recent years, retail investors have increasingly held passively-managed index funds, which track specific benchmark portfolios. For example, the market share of passive UCITS [26] rose from 11% in 2013 to 26% in 2023 [27]. This trend has mainly been driven by the cost advantages of index funds over actively managed funds, reflecting their lower resource intensity. Passive UCITS funds are on average about 60-80% cheaper than active funds [28]. Besides this cost advantage, index funds appeal to long-term investors because they are simple, transparent and diversified investment products that offer attractive long-term returns. For instance, between 2014 and 2023, the top 25% of passive equity funds generated higher returns after ongoing costs and one-off costs than the top 25% of their active peers [27].

However, as recently highlighted by the ECB, the rise of passive investing has increased the co-movement of stock returns within the euro area. This has made benchmark portfolio performance more volatile, undermining the benefits of diversification. In addition, passive funds may increase market capitalisation concentration and thus make equity markets more vulnerable to idiosyncratic

[26] Undertaking for collective investment in transferable securities.
[27] EFAMA, 'Factbook 2024'.
[28] ESMA, 'Cost and performance of EU retail investment products 2024', *ESMA Market Report*, No ESMA50-524821-3525, 14 January 2025.

risks from the largest companies [29]. These findings show that active investors also play an essential role in ensuring efficient market price formation and capital allocation.

Apart from financial assets, households also invest in other asset classes. For example, real estate represents a significant part of households' wealth. One in four households in the euro area own real estate property other than their main residence. This proportion gradually increased from 23.7% in 2010 to 24.1% in 2014, 24.9% in 2017 and 25% in 2021 [30]. These properties are not always bought as investments, but they can still generate capital gains if their value rises, as well as rental income. Over the last 15 years, the EU housing market has been a relatively attractive asset class, particularly when compared with bank deposits or government bonds. Since 2010, house prices have grown at an average annual rate of 3%, although there has been significant variation among countries. For example, house prices increased on average by 9% year-on-year in Estonia and 8% in Hungary, whereas they declined marginally in Italy and Cyprus between 2010 and 2023 [31].

The widespread increase in working from home, which was initially prompted by the COVID-19 pandemic and has since continued to a lesser extent, has also affected housing demand. For example, in a study on the London housing market, Richard (2025) showed that the prices of larger homes and properties located further from the city centre rose the fastest between 2018 and 2022. This may have increased income and wealth inequality [32]. Poorer households that were unable to afford the rising prices in the suburbs were forced to rent.

Investments in unbacked [33] cryptocurrencies, such as bitcoin or ether, are also becoming more common. These generally do not have the key characteristics of financial assets. In particular, they cannot be considered cash or cash equivalents because they are not recognised as legal tender and are not supported by sovereign governments. In addition, they do not represent an ownership interest in any entity or provide a contractual right to receive cash or another financial instrument. Furthermore, they do not generate cash flow (unlike real estate); they cannot be used productively (unlike commodities); and they may not provide clear social benefits (unlike gold jewellery). These cryptocurrencies were meant to serve as a digital medium of exchange, but they are primarily used as a (highly volatile) store of value. They can also be used for activities such as tax evasion, money laundering, terrorist financing and circumventing sanctions. Ultimately, without intrinsic (positive) value, their market valuation relies on speculation and sentiment that is driven by expectations of increasing demand and potential uses.

No official statistics are available on the holdings of unbacked crypto-assets by EU households. Quantifying ownership of these cryptocurrencies by geographic region is currently impossible because they can be held in wallets that are not linked to specific formally identified individuals or entities, including hardware wallets or other forms of self-custody [34]. Nevertheless, the overall crypto market capitalisation exceeded EUR 3.3 trillion by the end of 2024 after the price of

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[29] Dieckelmann, D., Siciliano, E. and Sowiński, A., 'Passive investing and its impact on return co-movement, market concentration and liquidity in euro area equity markets', *Financial Stability Review*, November 2024.

[30] ECB, 'Household Finance and Consumption Survey (HFCS)'.

[31] For a more in-depth discussion of real estate market developments, See e.g., 'Real estate in the aftermath of the pandemic: systemic risks and macroprudential policy tools to address them', in European Commission, *European Financial Stability and Integration Review* (EFSIR), SWD(2022) 93 final of 4 April 2022.

[32] Richard, M., 'Working from home: Effects on housing demand and inequality', *the ECB Blog*, 8 January 2025.

[33] By contrast, asset-backed cryptocurrencies (including stablecoins like USD Coin and Tether) minimise price volatility by maintaining a peg to external asset classes, such as fiat money or commodities. They are also backed by reserve assets. Algorithmic stablecoins also maintain a peg to the target currency but they are not backed by reserve assets.

[34] The nature of the distributed ledger implies that the owners of tokens can only be identified by a cryptographic signature.

bitcoin, which made up 53% of this market, more than doubled over the previous 12 months [35]. Less financially knowledgeable individuals may be drawn to unbacked crypto-assets due to the fear of missing out on extraordinary capital gains. A collapse in their market valuation could then lead to a redistribution of wealth at their expense. In December 2024, ESMA renewed its warning about the highly speculative and risky nature of many crypto-assets [36].

Box 2.2: Behavioural biases affecting households' financial decision-making

Traditional economic theories assume that individuals act rationally and have complete information for making financial decisions. By contrast, behavioural finance examines how psychological factors affect these decisions. It reveals that personality traits, attitudes and cognitive abilities (including biases and heuristics) significantly influence financial behaviour [37]. Household decisions therefore tend to systematically deviate from rational choices. The most common biases are summarised in Table 2.1.

Table 2.1 Overview of main behavioural biases

Bias	Description
Anchoring	Relying excessively on the first piece of information (the 'anchor') encountered when making decisions
Confirmation bias	Considering information matching preconceived beliefs and ignoring contradictory evidence
Disposition effect	Tending to sell profitable stocks too early to realise gains and holding onto losing stocks for too long to delay realising losses
Endowment effect	Choosing to continue owning an asset, even if there are more profitable alternatives
Framing	Making decisions based on how information is presented or 'framed'
Herding bias	Following others' judgements instead of making independent decisions
Hindsight bias	Thinking that some realised event could have been easily predicted
House money effect	Becoming less loss-averse after making large gains
Loss aversion	Feeling the pain of a loss more intensively than the pleasure of an equivalent gain
Mental accounting	Treating money differently depending on its intended use or origin
Overconfidence	Being overly confident in one's own knowledge and skills while disregarding potential risks
Recency/availability bias	Giving undue weight to recent experiences or the latest information when making predictions
Regret aversion	Avoiding taking decisive actions due to fear that they will seem suboptimal in hindsight
Representativeness	Estimating the probability of an event based on how closely it matches preconceived notions or stereotypes
Self-attribution bias	Attributing success to one's own effort and intelligence, and failures to external factors

Source: DG FISMA based on Bansal and Zahera (2018).

Past performance does not guarantee future returns, but evidence suggests that it does influence capital allocation decisions [38]. According to the Nobel-Prize-winning economist R.J. Shiller, this feedback loop mechanism (known as 'irrational exuberance') contributes to the regular emergence of asset-price bubbles. Moreover, studies on the psychological aspects of financial decision-making show that households display various behavioural biases, meaning they often make decisions that deviate from rationality (see Box 2.2. for an overview). Shiller (2015) therefore emphasises the importance of financial literacy and investor education.

[35] CoinMarketCap, 'Cryptocurrency prices, charts and market capitalizations'.
[36] ESMA, 'Warning on crypto-assets', No ESMA35-1872330276-1971.
[37] See e.g., Kumar and Goyal (2015) or Bansal and Zahera (2018) for a literature overview.
[38] See e.g., Barber et al. (2016).

2.2.2 Institutional factors

Households can be encouraged to save through various publicly supported schemes. According to the OECD (2024), the EU's Member States provide various financial incentives for long-term savings. These include tax benefits for pension or life insurance plans, nominal subsidies and matching contributions. Moreover, it is compulsory in several EU Member States to participate in supplementary personal pension schemes [39]. According to the ECB (2025) [40], national initiatives that are successful in mobilising savings toward long-term higher-yield products have certain key elements in common (e.g. appropriate tax incentives, flexibility and choice in product selection, and rebalancing strategies that accommodate varying risk preferences). By contrast, less successful initiatives often have complex rules and barriers to entry, focus on low-risk guaranteed returns and offer limited tax benefits.

There is no clear consensus in the academic literature on the overall effect of such publicly supported schemes on household saving. Tax-incentivised or subsidised schemes alter the composition of household asset portfolios by increasing holdings of eligible assets. The impact on aggregate saving levels is in principle uncertain [41], although recent research [42] indicates that tax subsidies for retirement savings may positively impact total private savings. It is important to note that tax incentives can also lead to distributional issues, because usually only individuals in higher income brackets qualify or have the means to fully benefit from them.

Most studies find that household savings increase when mandatory pension saving plans are in place [43]. Auto-enrolment schemes are designed to address the frequent issue of insufficient participation in voluntary pension schemes. By boosting participation rates, they can improve returns for pension-holders through greater scale and diversification [44]. In addition, pension tracking systems and dashboards can increase citizens' awareness of their expected retirement income, thus supporting financial planning.

The availability of, and trust in, public social security systems also influences household saving patterns [45]. These systems are designed to provide financial support during retirement, unemployment, disability or other circumstances that reduce earning capacity. People who feel that they can rely on these systems may save less because they are confident about their financial future. Changes in social security policies (e.g. modifications to benefit formulas, retirement age, or eligibility criteria) can impact public confidence and prompt shifts in saving patterns.

Financial literacy is also linked to sound savings behaviour. For example, financially literate persons hold more precautionary savings [46] and are therefore more resilient to income shocks.

[39] See e.g., OECD, '[Annual survey on financial incentives for retirement savings](#)', country profiles 2024, 9 December 2024.
[40] Arampatzi, A.S., Christie, R., Evrard, J., Parisi, L., Rouveyrol, C. and Overbeek, F.V., 'Capital markets union: a deep dive – five measures to foster a single market for capital', *ECB Occasional Paper Series*, No 2025/369.
[41] See e.g., Bernheim (2002) or Gelber (2011).
[42] See Christensen and Ellegaard (2023) and Goodman (2022).
[43] Jappelli, T. and Pistaferri, L., 'Tax incentives to saving and borrowing', *CEPR Discussion Paper*, No 3881, 23 May 2003.
[44] For more details on positive outcomes of auto-enrolment schemes, See e.g., European Commission (DG FISMA), LE Europe, Redington, Spark, Devnani, S. et al., *Best practices and performance of auto-enrolment mechanisms for pension savings – Final report*, Publications Office, 2021.
[45] See e.g., Feldstein (1974) or Attanasio and Brugiavini (2003).
[46] See Babiarz and Robb (2014) and Anderson et al. (2016).

They also better understand the impact of compound interest [47] and obtain higher returns on their savings [48]. Research also shows that they save more for retirement [49].

Financial literacy levels in the EU are too low. According to the 2023 Eurobarometer survey [50], only 18% of EU adult citizens had high financial literacy, while 64% had a medium level and 18% a low level. Significant differences exist between Member States, with over 25% of citizens scoring highly in financial literacy in the Netherlands, Sweden, Denmark and Slovenia but only 11% in Portugal and Latvia. Analysis of the survey results in the 2023 edition of the EFSIR [51] also highlights the need to target financial education efforts at women, young people, low-income individuals and those with lower levels of general education, because they tend to be on average less financially literate than other groups[49].

Most EU Member States have (or are in the process of designing) national financial literacy strategies. In its May 2024 conclusions on financial literacy, the Council [52] encouraged the other Member States to develop financial literacy strategies, with particular attention to financially vulnerable groups. The Commission has also developed financial competence frameworks. The EU/OECD-INFE financial competence framework for adults and the framework for youth promotes a common understanding of the financial competences required to make sound decisions on personal finance [53]. The Commission also plans to adopt a financial literacy strategy by Q3 2025 to empower citizens, raise awareness and increase their participation in capital markets [54].

2.2.3 Other individual and socio-economic factors

Households' asset allocation decisions are influenced by several other factors:

- Income and wealth levels and their distribution: higher income and wealth increase the capacity to save though more substantial and better diversified asset portfolios. Wealthier households have more scope to absorb losses and can therefore also invest in riskier assets generating higher returns. By contrast, lower-income and wealth households must prioritise liquidity and safety, because their limited savings are mainly held for precautionary purposes. Consequently, income and wealth inequality also influence overall households' asset allocation.

- Age and life-cycle stage: younger individuals may choose growth-oriented, riskier asset classes because they have time to recover potential losses. Older individuals nearing

[47] 87% of people with a high score on financial literacy correctly answered that more than EUR 110 would be in an account at the end of five years, when asked if someone puts EUR 100 into a savings account with a guaranteed interest rate of 2% per year, does not make any further payments into this account and does not withdraw any money. Only 16% of people with a low financial literacy score answered correctly.
[48] Deuflhard et al. (2018). For the Dutch sample in their study, a one-standard deviation increase in financial literacy is associated with a 12% increase compared with the median interest rate.
[49] For further details, see Chapter 3 'Financial literacy in the EU: trends, relevance and policy contribution' in European Commission, *European Financial Stability and Integration Review* (EFSIR), SWD(2023) 171 final of 7 March 2023.
[50] European Commission, 'Monitoring the level of financial literacy in the EU', *Flash Eurobarometer*, 525, July 2023.
[51] Ibid.
[52] Council of the European Union, 'Council approves conclusions on financial literacy', 9930/24, 14 May 2024.
[53] The frameworks are available for voluntary take-up and can support public policy, financial literacy programmes, the development of educational materials and curricula, and individuals. They are also intended to facilitate international cooperation and the exchange of good practices within the EU.
[54] Communication from the Commission to the European Parliament, the Council, the European Central Bank, the European Economic and Social Committee and the Committee of the Regions, Savings and investments union, a strategy to foster citizens' wealth and economic competitiveness in the EU, COM(2025) 124 final of 19 March 2025.

retirement usually prefer safer, income-generating assets because they want to avoid significant losses on their accumulated savings.

- Marital status and family structure: married individuals and/or those with dependents may prioritise stable, low-risk financial products in order to ensure their family's financial security.

- Employment status and job security: stable employment and job security encourage more risk-taking, while job uncertainty often leads to a preference for liquid and low-risk assets.

- Cultural and social norms: cultural attitudes towards saving also significantly influence asset allocation. Household portfolios tend to be more conservative in societies where there is a high level of trust in established financial intermediaries and no tradition of direct participation in financial markets.

- Macroeconomic environment: inflation, interest rates and financial market conditions affect household confidence in different asset classes. During periods of economic uncertainty and/or financial market turbulence, demand for safer liquid assets tends to increase and this can sometimes trigger a fire-sale of riskier assets. Conversely, a low-interest rate environment may encourage the search for yield.

- Access to financial markets: geographic location and technological access impact the availability of financial products and therefore influence asset allocation. Digitalisation has significantly expanded the range of financial products that are accessible online.

This indicates that changes in household asset composition depend on various developments. Some factors evolve gradually, such as demographics and family structures. By contrast, technological advances can quickly affect access to financial markets and the range of available products. Social media might also affect financial decision-making, for instance by amplifying the 'fear of missing out' (FOMO). For example, ESMA (2025) demonstrates that by contributing to their popularity and rise in prices, social media has been a key enabler of the growth of some crypto-assets [55]. Policymakers could therefore accelerate changes in household saving patterns by focusing on those factors that can be swiftly adjusted.

2.3 Conclusion

EU households have on average saved around 13% of their disposable income over the last 15 years. They have accumulated financial assets that now exceed 200% of GDP. Most of these assets are held through financial intermediaries, with nearly one third in cash and bank deposits. By contrast, direct holdings of listed shares and debt securities make up less than 10% of their financial assets.

The purchasing power of accumulated deposits has tended to decline over time because average interest rates on deposits held in the EU were mostly less than average annual consumer price inflation over the last 15 years. In addition, the relatively low yields on 10-year benchmark bonds reflected accommodative monetary policies in the low-inflation environment that prevailed in most developed economies during the 2010s. However, major stock markets have experienced significant, albeit uneven, growth. Volatility in these markets has been broadly similar since the global financial crisis.

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[55] ESMA, *Report on trends, risks and vulnerabilities*, No ESMA50-524821-3584, 13 February 2025.

Real estate has generally proved to be an attractive asset class in recent years as house price growth has outpaced consumer price inflation in most EU Member States. Conversely, unbacked crypto currencies and coins have recorded large valuation gains in 2024 but remain a highly speculative and risky investment.

Historical evidence suggests that EU households could achieve higher returns by holding more diversified asset portfolios. Their exposure to stock markets (whether directly through holdings of listed shares or indirectly through investment or pension funds) is currently relatively low. On average, long-term equity returns have been higher than the interest on saving deposits. However, equity investments are more volatile. Retail investors should therefore be aware of the risks and include these investments in their portfolios only to the extent they match their risk tolerance and investment time horizon.

EU Members States offer various financial incentives for long-term savings, such as tax advantages for pension or life insurance plans, nominal subsidies or matching contributions. Appropriate tax incentives, flexibility and choice in product selection, and rebalancing strategies that cater to different risk preferences are key aspects of successful national schemes. Evidence also shows that auto-enrolment in mandatory pension saving plans mitigates the risk of low participation in voluntary schemes and therefore leads to higher overall household savings.

As part of its savings and investments union strategy, the Commission plans to introduce measures by Q3 2025 to create an EU blueprint for savings and investments accounts or products, drawing on existing best practices. By Q4 2025, the Commission will also issue recommendations on the use of, and best practices for, auto-enrolment, pensions tracking systems and pension dashboards.

In addition, most EU Member States either have or are in the process of designing national financial literacy strategies. The existing national strategies should be periodically reviewed and evaluated to ensure that they remain effective and integrate new trends in finance. Access to financial markets, facilitated by technological advances and influenced by social media, is another determinant of saving decisions which could be targeted and affected by policy actions.

Chapter 3 ARTIFICIAL INTELLIGENCE IN FINANCIAL SERVICES

By Max Langeheine

3.1 Introduction

Artificial intelligence (AI) already affects many aspects of our lives. Respective AI algorithms and systems are being used in all economic sectors, including financial services. The ability of current AI systems and likely advances in the coming years are resulting in an increasing uptake of these systems and significant investment in AI development.

Provided that AI systems work as intended, AI can boost productivity significantly by automating tasks, improving data analysis and providing easy-to-access human-machine interfaces. Like other key technologies, AI is expected to have a major impact on competitiveness and a global race to develop and advance AI systems has already begun. Depending on cost/pricing and future innovation, these technologies will become readily available and will be able to automate tasks in an increasing number of areas, including financial services.

AI also involves risks. These mainly relate to the limitations of current systems, wrong interpretation of data and a resulting output of incorrect data. AI systems will undoubtedly become more accurate, but the extent to which all the currently existing limitations can be overcome still remains unclear. Irrespective of existing limitations, AI systems already provide economic value in some areas where they deliver faster and more accurate output than humans (especially if this involves highly repetitive tasks).

This chapter examines how AI is used in financial services and evaluates the key risks and benefits.

3.1.1 Artificial intelligence technology and development

At the core of any AI system there is some kind of machine learning (ML) software that can prompt a computer to act without being explicitly programmed. ML can be described as the creation of models by training an algorithm. This is a key difference from static hard-coded algorithms that are designed to perform specific well-defined tasks. It allows ML to solve coding problems that would otherwise be highly complex, but it also implies that ML systems only produce 'predictive outcomes' that still feature some remaining uncertainty that is derived from the statistical models that has been used.

AI can mimic cognitive functions associated with human intelligence, such as being able to process visual input, understand and respond to spoken or written language, analyse data and make recommendations. AI systems are based on ML when it comes to processes needed to extract knowledge from data and 'learn' from it autonomously. Large language models (LLMs), which generate human-like text, and other transformer models [56] that have been driving recent advancements in Generative AI systems (GenAI) cannot operate without these base ML operations.

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[56] More accurate actual contextualisation is feasible using Transformer models that incorporate selective attention and the weighing of different pieces of input data. They require less training time and were introduced in 2017. For further information, See e.g., Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł. and Polosukhin, I., 'Attention is all you need', *Advances in neural information processing systems*, 30, 2017.

Figure 3.1 shows the interrelation and overlaps between AI, ML, GenAI, LLMs and Natural Language Processing (NLP). In particular, GenAI systems often draw on LLMs and NLP because they make it possible to understand text and generate textual output.

Box 3.1 Generative AI (GenAI) and transformers – key drivers of recent AI deployment

Machine learning and Generative AI (GenAI) are two key but distinct technologies. They have both contributed to automation and serve specific purposes, but they operate in fundamentally different ways.

Machine learning is a subset of AI. It focuses on developing systems that learn from data, recognise patterns and make decisions with minimal human intervention. These systems become more effective over time as they process more data, thus enhancing the accuracy in predictions and decisions. In finance, a key application is the development of predictive models for stock price forecasting or credit assessment based on algorithms that analyse market trends and historical data.

GenAI is based on neural networks. These networks emulate the brain's set-up and store information in the network so that it does not have to be explicitly written into the program.

Neural networks are at the core of leading approaches to designing and training AI. This includes tasks, such as understanding language, machine translation and answering questions. In recent years, a significant leap has been made in this area through large language models (LLMs [57]) which can create natural language outputs. These LLMs use a type of neural network called a 'transformer model'. They are an example of GenAI. In finance, LLMs are already actively used for customer support or AI-augmented investment research and advice.

GenAI more broadly refers to a form of AI that creates new text, images, video, audio or other content that is based on user queries and the data that it was trained on. Neural networks based on transformer-architectures were a crucial breakthrough and have significantly improved AI systems' ability to capture context (e.g. the interplay of words in a sentence) and mimic understanding. Transformers are more efficient than traditional recurrent models because they process input simultaneously instead of handling steps sequentially.

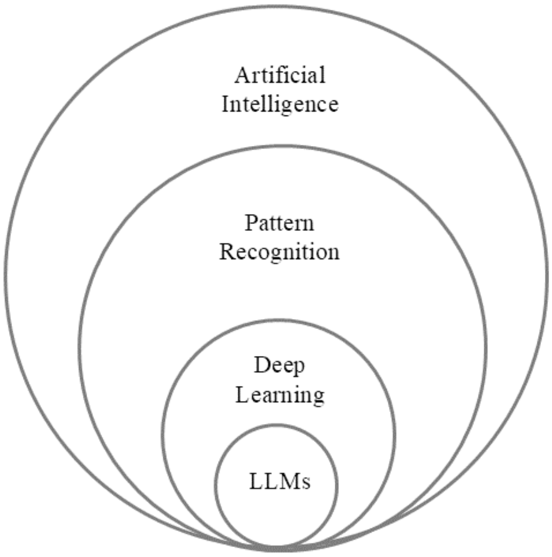
These systems are not based on specific instructions on how to identify, manipulate or interact with data. They are instead given an amount of data to 'train', with each iteration of training providing feedback on what the result should have been and the system adapting the network parameters [58] accordingly to increase its accuracy.

In particular, these systems have no true understanding of the operations carried out. Each training iteration is based solely on stochastic processes and output is based on probabilities rather than 'knowledge'. These systems can be highly accurate, but they are subject to several limitations (see Section 3.3.1).

[57] LLMs are models that are pre-trained on large amounts of textual data.

[58] Neural networks are structured as multiple layers of nodes which can pass information between them (similar to neurons in the brain). The training of the model modifies the weighting and bias of individual nodes across the various layers in a manner until output matches the intended results.

Figure 3.1: Layers of AI



Source: DG FISMA.

3.2 Benefits and applications of AI

3.2.1 Benefits of AI in financial services

AI systems have the potential to become faster and more accurate than 'traditional' systems and processes. These benefits would come on top of more general efficiency gains related to automation (avoiding human error and bias, 24/7 availability, etc.). These advantages may lead to improved existing services and the development of new innovative products and financial services, such as highly individualised product offerings.

AI should raise productivity in a way that goes beyond what could be achieved using other automation technology which, in general, only automates existing processes [59]. By contrast, AI can also generate and test ideas. This research and innovation potential can further boost productivity [60].

Current AI systems still face various problems, such as errors and bias (see Section 3.3.1), but market participants are keen to develop and implement AI systems (see Section 3.2.2) due to their potential and steadily expanding range of applications. Even small competitive AI-derived advantages can be crucial both for profitability and for long-term business viability.

Recent surveys on AI deployment indicate that new technological software and hardware advances make it possible for AI systems to effectively process more abstract input (e.g. human language, audio and videos). Developments in recent years have especially included advances in the form of GenAI (see Box 3.1). These new systems go beyond mere data analysis and allow AI systems to be used in areas such as customer support that require much greater flexibility in handling input and output.

[59] Filippucci, F., Gal, P., Jona-Lasinio, C., Leandro A. and Nicoletti G., 'The impact of Artificial Intelligence on productivity, distribution and growth: Key mechanisms, initial evidence and policy challenges', *OECD Artificial Intelligent Papers*, No 15, April 2024.
[60] Cockburn et al. (2019).

GenAI models are a significant advance on previous AI approaches, which primarily focused on understanding and processing information. The deployment of GenAI and other innovative AI systems will impact a wide range of areas, including crucial operations such as risk management. It should also allow banks and other financial services providers to deliver innovative customer solutions, while also streamlining costly and mundane tasks. AI-powered automation can also streamline various processes, such as internal processing, fraud detection and customer service. A broad spectrum of AI applications already exists today, ranging from automated trading systems to investment research and bespoke banking services.

Overall, adopting AI is likely to drive significant efficiencies, especially once the initial up-front costs have been recovered. As with similar enabling technologies, first-movers face significant risks but may reap substantial long-term benefits from their investments. It is not yet clear in which areas AI is (or will become) superior, but market participants clearly recognise its potential, even if doubts concerning AI's accuracy and effectiveness remain. Many EU financial service providers are already investing in AI systems to avoid potential future competitive disadvantages. AI is a technology that is likely to reshape the whole economy. EU market participants will have to embrace its advantages in order to remain globally competitive.

3.2.2 State of AI deployment in financial services

The uptake and deployment of AI in financial services varies between different industry sub-sectors. A consultation carried out by the Commission in H2 2024 [61] showed that the banking and payments sectors are generally more advanced users of AI. Similarly, traders and portfolio managers have used AI technologies for many years. Tech-driven entities such as high-frequency traders continue to stand at the forefront of AI development. Market infrastructure operators also use AI quite widely, primarily to automate routine tasks, improve data analytics and enhance risk management. AI has also started to support regulatory compliance, client service, marketing, employee productivity and data optimisation in various sectors, including also asset management and insurance providers.

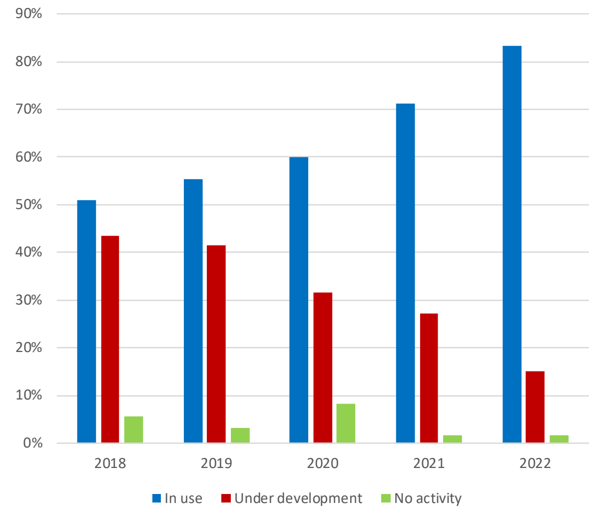
Comments received during the targeted FISMA consultation [62] suggest that financial supervisors are also increasingly using AI systems. The technology is particularly useful for organising and analysing supervisory data as well as linking these datasets with other unstructured sources. The strong pattern recognition abilities make AI particularly suitable for dealing with big datasets and for monitoring that is intended, for instance, to detect illegal activities, such as market abuse and violations of AML or CFT rules (supervised entities may similarly use AI internally). Supervisors are looking to expand their knowledge in this area, not only to assess the use of AI by supervised entities but also to employ AI for their monitoring and analytical tasks. Improved AI capabilities are expected to enhance supervision across the board, including in key areas such as the assessment of financial stability and systemic risk, market integrity and consumer protection.

Most EU banks are already using AI according to the 2024 EBA risk assessment survey [63]. More than 85% of respondents stated that they actively use AI [64]. Already in 2022, more than 80% of surveyed EU banks were actively using AI (see Chart 3.1) and the deployment of AI is accelerating. The EBA survey suggests that this may be linked to a shift away from the developmental and testing phases of AI systems. Only a small number of banks are still only in

[61] European Commission: DG FISMA, 'Targeted consultation on artificial intelligence in the financial sector'.
[62] Ibid.
[63] European Banking Authority (EBA), 'Artificial Intelligence', *Risk Assessment Report*, November 2024.
[64] See Question 26 in EBA, *Risk Assessment Questionnaire*, Autumn 2024.

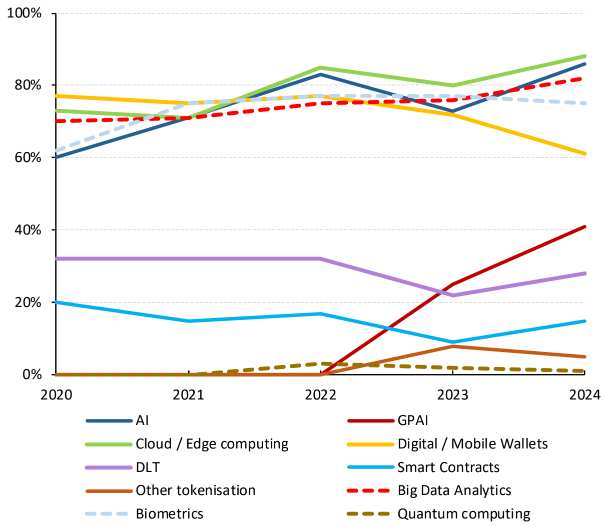
the pilot/testing phase. Compared with other new technologies used by banks, AI shows a very high penetration and only cloud/edge computing outpaces AI (see Chart 3.2).

Chart 3.1: AI trends in banking



Source: EBA, Risk Assessment Report, December 2022.
Note: activity and use of AI in the EU banking industry.

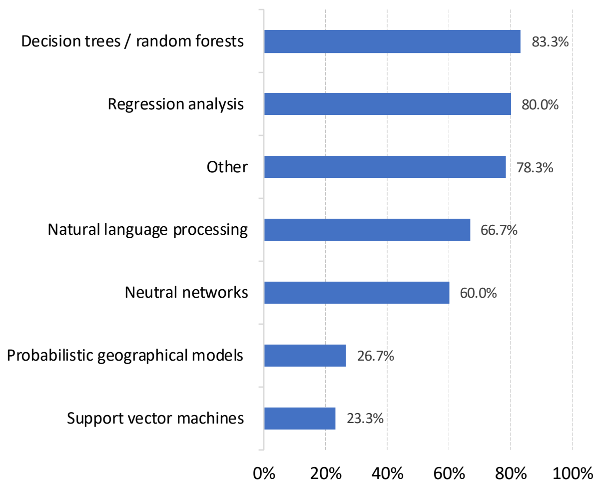
Chart 3.2: Use of technology by EU banks



Source: EBA, Risk Assessment Questionnaire, Autumn 2024.
Note: use of different technologies by EU banking industry.

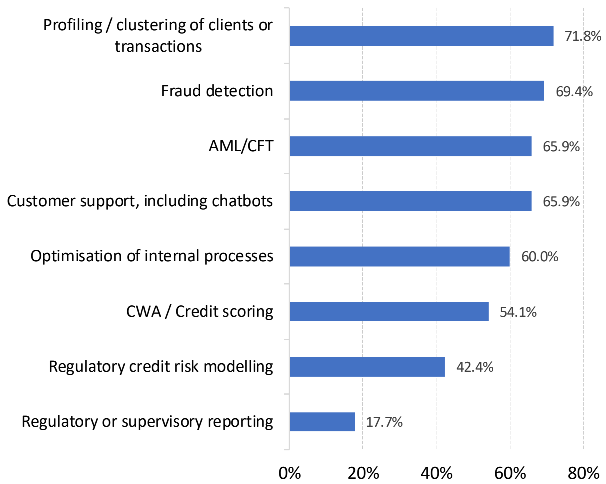
AI is commonly used by banks for client and transaction profiling (for commercial purposes), fraud detection, AML/CFT and customer support (see Chart 3.4). EU banks are using AI in various applications such as regression analysis, decision trees, NLP and neural networks (see Chart 3.3). In terms of specific use areas within banks, AI is often used in areas such as client and transaction profiling (for commercial purposes), fraud detection, AML/CFT and customer support (see Chart 3.4).

Chart 3.3: Uses of AI by EU banks per type of application



Source: EBA, Risk Assessment Questionnaire, Autumn 2024.
Note: data as of August 2024.

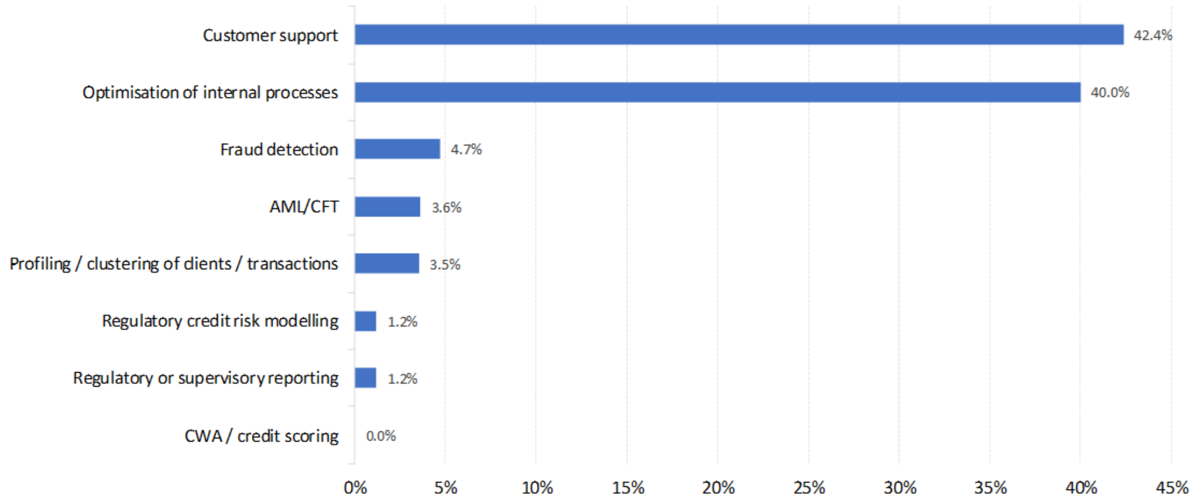
Chart 3.4: Uses of AI by EU banks per use case



Source: EBA, Risk Assessment Questionnaire, Autumn 2024.
Note: data as of August 2024.

General Purpose AI system (GPAI [65] – a term sometimes used interchangeably for GenAI) activity is by contrast still largely limited to testing (see Chart 3.5). Limited experience and higher error rates mean that GenAI systems are still mostly limited to customer support and optimising internal processes [66] where the risks of financial damage are low. Their use by banks has nevertheless greatly increased since 2023 (see Chart 3.2). Almost a third of the banks that responded to the 2024 EBA risk assessment survey stated that they implemented GPAI in at least one use case. It has been estimated that the global GenAI market in financial services will grow significantly from USD 1.09 billion in 2023 to over USD 12 billion by 2033 [67].

Chart 3.5: Proportion of EU banks using GPAI per use case



Source: EBA, *Risk Assessment Questionnaire*, Autumn 2024.
Note: data as of Autumn 2024.

3.2.3 Abilities of AI and applications in financial services

The range of possible applications of AI is almost limitless. The list of use cases in financial services provided in this section cannot be exhaustive. In addition, most AI systems will combine abilities.

Predictive analytics

One of AI's key advantages is its analytical and predictive powers. The ability to analyse and recognise patterns and links in big or abstract datasets can be used in various areas of financial services such as risk assessment or pricing practices. These systems are therefore relevant in essentially all areas of financial services, including trading, banking and insurance. AI is primarily used to swiftly explore vast datasets to improve the accuracy of existing models. It can also enable the creation of models to consider factors other than hard data, such as market sentiment or behavioural aspects.

AI is already used in algorithmic and high-frequency trading. After human traders have set the algorithm parameters, AI is used in pricing models and real-time risk management where AI

[65] This is an AI system that can be adapted to, and used in, a wide range of applications for which it was not initially designed.
[66] See Question 27 in EBA, *Risk Assessment Questionnaire*, Autumn 2024.
[67] Statista, '*Market size of generative artificial intelligence (AI) in the financial services industry from 2022 to 2023*', 21 February 2025.

create alerts or acts based on set parameters. In addition, increased model accuracy based on AI systems is also promising for liquidity management.

Banks and asset managers are also starting to deploy AI models to help price credit and assets. In particular, banks are testing systems to better assess credit risks. AI may better predict and assess loan risks and can furthermore streamline the process and approvals for borrowers by automating various tasks such as risk assessment, credit scoring and document verification. Insurance pricing is another area which could see large efficiency gains driven by AI, because it can help to reduce information asymmetries (for example, through telematics-based auto-insurance pricing). Both credit risk and insurance premiums are areas where ethical and data privacy considerations trigger more stringent requirements under the EU Artificial Intelligence Act (see Section 3.3.2).

Importantly, AI systems can also be used for pricing decisions in any market setting. This includes decisions on prices charged to downstream customers and clients, where AI systems can help to develop strategies to improve profitability. Predictive analytics can be used, for example, to better estimate the maximum price a specific client is willing to pay (discriminative pricing).

Autonomous systems

A key objective of many AI systems is to make decisions independently or at least minimise manual involvement. Autonomous systems aim to achieve this goal. Systems can vary in complexity from automation of simple repetitive tasks to more complex autonomous behaviour. Errors are usually addressed by including automated and/or human monitoring systems, especially if errors could be very costly (as, for example, in trading applications).

Increasing automation has been a long-standing phenomenon in financial services. Key examples include autonomous trading systems and the automation of back-office processes such as supervisory and internal reporting, data retention and other repetitive compliance functions. AI is likely to help in streamlining processes further and may permit better detection of errors (e.g. reporting errors). These more autonomous systems drive efficiencies by minimising human labour but may require significant up-front investment, especially for complex tasks. Even the most advanced current AI systems require human oversight if they operate in a dynamic environment where contextual understanding is required.

Optimisation

AI can help find the optimal solution to specific problems using trial and error. This approach has many different applications in financial services, although these systems cannot assess whether the optimal solution is acceptable or not. Scenario-based simulations, for example, can help financial service providers, regulators and supervisors to monitor activities and manage risks. Similarly, finding optimal approaches to bidding and real-time auctions can support trading applications. Iterative problem-solving can improve data-modelling [68]. Optimal solution-finding is also a challenge for supervisors and regulators. Approaches like AI-based scenario analyses can help to determine the best course of action in various scenarios.

[68] See e.g., Khalil et al. (2025).

Pattern recognition and detection of anomalies

AI systems are highly efficient in spotting patterns and abnormalities in data. This makes them well-adapted to detect and monitor suspicious behavioural patterns and transactions. These activities can be helpful for anti-money laundering (AML), countering the financing of terrorism (CFT), know-your-customer (KYC) and other types of financial crime, fraud and cyber security threats (see Box 3.2).

AI capabilities in this regard can also help supervisors in various ways. AI systems can more effectively and efficiently analyse (big) data. This may enable a much more systematic analysis of data streams. Systems can also help to detect flaws in reporting and could automate respective requests to a misreporting entity, thus freeing up resources. AI can also be used to connect and reconcile reported data (possibly in different reporting frameworks).

Box 3.2 AI and cybersecurity

AI will have a significant effect on future cybersecurity. These systems can present both a potential vulnerability as well as a formidable tool for enhancing security measures.

AI systems inadvertently give rise to new risks that need to be considered and addressed as financial service providers come to rely more heavily on AI. There are two main points to consider when developing robust cybersecurity:

- increased attack surface – the integration of AI systems into operations can create new opportunities for exploitation by cybercriminals. Targets could include vulnerabilities in AI models or manipulation of training data; and
- explainability – limited understanding of how AI systems operate internally (see Section 3.3.1) and the resulting opacity can hinder the identification and correction of security vulnerabilities.

In addition, malicious actors can use AI models to identify potential target systems and help with the coding of malware, making it easier and cheaper for hackers to attack systems and evade detection. AI tools can also help with more sophisticated attacks. For example, visual or audio AI output can be used to create 'deepfakes' that could remain undetected by normal fraud detection.

Conversely, AI's capabilities make it a crucial support in the fight against cyber threats. Its capabilities can enhance threat detection and automate incident responses. Coupled with the ability to adapt to evolving risks, it may make AI indispensable for countering future cybersecurity threats. The advantages of AI in this regard include:

- advanced threat detection through real-time analysis of vast sets of data to uncover patterns and anomalies indicative of cyber threats. This enables proactive detection and provides better options for preventing attacks;
- automated incident response[69] allowing human experts to concentrate on addressing more sophisticated threats;
- learning and adaptation, which can ensure that security measures evolve in accordance with the changing landscape of cyber threats. AI's dynamic learning capabilities should enhance the long-term effectiveness of cybersecurity systems; and
- pattern recognition, which can spot various kinds of unusual user behaviour. This can help to mitigate cyber risks and deal with ongoing treats. For example, risky user behaviour could be identified and sensitive information could be blocked from leaving a financial institution's

[69] See also incident reporting in the Digital Operational Resilience Act (DORA).

network. Integration of AI into cyber security can generate cost savings, boost productivity and mitigate labour market shortages for information technology (IT) experts.

The effective leveraging of AI in cybersecurity calls for a multifaceted approach in order to minimise potential vulnerabilities while maximising defensive capabilities. Concepts such as security by design and cross-industry collaboration can help in meeting these challenges. AI may be needed to effectively counter future malicious activity (including AI-driven activities), so there is a need for sufficient flexibility in deploying AI-based cyber security. In addition, safeguards (particularly monitoring by supervisors) are needed in order to create a more secure and resilient financial ecosystem.

The ability to spot and trade certain price patterns is also widely used in automated trading systems. AI-driven pattern recognition can help in detecting and analysing behavioural patterns of consumers and clients in order to better identify their individual needs and offer customised services.

Human-machine interactions

The advent of GenAI and highly scalable LLMs and similar transformers for audio or visual data such as large action models (LAMs [70]) is increasingly shaping human-machine interactions. Financial institutions are using text-based and voice-based systems that use AI models in customer support functions. Systems such as chatbots are being used to lower overhead costs. AI bots were very error-prone at the outset , but more recent AI bots are significantly more flexible and effective. Increased flexibility allows AI to be used in other areas, including claims management or investment research and advice. AI systems generally allow these services to be provided more cheaply and 24/7.

Better human-machine interactions make AI systems more accessible, including for people without prior IT experience. It makes it much easier to use AI and lowers implementation and training costs for employees using AI.

Adaptive personalisation

AI systems allow much more advanced behavioural analysis and can enable highly personalised product offerings. This will help drive the provision of ‘embedded finance’, which seeks to provide a seamless customer experience tailored to the customer’s needs. This can mean displaying relevant content; recommending relevant products; or providing personalised recommendations and guidance, such as personal finances management.

Taking account of individual consumers’ characteristics can be very useful for financial services providers and may enable better tailored and possibly cheaper services. Individual credit assessments could, for instance, replace group-based credit-scoring systems. However, the individualisation of product offers can also work against the consumer and can undermine functions such as mutualisation of risks, for instance in health insurance.

[70] LAMs are models that try to understand and execute complex tasks by translating human intentions into action.

3.3 Limitations of AI and risks in financial services

3.3.1 Limitations of AI

AI has made significant advances in recent years, but certain key limitations remain. These limitations can drive risks, including in financial services applications. The following section provides a short overview of AI's current limitations.

Lack of understanding and common sense

AI systems are effective in specific areas but lack a true understanding of the world. Systems operate based on stochastic calculus and pre-trained patterns but without understanding the underlying concepts. AI systems can be trained to mimic understanding but still lack common-sense reasoning, intuitive understanding and contextual awareness.

This limitation is partly due to a lack of sufficient microdata that would allow AI systems to be trained to be able to understand at a deeper level (see Box 3.3). The 'decoupling of scale' principle means that an AI system does not need to understand the meaning or significance of tokens (a digital representation of some data) to carry out analysis or make predictions. However, while larger-scale effects can be modelled without detailed knowledge of smaller scale interactions, these emergent models cannot be used to deduce the underlying (lower-scale) structure. For AI systems, this means that words, videos and other data fed into the system during training are insufficient for it to understand or replicate human behaviour. The training data are produced by humans but do not reflect the true micro aspects of the system (human thought). Some scientists postulate that true intelligence cannot occur via pure computation [71], implying that AI will never reach true understanding. By contrast, others argue that it is feasible with sufficient training data, number of nodes, and intelligent model set-up and structuring.

Data dependency and quality

AI's effectiveness is heavily reliant on the quality and quantity of training data. Biased or incomplete datasets can skew AI results, reinforcing existing prejudices or producing inaccurate outputs. Ensuring diverse and representative data remains an ongoing challenge in financial services. The Commission's consultation [72] demonstrated this, with 52% of respondents citing difficulties in obtaining high-quality and comprehensive datasets. Challenges included issues with data quality and data-pooling; lack of automated interfaces and standardisation; and privacy concerns.

Some reports [73] suggest that most existing high-quality data are already being used. Synthetic (generated) data could overcome this data limitation, but it could also introduce self-reinforcement errors which may undermine improvements that would normally come from more training data.

Real-time learning and adaptability

The ability to learn and adapt in real time to dynamic environments is a distinctive human trait that AI systems are still struggling to replicate. AI can certainly adapt to new input in expected

[71] See e.g., Penrose (1989).
[72] European Commission (DG FISMA), '*Targeted consultation on artificial intelligence in the financial sector*'.
[73] See e.g., Villalobos, P., Ho, A., Sevilla, J., Besiroglu, T., Heim, L. and Hobbhahn, M., 'Will we run out of data? Limits of LLM scaling based on human-generated data', *arXiv preprint,* No arXiv:2211.04325, 4 June 2024; or Milmo, D., 'Elon Musk says all human data for AI training 'exhausted'', *The Guardian*, 9 June 2025.

form/formats but hits clear barriers when confronted with truly novel and unexpected input. Cross-domain learning and reasoning is still out of reach today. Developing such systems would be an enormous breakthrough because it would enable artificial superintelligence (ASI) that would surpass human intelligence.

Human cognition allows continuous learning and adjustment, whereas AIs today often require lengthy retraining and the input of significant additional data. However, AI systems may be able to draw deeper insights from data and may outperform humans in the specific tasks that they are trained for.

Real-time adaptation and learning would significantly improve AI's operations. However, it could also raise considerable issues in terms of reliability because adaptations could be wrong and prompt erroneous behaviour. Additional control of these systems is therefore necessary.

Ethical and moral considerations, emotional intelligence and empathy

AI systems lack inherent ethical frameworks and moral reasoning. They make decisions on the basis of learned patterns. This may inadvertently introduce biases that are already present in the data they are trained on. Programming for 'ethical considerations' and the ability to make morally sound choices remains challenging for AI [74].

Understanding and responding to complex and possibly conflicting human emotions also remains a hurdle. Significant progress has been made so that AI systems can understand abstract input (e.g. NLP), but genuine emotional intelligence and empathy are much more complex traits. Furthermore, testing emulation of empathy versus 'true' empathy is not easy and approaches used remain very controversial [75]. However, AI can nonetheless help to spot bias, including in human behaviour. Moral intelligence may turn out to be merely an issue of correct set-up and sufficient training, possibly within hard-coded constraints [76].

Interpretation of operations and accountability

Many current AI models are so complex that it is not possible to reconstruct and understand the various steps taken to arrive at specific outputs. Acceptance, usability and trust in AI models is crucial (especially in critical applications like risk management) but is hampered by AI model processes that are not transparent ('black boxes').

Accountability issues also arise if AI operations cannot be reconstructed or explained, particularly in the case of AI systems trained by a third party. Unlike decisions taken by humans, the decision maker cannot be asked to explain the reasoning behind a decision.

Resource-intensiveness

Training advanced AI models requires significant computational power and consumes a lot of energy [77], raising environmental concerns. It may also act as a barrier to market entry and restrict

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[74] See e.g., Hua et al. (2024).
[75] See e.g., Perry (2023) or D'Cruz, J., Kidder, W. and Varshney, K.R., 'The empathy gap: Why AI can forecast behavior but cannot assess trustworthiness', *CEUR Workshop Proceedings*, 2021.
[76] See e.g., Borenstein and Howard (2021).
[77] Estimates suggest that a simple AI search query uses about 10 times more energy than a normal search engine. Generative AI systems might use around 33 times more energy to complete a task than task-specific software. See also, Luccioni, S., Jernite, Y. and Strubell, E., 'Power hungry processing: Watts driving the cost of AI deployment?', *Proceedings of the 2024 ACM conference on fairness, accountability, and transparency*, June 2024, pp. 85-99. For instance, training a model such as GPT-3 is estimated

access to advanced AI applications to organisations with extensive computing resources (see Box 3.3), thereby contributing to increased market concentration (see Section 3.2.3). Future innovations may significantly reduce the resource-intensiveness of AI training (see, for example, DeepSeek[78]).

Absence of creativity and originality

Today's AI systems may seem capable of generating new content, but they are still struggling to achieve genuine creativity and original thinking. AI systems cannot innovate, envision abstract concepts or produce innovative ideas that go beyond the patterns present in their training data. GenAI can produce new output such as an image or a poem, but the results always depend on training and user input. Similarly, iterative trial and error approaches may generate innovative approaches to problems, but it is unclear whether this can be regarded as creativity rather than mere testing of available options. This limitation is closely linked to AI systems' lack of true understanding. This suggests that solving new problems with AI today requires human input, steering and possibly retraining.

3.3.2 Risks of AI in the financial services sector

Many risks that arise from the use of AI are linked to its limitations (see Section 3.3.1). A lack of understanding and common sense can result in AI models providing erroneous and even nonsensical output. Likewise, the inability to grow beyond trained patterns and adapt to new situations will reduce AI's reliability, limiting its accuracy and usability.

If AI models produce erroneous output, this can cause serious financial and reputational damage to operators and harm consumers, especially if models have significant autonomy. Financial stability concerns may even arise if such mistakes are produced within systemically relevant entities [79].

However, AI-related risks in the financial sector arise not only from AI's own limitations but also from external factors, such as cyber risks. Interestingly, some direct benefits of AI (e.g. increased speed) also increase risks in financial markets.

When assessing these risks, it is important to note that automation (including ML-based automation) has been making continuous progress in several areas of financial services. All forms of automation involve inherent risks, such as loss of control, but they can also enhance safety by reducing (human) errors and improve efficiency for consumers. The adoption of new technologies is common in financial services and the regulatory framework has been adapted over time to address specific risks.

The use of AI in financial services appears to be a continuation of the drive towards more automation. Market players are attracted by efficiency gains, but they are also aware of the constraints and need for monitoring. However, AI's ability to automate a growing range of tasks

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to use just under 1 300 megawatt hours (MWh) of electricity, which is roughly equivalent to the annual power consumption of 130 homes in the US. It is estimated that training the more advanced GPT-4 requires 50 times more electricity. See also World Economic Forum (WEF), '*AI and energy: Will AI help reduce emissions or increase demand? Here's what to know*', 22 July 2024; Luccioni et al. (2023); and *The Economist*, 'Data centres improved greatly in energy efficiency as they grew massively larger', January 2024

[78] GenAI launched in January 2025 – see DeepSeek

[79] See, ECB, *Financial Stability Review*, November 2024; and ESMA, 'Artificial Intelligence in EU investment funds: adoption, strategies and portfolio exposures', *Trends, Risks and Vulnerabilities Risk Analysis*, No ESMA50-43599798-9923, 25 February 2025.

can introduce new risks. This is particularly the case when AI systems are integrated into wider IT infrastructure or operate with little or no oversight.

Reliability of AI and dependence on AI

The accuracy and reliability of AI are crucial factors affecting the risks associated with its use in financial services. These factors will ultimately determine the level of trust in these systems and the extent to which financial service providers are willing to use them. Market players may be comfortable employing AI in low-risk areas such as customer support, but it would be unwise to fully trust current AI models in critical business operations without close monitoring and retaining the ability to intervene manually.

Significant drivers of reliability issues in AI include a lack of understanding of tasks; the quality and quantity of training data; and the inability to adapt to new situations in real time without retraining. However, AI systems are starting to outperform humans in an increasing array of tasks, particularly in handling 'big data' and executing repetitive operations. AI is prone to some errors, but financial institutions may increasingly substitute it for human resources in order to achieve efficiency gains [80]. In specific areas (e.g. investment research, trading or risk management), the absence of emotions and moral considerations in AI might even be seen as advantageous.

The limitations of AI remain widely apparent, but market participants will have ample incentives to address the resulting risks via monitoring and by maintaining a high degree of control. This does not mean that there is no need for supervisors to engage in further independent monitoring, especially where market actors may not bear the full costs associated with risks (moral hazard). However, high risks of faulty AI-functioning may deter full and uncontrolled automation using AI. Even high-frequency trading (HFT) systems, which are arguably at the forefront of automation and ML/AI use in financial services, still use traders to monitor operations and set trading parameters. In addition, HFT trading systems feature kill switches for the rapid termination of algorithms' operations. The risks of financial loss are such that other financial institutions are likely to use AI in critical business operations in a similar manner. A key problem for AI is the evaluation of multiple objectives (e.g. profit maximisation, staying within the limits of a legal framework and behaving ethically). AI systems often end up prioritising objectives in unintended ways, especially where there are high-level incentives and when faced with input which differs from training datasets [81]. AI use will therefore probably not go beyond AI-augmented human decision-making in key areas in the coming years.

The extent to which risks arise is crucially driven by the degree of dependence on AI. In the absence of such a dependence, there is always the option of turning off the system to minimise any damage and prevent risks from spreading to other internal systems or the wider market. There is currently no evidence that the EU's financial services sector is substantially dependent on AI. Erroneous AI operations in areas like customer support, reporting or back-office may be a nuisance and could result in financial loss, but systems can still be shut down and decoupled with relative ease. In addition, back-up systems (e.g. human-to-human customer support) often remain in place. It is nevertheless very likely that improved accuracy will result in AI being increasingly integrated into various processes and carrying out more functions with full autonomy. Systems will become more reliable, but risks resulting from more integrated systems cannot be excluded

[80] See e.g., Hoskins, P., 'Singapore's biggest bank DBS to cut 4 000 roles as it embraces AI', *BBC*, February 2025.
[81] Danielsson, J. and Uthemann, A., '*On the use of Artificial Intelligence in financial regulations and the impact on financial stability*', June 2024.

– especially if it would no longer be feasible to shut down AI processes. Depending on the entity and subsector, these risks could also be systemically relevant. Even if AI systems were to operate flawlessly in isolation – an unrealistic assumption – external factors such as cyber risks would still be present (see Box 3.2). Increased dependence on AI also increases systemic risks related to the more general use of ICT processes such as blackouts. Continuing monitoring by supervisors of the use of AI and assessing possible increases in dependency appears to be warranted.

Reliability-related hazards should be weighed against the possible benefits that AI systems can offer, including the ability to carry out continuous non-emotional and exact analysis. It would appear prudent to employ these systems in areas where AI outperforms human-based decision-making (especially where it touches on aspects such as risk management), if only as a run-along secondary process that informs and assists human decision-making. Some difficulties may arise (e.g. non-transparent decision-making), but side-by-side operation would ensure that AI's benefits can be realised without any loss of control over actual decisions. AI can also reduce risks in systems and processes which are already automated (by performing additional 'smart' checks) and prevent human errors (e.g. in software updates – see CrowdStrike [82]). AI can similarly help to mitigate cyber risks and assist with fraud detection (see Box 3.2). Using AI will ultimately lead to some degree of dependence on it (as is the case with other technologies), but it need not increase financial stability risks if it is managed correctly.

Box 3.3 Possible limits to scalability of AI. Implications for AI development, valuation and financial market risks.

Until recently, it has been possible to scale AI systems extremely well with computational power and larger training datasets. The premise that simple models trained on vast datasets often outperform more complex models trained on less data [83] has fuelled significant investment with total market size expected to exceed USD 1 trillion by 2027 [84].

However, there are increasing signs that this scaling hypothesis may not hold beyond a certain size and complexity. OpenAI's experience with its next-generation 'Orion' model matched the performance of its predecessor (GPT-4) after completing only 20% of its training process – as predicted by the scaling hypothesis [85] – but further training only delivered small incremental improvements. In its final trained state Orion was even underperforming GTP-4 in certain areas such as programming. Increasingly diminishing returns have slowed down AI development. Google's Gemini 2.0 has not met its targets and there are rumours that Anthropic has halted development on its new flagship Opus [86].

The scaling issues broadly fall into three interrelated categories: (i) data; (ii) computation; and (iii) system architecture. To achieve optimal model performance, computational power and data should scale proportionally [87]. Computational power presents a challenge given vast energy and cooling demands, but these demands remain manageable. Some firms are even turning to in-

[82] On 19 July 2024. a content update was sent to CrowdStrike Falcon clients on Windows devices which resulted in 'blue screen' errors. This problem affected millions of computers and some called it the 'largest IT outage in history'. The error was ultimately a simple coding error with the number of input fields (in the update) not matching the number of fields expected by the system. For further details, see e.g., Kerner, S.M., 'CrowdStrike outage explained: What caused it and what's next', *TechTarget*, 29 October 2024.
[83] See Halevy, A., Norvig, P. and Pereira, F., 'The unreasonable effectiveness of data', *IEEE Intelligent Systems*, 2009.
[84] Rai, S., 'AI market will surge to near USD 1 trillion by 2027', *Bloomberg*, 24 September 2024.
[85] Gambe, L., 'OpenAI's Orion model reveals challenges in scaling AI', *Budget*, November 2024.
[86] Bastian, M., 'OpenAI's new Orion model reportedly shows small gains over GPT-4', *The decoder*, November 2024.
[87] Hoffmann, J., Borgeaud, S., Mensch, A., Buchatskaya, E., Cai, T., Rutherford, E., Casas, D.D.L., Hendricks, L.A., Welbl, J., Clark, A. and Hennigan, T., 'Training compute-optimal large language models', arXiv, No 2203.15556, March 2022.

house nuclear power [88]. Data are a bigger challenge, with some researchers estimating that a 100 000-fold increase in training data compared with what is currently available would be needed for an AI to write a scientific paper [89]. These training data do not exist at present and efforts to work with synthetic data to make up for the shortage of real data may create new problems [90]. The architecture of current AI models is a further factor that appears to impede reliability because it requires specific training data in order to function effectively. Models continue to struggle with unexpected or rare input that is insufficiently captured in training data. AI systems excel at interpolation but extrapolation (i.e. making predictions and reasoning about new situations that are unfamiliar from training data) remains a major challenge. This difficulty stems from AI's reliance on stochastic processes and lack of true 'understanding'. It remains an open question whether scaling can bridge this architectural gap.

The idea that superintelligent AI can be created via scaling has been a key driver of investment in the sector in recent years. Market valuations of big-tech and AI-related services/suppliers such as Nvidia are partially based on this scaling hypothesis. They could therefore suffer substantial losses if this hypothesis does not hold true. The launch of DeepSeek in January 2024, which challenged the notion that AI requires billions of investments in advanced AI chips [91], demonstrated how significant market impacts could be. For example, Nvidia lost a record USD 589 billion of market capitalisation in a single day, although the share price did rebound in the following days [92].

In a recent assessment [93], ESMA noted that a 'sector-specific downturn could have broader implications and knock-on effects' due to the increased weightings of AI companies in broader indices; and that exposure(s) in less liquid segments (debt, private equity markets) 'warrant(s) particular attention'. Higher AI market concentration and the resulting lower diversification in equity portfolios may also drive risks. The impact of correlated adverse conditions on fund portfolio valuations could be sizeable and have a systemic impact. This is in line with previous ECB conclusions that highlighted concentration and asset-price bubble risks. The ECB furthermore notes that there could be adverse global spillover effects if earnings expectations for these firms are not met [94]. Given AI's current market importance, hard limits to models' scaling and stalling AI development may not have stark systemic impacts (not yet at least) but could contribute to a wider repricing of tech-asset. As with every technology, new breakthroughs may significantly undermine previous investments and, while beneficial to consumers, can pose unexpected threats to incumbent technologies and business models.

Accelerated transmission and level of control

A key benefit of AI is that it can perform (complex) analysis faster, especially if big data and unstructured sources are involved. This allows faster reactions in the market. The extent to which

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[88] Penn, I. and Weise, K., 'Hungry for energy, Amazon, Google and Microsoft turn to nuclear power', *New York Times*, October 2024 – Interestingly, the human brain still outperforms AI in many areas but uses only about 20 Watts. See e.g., Kováč, L., 'The 20 W sleep-walkers', *EMBO Reports*, 11 January 2010.

[89] Barnett, M. and Besiroglu, T., 'The direct approach', *Epoch AI Blog*, April 2023.

[90] Models trained on synthetic data may amplify the limitations of their predecessors. Intelligence is required to evaluate intelligence, so this approach could result in circular loops which impede improvements to AI models.

[91] J.P. Morgan has warned that this could lead to a 24% reduction in capex spending by AI companies. This would be detrimental to revenue of data centre and infrastructure companies. It would also prompt write-offs on existing hardware.

[92] Saul, D. and Roeloffs, M.W., 'DeepSeek Panic: Nvidia stock makes history again with USD 260 billion rebound', *Forbes*, 28 January 2025.

[93] ESMA, 'Artificial intelligence in EU investment funds: adoption, strategies and portfolio exposures', *Trends, Risks and Vulnerabilities Risk Analysis*, No ESMA50-43599798-9923, 25 February 2025.

[94] ECB, *Financial Stability Review*, November 2024.

processes are sped up will depend on the individual models, the setting and the degree of automation.

In financial services, a decrease in reaction time can bring about significant benefits, for instance in risk management. However, it also means that new data and market ‘signals’ are digested faster, increasing the speed of transmission throughout markets. This should in theory increase market efficiency because new information would be more quickly reflected in prices and market behaviour. Conversely, it could also be destabilising in some cases and especially if there is substantial herding. Rapid signal transmission can disturb markets excessively and lead to price and behavioural distortions, resulting in lower efficiency.

The growing importance of HFTs in capital markets since the mid-2000s exemplifies these impacts. Highly automated, low-latency-driven trading algorithms have accelerated the processing and propagation of new information [95] and fast-paced order entry/cancellation has given rise to some destabilising effects, including flash crashes. However, faster risk mitigation abilities have also led to lower bid-ask spreads and trading costs. These efficiency gains explain why trading venues are continuously competing to implement faster matching engines and decrease signal turn-around times. Regulatory measures have been implemented in turn, notably in the form of circuit breakers and kill switches [96] to mitigate stability risk and control issues.

Key safety factors for fast-paced networks are the ability to maintain sufficient control to interact, steer and (depending on context and criticality) halt operations. These are also relevant for the operation of AI systems. The need for regulatory guidance or intervention strongly depends in turn on the type of AI activities, the level of integration and possible stability risks.

As AI continues to be deployed, it is possible that significant integration of AI into systems could at some stage hinder or even prevent a complete shutdown. It is therefore important to monitor such risks as the use of AI in the financial sector grows. It is for the time being unlikely that there are any significantly strong dependencies on AI, especially in critical functions that could lead to systemic impacts.

AI’s superior performance in some areas means that it will also help mitigate risks in high(er) speed interactions, for example by checking flaws in human input or by monitoring other automated systems. This will also benefit supervisors, who can use AI to monitor activities, intervene faster when necessary (such as through near-real-time monitoring with immediate alerts) and integrate different sources of information. The realisation of these benefits will depend not only on AI development but also significantly on the quality and quantity of data available. With proper management and governance, AI and the increased speed it offers should enhance efficiency and may reduce overall systemic risks.

Data are increasingly becoming a key driver of competitive advantages in the AI industry and in the financial services sector. Providers that can train their AI systems with more and higher-quality data will generally outperform competitors due to the increased accuracy of their AI

[95] High-frequency traders were also among the first users of NLP and ML in the financial services sector. These systems also incorporated unstructured external information in the operations of their algorithms (e.g. automatic analysis of the meeting minutes of the US Federal Reserve (FED)).

[96] See MiFID II (Directive 2014/65/EU of the European Parliament and of the Council of 15 May 2014 on markets in financial instruments, OJ L 173, 12.6.2014) and MiFIR (Regulation (EU) No 600/2014 of the European Parliament and of the Council of 15 May 2014 on markets in financial instruments, OJ L 173, 12.6.2014). Other measures include market-making obligation, co-location and tick-size regimes.

outcomes. Data availability is one of the main limitations in areas like GenAI (where knowledge is trained on what is mostly a blank neural network).

Many players in financial services will not develop their own AI systems but rely, at least partially, on third-party providers. Unless there are new innovative breakthroughs, it can be expected that the AI market will become more concentrated due to network effects in data collection and related improvements in AI training outcomes. There is a strong reliance on US-based providers and EU providers only have limited market shares. Recent market analysis shows that US providers dominate the market for Generative AI models. The four largest providers (Open AI, Microsoft, Amazon and Google) are all US-based and together control more than 80% of the market [97]. Data are not only strategically important for individual market actors but are also a key factor for EU autonomy in AI development.

Economies of scale and scope mean that a highly concentrated market can benefit EU AI users, including those in the financial services sector. It is nevertheless likely that the market will tend towards concentration levels that are suboptimal for consumers, because leading AI providers will capture more data from human-based input than competitors. This could in the future create strategic dependencies on extra-EU AI providers, posing a risk to the EU industry (including the financial services sector) and potentially affect also financial stability.

Regardless of the effects on pricing and choice, excessive market concentration could lead to increased risks of herding behaviour, including in financial services. Such risks are more likely to emerge if operators use a small number of identical or very similar AI models. Furthermore, the limited availability of usable high-quality training data is an important contributing factor (see Section 3.3.1).

The use of identical training data can compound similarities in the output of AI models, thus causing herding behaviour or systemic biases. In financial services, this could cause distorted asset prices and a mispricing of risks. Various institutions and supervisors (including the ECB [98], the International Organization of Securities Commissions (IOSCO) [99] and the Financial Stability Board (FSB) [100]) have flagged up market stability as a key AI-related risk. Exclusionary effects such as bias in credit assessments, which could disproportionately affect specific customer groups, might also become more apparent [101].

Bias and herding result in market inefficiencies. Herding is more prevalent in market downturns because investors tend to become more risk-averse and there are indications that AI acts similarly [102]. However, as AI systems continue to learn from past mistakes, it is possible that they might learn to act as contrarians in order to exploit herding inefficiencies instead of contributing to herding.

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[97] Anton K. and Jai V., '*Concentrating Intelligence: Scaling and Market Structure in Artificial Intelligence*', *NBER Working Paper*, No 33139, November 2024.
[98] Leitner, G., Singh, J., van der Kraaij, A. and Zsámboki, B., '*The rise of Artificial Intelligence: benefits and risks for financial stability*', *ECB Financial Stability Review*, May 2024.
[99] IOSCO, *The use of Artificial Intelligence and machine learning by market intermediaries and asset manager*, No FR06/2021, September 2021.
[100] Financial Stability Board (FSB), *The financial stability implications of Artificial Intelligence*, 14 November 2024.
[101] See e.g., Dwyer, L, Francis, W. and Tyagi, S., *Research Note: A pilot study into bias in natural language processing*, Financial Conduct Authority (FCA), 9 January 2025; Langenbucher, K., 'Consumer credit in the age of AI – Beyond anti-discrimination law', *ECGI working paper series in law* 663/2022, February 2023; and Sargeant (2022); or Nagarajan, N. and Guedel, A. *Artificial Intelligence in finance and the problem of bias*, 2025, mimeo.
[102] Ballis and Anastasiou (2023).

Bias and herding risks will be crucially dependent on the degree of similarity between the AI models being used. Herding risks could be amplified if there is strong convergence between the models that are being used. Different training and human-set parameters may nevertheless provide a high variety of AI output to counteract the market destabilising effect. There could also be an anti-herding effect if (some) AIs learn to act as contrarians.

Ultimately, AI-to-AI interactions are likely to face similar issues to those faced by human-to-human interactions (including pre-emptive runs and multiple equilibria) even with fully rational settings.

Regulators already have experience in curbing herding with circuit breakers and redemption-gating. If the wider use of AI does produce significant new destabilising risks in financial markets, similar measures could be developed to slow down destabilising trends and allow system resets.

Consumer protection and data privacy; and general protection of health, safety and fundamental rights

The widespread adoption of AI (particularly GenAI) entails a spectrum of potential societal risks [103] and challenges for consumers and users of financial services. The risk of financial scams is a key concern. AI lowers costs for malicious actors and makes it easier for them to set up sophisticated scams. Data privacy and ethical concerns also arise due to the vast amount of personal data that might be used to train AI models.

These risks, which have also been flagged by the ESAs [104], should be weighed against the advantages consumers may experience thanks to more personalised and cheaper financial services. For example, AI can offer tailored financial planning services and products by analysing individual consumer patterns. These services were only available to more affluent consumers in the past.

AI can also help supervisors to monitor financial markets and consumer risks, enabling them to detect and respond faster and more effectively to market manipulation, anomalies and fraud. AI is therefore not only a source of risk but can also help in supervision and enforcement.

The EU Artificial Intelligence Act [105], which applies to providers and deployers of AI systems, already tackles some of the consumer risks of AI in financial services. The Act follows a risk-based approach, tailoring rules to the intensity and scope of the risks that AI systems can generate.

The Act explicitly prohibits activities that pose 'unacceptable risks', where AI is inherently harmful and is considered a threat to human safety, livelihoods and rights. In the area of consumer protection, these prohibitions specifically address systems which are intended to:

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[103] See Weidinger, L., Uesato, J., Rauh, M., Griffin, C., Huang, P.S., Mellor, J., Glaese, A., Cheng, M., Balle, B., Kasirzadeh, A. and Biles, C., *Taxonomy of risks posed by language models*, Proceedings of the 2022 ACM conference on fairness, accountability, and transparency, June 2022; Shevlane, T., Farquhar, S., Garfinkel, B., Phuong, M., Whittlestone, J., Leung, J., Kokotajlo, D., Marchal, N., Anderljung, M., Kolt, N. and Ho, L., *Model evaluation for extreme risks*, arXiv preprint, No. 2305.15324, 25 May 2023.

[104] See e.g., ESMA, *On the use of Artificial Intelligence (AI) in the provision of retail investment services*, ESMA35-335435667-5924, 30 May 2024; and EIOPA, *Artificial Intelligence governance principles: Towards ethical and trustworthy Artificial Intelligence in the European insurance sector*, 2021.

[105] Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act), OJ L 2024/1689, 12.7.2024.

- manipulate or deceive individuals with the objective or the effect of materially distorting the behaviour of a person, leading to significant harm;
- exploit vulnerabilities due to the age, disability or the specific socio-economic situation of a person, with the objective or effect of materially distorting the behaviour of that person, leading to significant harm; and
- evaluate or classify individuals according to their social behaviour or personal characteristics, leading to detrimental or unfavourable treatment in unrelated contexts or in a disproportionate way.

Many potential cases of discriminatory, fraudulent or exploitative activities are therefore covered, including in financial services. A key challenge for supervisors will be to identify (and legally prove) potential violations of rules.

By contrast, high-risk AI systems cover systems that are designed to be applied to specific use cases, where AI may cause harm but is not inherently harmful. Examples of such high-risk AI systems in financial services are (i) AI systems used in the credit assessment of individuals; and (ii) AI systems used in risk assessments and pricing for individual life and health insurance. The Act imposes additional requirements on providers of high-risk AI systems. Specifically, actors in this category must:

- ensure that training, validation and testing datasets follow data governance practices to detect and prevent biases;
- ensure that the AI system undergoes a conformity assessment;
- ensure that the AI system is designed to be transparent enough for users to interpret the system's output;
- register themselves and the AI system in the EU database; and
- inform the relevant authority/providers and take corrective action or suspend the use of the system if they identify a serious incident.

Deployers of high-risk AI systems have additional obligations that are particularly related to correct use; ensuring the sufficient training and competence of persons dealing with the AI system; and storage of logs. Some deployers of high-risk AI systems (including those using the two high-risk AI use cases in the area of financial services) have to carry out a fundamental rights impact assessment prior to the first use.

From the consumer's perspective, the use of high-risk AI systems in financial services is mitigated by a range of rights. These rights include (i) the right to request human intervention from the creditor when creditworthiness assessments involve automated processing [106]; and (ii) the right to be clearly informed when price offers are personalised using automated processing of personal data [107].

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[106] See e.g., Directive (EU) 2023/2225 of the European Parliament and of the Council of 18 October 2023 on credit agreements for consumers and repealing Directive 2008/48/EC (Consumer Credit Directive), OJ L 2023/2025, 30.10.2023.
[107] Idem.

The Act introduces transparency obligations for some AI systems, including GPAI systems. The wide availability and increasing capabilities of those systems have a significant impact on integrity and trust in the information ecosystem, raising new risks of misinformation and manipulation at scale, fraud, impersonation and consumer deception. Providers of AI systems that generate synthetic audio, image, video or text content must ensure that the output of the AI system is in a machine-readable format and detectable as artificially generated or manipulated. If an AI systems is intended to interact directly with natural persons, its provider must ensure that it is designed and developed in such a way that those natural persons are informed that they are interacting with an AI system. Deployers of an AI system that generates or manipulates image, audio or video content that constitutes a deep fake must disclose the fact that the content has been artificially generated or manipulated. These obligations can be relevant, for example, where chatbots are introduced in financial services customer service applications.

The Act complements EU financial services legislation, which includes a range of sector-specific EU legal acts that (i) are applicable to regulated entities in the financial sector with a view to ensuring prudential supervision, financial stability and consumer protection; (ii) impose obligations that are not specific to AI; and (iii) apply regardless of the technology used for the provision of the financial services. The Act is based on the assumption that some of the procedural obligations for providers and deployers of high-risk AI systems in relation to risk management, post-marketing monitoring and documentation can be integrated into existing obligations and procedures for internal governance and risk management applicable to regulated financial institutions under EU financial services legislation. This means that these obligations must be fulfilled but that there is a possibility for consistency with, and integration into, relevant existing processes that the regulated financial institutions have already in place. Furthermore, in order to avoid overlaps, limited derogations or exceptions are envisaged in relation to the quality management system of providers and in relation to the monitoring obligations placed on deployers.

Explainability and accountability

Many of today’s AI systems operate in such a complex manner that it is no longer possible to understand why specific output is provided / generated and how it is derived. AI’s limited explainability is a factor linked to the four preceding risk areas. It is an open question whether (full) explainability is needed – given that human decision-making, which AI may replace, is also not necessarily understood in detail either. However, internal managers and external supervisors in many areas (including many applications in financial services) will want to understand who has proposed or taken a decision – and why.

The vast capabilities of systems mean that it may be useful to impose different standards of explainability of decisions that are based on AI output. It is nevertheless also necessary to avoid excessive requirements hindering AI development and deployment in the EU (for example, by mandating full explainability of every output).

Legal accountability is a key area that may require amendment or extension of existing regulation and rules, particularly to avoid moral hazard arising when third parties such as consumers suffer damage rather than the entity which used the faulty AI system. It is not always clear at present which party is responsible for erroneous AI output, especially when one or more third-party providers are involved.

Box 3.4 Implications of AI use for supervisors

The use of AI creates specific problems for supervisory authorities. AI can be used to maintain stable financial systems but can also cause instability.

The following microprudential and macroprudential effects can be expected.

- AI generally helps microprudential regulation because a lot of data are readily available (or can be gathered, for instance through web-scraping) and because the rules generally remain unchanged within the timescales in which decisions are made. In addition, the costs of mistakes are (comparatively) small and potential (AI) flaws will not lead to systemic risks.
- Effective execution is generally less accurate for macroprudential considerations due to the rarity of events, data-quality issues and lack of data-sharing (data silos) [108] . In addition, political decisions may unexpectedly amend existing ruleset(s), creating significant problems for AI.

Financial stability is impacted by three key vulnerabilities: (i) a high degree of leverage; (ii) the self-preservation instinct (running for liquid assets in times of stress); and (iii) system opacity, complexity and asymmetric information (giving rise to mistrust in the system). Financial crises are generally driven by 'unknown unknowns' in one or more of these areas, making it impossible for supervisors to act in advance. AI can help in identifying these factors by assessing different threat vectors and cutting through highly complex interactions and opaque interconnections. However, AI systems and their use are also 'unknown unknowns'.

In addition, authorities are already competing today with the private sector for scarce human, data and computation resources. Costs are often much higher than the authorities are accustomed to. This competition is likely to intensify further as AI becomes increasingly used.

AI will also help supervisors to identify and deal with endogenous risks (risks arising from the interactions of market participants) which only become visible in times of extreme market stress. Using AI to run scenario analyses and compare past behaviour can help to capture these risks earlier and devise potential means to react if they materialise.

AI may eventually become a strong tool to support crisis resolution, but it must overcome the same conceptual problems as humans – notably data scarcity, 'unknown unknowns' and endogenous structural changes (unexpected political decisions).

Another crucial question concerns accountability. Who is responsible when a regulator's AI makes decisions or provides crucial inputs for human decisions. How can a regulated entity challenge such decisions?

It may not always be possible to resolve issues related to limited AI explainability, but there will be strong reasons to try to do so, primarily because it can improve AI system coding. However, certain operations of AI systems may remain too complex to be understood in any direct manner. Regulators and supervisors in financial services should continue monitoring how a lack of explainability can pose risks and should promote developments that enhance transparency. Even in cases where no direct financial stability risks result from the non-explainability of AI output, it is still possible that other risks might materialise (e.g. cascade market sell-off or biases

[108] A typical OECD country only suffers a systemic crisis once every 43 years. See Laeven L. and Valencia F., 'Systemic banking crises revisited', *IMF Working Paper* 18/206, 14 September 2018 – See also Danielsson, J. and Uthemann, A., *On the use of Artificial Intelligence in financial regulations and the impact on financial stability*, June 2024.

affecting consumer interests) and raise questions about why events occurred and who (or what) is responsible.

3.4 Conclusion

AI clearly has the potential to transform both the provision and supervision of financial services. Indeed, it has already done so to some extent. AI currently offers significant opportunities to improve productivity and efficiency. To remain competitive, EU financial institutions and other market players need to continue developing and using AI. AI can reduce costs in areas like compliance and customer support; facilitate new products and 24/7 services; and enhance pattern recognition and analysis. The extent to which this is beneficial to providers and consumers will depend on the area of deployment, possible limitations and future developments which may help overcome them. Further capacity-building (both among deploying entities and supervisors) will drive trust in these systems and advance experience in handling them.

The use of AI in financial services can drive or amplify risks. The current adoption of AI in financial services does not yet seem to raise significant systemic risk concerns. However, growing reliance on AI means that risks to financial stability will be inevitable (as is already the case for other technology). A more thorough assessment of the individual specific settings of AI systems and risk-monitoring facilities would accurately capture the state of AI integration. The high error rates of current systems should prevent excessive reliance on AI. Critical systems should be monitored (as is the case for human-to-human processes) and it should be possible to decouple them or switch them off. Such risks therefore still appear to be limited. By contrast, risks such as excessive herding may or may not materialise – depending on competition, innovation and user preferences.

Both entity-level risks and new risks for consumers are likely to grow as AI use continues to increase in the coming years. As AI systems become more effective, people monitoring these systems may increasingly trust them and become reluctant to question their results. There is also a significant strategic risk if the EU's financial services sector falls behind in developing and using AI [109]. Missing out on AI's significant efficiency gains could significantly impair its international competitiveness.

AI involves risks but also helps to manage existing and new risks. In some areas such as cybersecurity, the use of AI may even become essential to countering malicious use of AI, including malicious AI. Financial services actors also have experience in adopting new technologies. Bigger financial institutions and major infrastructure operators tend to exercise caution when deploying and monitoring new technology. In areas where AI could impact core business operations and/or revenue streams, there is also an natural drive to minimise risks (as it will maximise profits).

AI's innovative nature and far-reaching capabilities call for both the monitoring and identification of high-risk areas (hence the EU's Artificial Intelligence Act). If risks are excessively high, new obligations may be needed to ensure that sufficient control is maintained. However, overly restrictive and rigid frameworks could significantly undermine AI deployment to the detriment of both service providers and consumers. Prudent AI development could be facilitated via regulatory sandboxes to facilitate the development and testing of innovative AI

[109] In H1 2024, more than USD 35 billion was invested globally in AI start-ups. Only 6% of this was invested in the EU. See Martens, B., 'Catch-up with the US or prosper below the tech frontier? An EU Artificial Intelligence strategy', *Bruegel Policy Briefs*, 21 October 2024.

systems under regulatory oversight before these systems are placed on the market or otherwise put into service. Facilitating data use, access and re-usability (including in the form of common standards) could also lower entry barriers and promote competition.

Adequate data and competition policy can ensure that fair competition drives market efficiencies in financial services and other sectors. Excessive concentration (especially in the area of data) could undermine AI's benefits, increase costs for users and consumers, and lead to economic dependencies.

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