STUDY

Requested by the AIDA committee

European Parliament

Artificial Intelligence market and capital flows

Artificial Intelligence and the financial sector at a crossroad

Policy Department for Economic, Scientific and Quality of Life Policies
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Abstract

This paper studies the transformation that Artificial Intelligence (AI) is bringing to the financial sector and how this sector can contribute to developments of AI applications. The study addresses the contribution of AI to a more efficient, open, and inclusive financial sector and the challenges of the AI transformation, and it provides recommendations for policies and regulations of AI and financial services.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AIDA	Special Committee on Artificial Intelligence in a Digital Age
AIFMD	Alternative Investment Fund Managers Directive (Directive 2011/61/EC)
AMF	Autorité des marchés financiers (financial markets authority)
AML/CFT	Anti-money laundering and combat the financing of terrorism
AMLD	Anti-money laundering directive (Directive (EU) 2015/849)
ANN	Artificial neural networks
API	Application programming interface
BCBS	Basel Committee on Banking Supervision
BDA	Big Data Analytics
Bigtech	Large technology-based companies, such as Amazon, Facebook, Google, Apple, Microsoft, Alibaba
CMU	Capital Market Union
CRD IV	Capital Requirements Directive IV (Directive (EU) 2013/36)
EBA	European Banking Authority
EC	European Commission
ECB	European Central Bank
EIF	European Investment Fund
EIOPA	European Insurance and Occupational Pensions Authority
EMD	E-Money Directive (Directive (EU) 2009/110)
ESAs	European Supervisory Authorities
ESMA	European Securities and Markets Authority
ESRB	European Systemic Risk Board
EU	European Union

FCA	Financial Conduct Authority
Fintech	Financial intermediaries relying on digital technologies
FSB	Financial Stability Board
FTC	Federal Trade Commission in the US
GDPR	General Data Protection Regulation
IoT	Internet of things
MiFID II	Markets in Financial Instruments Directive (Directive 2014/65/EC)
ML	Machine Learning
NLP	Natural Language Processing
POS	Point of sale devices for financial transactions
PSD2	Payment Services Directive (Directive II (EU) 2015/2366)
PSPs	Payment service providers
RegTech	Regulatory Technology
SEPA	Single Euro Payments Area
SupTech	Supervisory Technology
UCPD	Unfair Commercial Practices Directive concerning unfair business-to-consumer commercial practices in the internal market, (Directive (EU) 2005/29)
UK	United Kingdom
UNSGSA	United Nations Secretary-General's Special Advocate for Inclusive Finance for Development
US	United States

EXECUTIVE SUMMARY

The advent of Artificial Intelligence (AI) is already profoundly impacting the financial markets and services (i.e., the financial sector). In this scenario, AI is relevant both as a technology that enables and facilitates financial services and an investment opportunity for the financial industry. The implications of AI will be profound because the financial sector is a crucial ingredient of modern economies, and AI is becoming a general-purpose technology with rapid diffusion and market applications.

This study investigates (chapter 1) to what extent AI is transforming decision-making in financial markets and services, including credit markets, stock and money markets, derivatives and futures markets, insurance markets, foreign exchange markets, payment systems, and financial infrastructure markets. This study does not share the futuristic view of completely autonomous and AI-centric financial markets and services, at least any time soon. However, it is recognised that financial operations are ideal for the application of AI and automation. It is illustrated where this process is already in motion, who are the key players, and that AI is transforming traditional financial activities, also helping new players to offer new financial services.

It is explained why and to what extent (chapter 2) the combination of AI and its market applications in the financial sector will be a source of efficiency and prosperity, as it happened with other general-purpose technologies. It also discusses "success stories" where AI shows its full potential. In particular, the study considers how AI can facilitate access to finance, fight against fraudulent financial transactions, customise financial services, and offer new opportunities and jobs in the financial sector. Overall, if properly adopted, AI can be a democratisation factor of the financial industry.

At the same time, (chapter 3) the several and new challenges emerging with the diffusion of AI in financial markets are identified and discussed. The adoption of AI should not be taken for granted as several factors may limit it. AI systems may end up unfairly discriminating in credit markets, for example, or coordinating with a risk of collusion. Explainability and privacy concerns are especially relevant for financial services applications of AI. AI brings significant changes in the financial sector that will transform the relationship between financial institutions and their clients, the market structure of the industry, and that will displace some of the activities currently performed by humans. It will be necessary to learn to cohabitate with new and AI-related sources of instability of financial markets.

The instinctive reaction to such a long list of complex issues with AI applications in the financial sector could be that of restricting these applications to a per-se fragile environment such as the financial sector. The study explains (chapter 4) that this attitude is wrong provided that the issues are properly understood and well addressed. Since the financial sector is heavily regulated, and for good reasons, the study discusses how AI interacts with existing regulations and how AI-specific, "horizontal" regulations could impact the financial sector. The study provides specific recommendations that could put in place to fully harness the benefits of AI in the financial sectors while keeping its challenges under control. These recommendations pertain to AI regulations and their impact on the financial sector, together with specific recommendations for financial institutions adopting AI solutions and recommendations about managing risk in financial markets. Recognising that regulators will profoundly influence the adoption of AI in financial markets and its applications, the study proposes some recommendations to support the transformation offered by AI, avoiding stifling its innovations and applications for the financial sector.

Finally, the study illustrates (chapter 4) what incentives one could put in place to facilitate safe AI applications for the financial sector and how financial markets can, in turn, support with investments the research and development of AI applications. Some interesting best practices are also discussed that could be adopted and further expanded.

1. OVERVIEW OF AI AND THE FINANCIAL SECTOR

1.1. Background

This study begins with two observations. First, the financial sector, the combination of financial markets and services, is a necessary building block of modern economies. A well-functioning and developed financial sector is vital for the growth and prosperity of modern economies. It mobilises savings and funds towards the most valuing investments, allowing more and better future consumption and further investments. That is, the financial sector is a necessary ingredient for growth. Second, in the last decades, the digital transformation of economies and societies has progressed very rapidly. This transformation is already occurring in many fields and our daily lives with opportunities and challenges. In this context, Artificial Intelligence (AI) is becoming a general-purpose technology with implications for virtually all sectors and their business models.

The financial sector is not exempt from this process and relates with AI on two dimensions. This sector is experiencing some of the most developed and advanced applications of AI, and, at the same time, it provides the funding for developing further new AI applications.

In this study, the intertwined relationship between AI and the financial sector will be discussed. The focus will be on the developments of AI and the financial sector from around 2010 onward, which is when the renewed interest in research and investments in AI took off again, particularly with the successes in the sub-field of machine learning (ML) [1].

In the last ten years, three factors have primarily contributed to the renewed interest in AI. First, the significant reduction of the cost of computing and data storage (especially with new possibilities in cloud computing as a service) lead to a substantial increase in demand for these services. Second, the process of digitalisation has offered large amounts of data (Big data) that, combined with AI generate valuable market applications. Finally, some successful applications of classification algorithms, such as with image recognition and, more recently, in Natural Language Processing (NLP), have concretely shown tangible market value. Had AI remained in the labs and in academia, it would not be the subject of discussion now. The concomitant advancements in the research on AI and actual market applications are now fuelling the present attention to AI, with a reinforcing cycle that is investigated in this study.

Instead of providing yet another definition of AI, it is better to begin this study by discussing the reinforcing cycle between AI and market applications[2]. When more data become available for analysis with better tools, the cost of information drops. Such cost reduction implies a decrease in the price of predictions for decision-making, which means assessing the likelihood of future and uncertain events and predicting how to correctly classify, for example, images and credit borrowers into different categories (Agrawal et al., 2018). Decision-making thus becomes not only more precise (that is, with reduced errors) and faster, for example, when AI assists doctors in diagnosing pathologies, but it is also transforming itself. With cheaper predictions, new possibilities emerge where decision-making is

[1] Interest on AI has followed hype cycles over time, with several "up and downs" (the winters of AI). See Wooldridge (2020) for an accessible and thorough description of the history of AI.

[2] The European Commission has provided a definition in the recent proposal "Artificial Intelligence Act", EC (2021), in Article 3, "'artificial intelligence system' (AI system) means software that is developed with one or more of the techniques and approaches listed in Annex I [(a) Machine learning approaches; (b) Logic-and knowledge-based approaches; (c) Statistical approaches] and can, for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations, or decisions influencing the environments they interact with". For a broad discussion about what is AI see Wooldridge (2020).

delegated to autonomous systems, such as self-driving cars. Valuable market applications of AI attract investments and generate more data, eventually making AI predictions better and cheaper.

This sequence of implications is making AI a genuinely transformative and general-purpose technology, and one can expect the consequences to be at least as profound as with other general-purpose technologies in the past, such as the advent of electricity.

AI profoundly affects and transforms decision-making in financial markets and services, including credit markets, stock, money and derivative markets, insurance markets, payment systems, and financial infrastructures. The process transforms the typical activities performed in these markets and allows for a new range of financial services, inducing innovations on transactions, assets and improving access to financial markets and services.

Financial markets and services are the ideal and natural field of application of AI and digitalisation. They are almost by definition immaterial, and all financial services, for example, providing credit to a client, executing a payment, providing insurance coverage, and investing in equity, ultimately rely on information processing. Consequently, financial markets have been using algorithms for decades and even before the recent developments of AI.

Although various financial markets and services perform many diverse activities, they share two key elements: (i) the interactions between different and differently motivated players and (ii) the information that these players use in making their decisions. In markets, in fact, "we are never alone" because transactions of any type necessarily involve different sides, such as buyers and sellers. The second key element, information, is the most crucial driver of financial transactions and risk management. Buyers and sellers are willing to perform opposite, apparently contradicting, buying and selling decisions because of different needs and because they hold different information. Information is also the critical ingredient of risk management, that is, the practice of mitigating the consequences of the stochastic movement of prices and values of assets.

For these reasons, the financial sector is now experiencing a more profound transformation with the diffusion of commercial applications of AI than other sectors. Although financial markets and services are still and will remain dominated by humans in the foreseeable future, the diffusion of AI is coming and fast, with many activities already performed by AI.

A recent survey conducted for the World Economic Forum (2020) has shown that a large majority of players in finance worldwide (85%) already use some form of AI and a large group (65%) expects to become an adopter of AI for mass financial operations[3]. A joint survey of the Bank of England and Financial Conduct Authority (FCA, 2019) shows that most financial firms are currently building the infrastructure to deploy large-scale AI, with 80% already using AI in some form.

Applications of AI in the financial sector are also changing the type of players populating these markets and their business models, such as with Financial intermediaries relying on digital technologies (Fintech) firms and Bigtech firms (that is, large companies that rely on digital technologies in other non-financial markets)[4].

Although the futuristic view of completely autonomous and AI-centric financial markets and services seems irrealistic, it should be recognised that financial operations are ideal for applying AI and

[3] Similar figures have been consistently identified in other recent surveys such as the one by the Bank of England on ML applications in UK financial markets (Bank of England, 2019).

[4] In 2017 Amazon announced that its lending activities reached $3 billion in loans to small businesses since 2011 to help them grow their business. See Business Wire, https://www.businesswire.com/news/home/20170608005415/en/Amazon-Loans-More-Than-3-Billion-to-Over-20000-Small-Businesses.

automation. This process will displace some of the activities performed by humans. However, it can be envisaged that human judgment and oversight will continue to play an essential role, certainly for the foreseeable future, in the financial sector. The type of AI that one observes in financial services in the following decades will be "narrow-AI", which is applications to specific and well-defined environments. (It will not be the "strong-AI", which instead should acquire human abilities such as self-awareness and consciousness.) The demand for human judgment will increase, if anything, with the diffusion of AI applications in the financial sector.

Regulators worldwide have already noticed that the interaction between AI and the financial sector can have profound and important consequences, with opportunities and risks. For example, the Basel Committee on Banking Supervision published a report (BCBS, 2018) encouraging banks to exploit AI as an efficiency-enhancing technology. In 2017 the Financial Stability Board (FSB, 2017) identified several AI applications in the financial sector with benefits for individuals and SMEs. However, authorities have also pointed out that AI applications in the financial sector may also induce some specific risks, as discussed in the following pages.

Finally, many financial markets and services are subject to regulation and intense supervision. These interventions are specifically designed to maintain market functioning confidence, grant stability, and protect users (see box 1). The advent of AI in the financial sector will require more scrutiny, as illustrated in the following chapters, considering that some financial services are not subject to regulation, such as shadow banking (see box 1). As in other environments, regulators will profoundly influence the adoption of AI in financial markets. It will be essential that lawmakers and regulators deploy their activities supporting and favouring the transformation offered by AI, avoiding stifling innovations and applications in the financial sector.

Box 1: The financial sector and its regulations

The term "financial sector", includes the markets, institutions, and services that pertain to finance activities, that is, the activities that involve the exchange of financial funds or assets. Specifically, financial markets are the organizations where these exchanges take place. They are organised with specific functioning rules (such as the stock markets, in which case they are called "exchanges"), and they rely on market infrastructures. Financial assets are the different types of funds that are the object of exchange, such as credits, bonds, and stocks. Financial institutions are specialised and generally licensed intermediaries, such as banks and mutual funds, that act between and in some cases on behalf of traders in financial markets. Financial services are explicitly or implicitly provided by financial institutions to traders, such as matchmaking, maturity transformation, screening, and monitoring.

The financial sector is subject to broad and encompassing regulation compared with most of the other sectors in an economy. Financial sector regulation is destined to maintain confidence in the financial system, guarantee its stability and protect customers of complex and sophisticated services. The justification for financial regulations is twofold. Financial markets are characterised by an endemic presence of asymmetric information between players (traders, and institutions in the financial sector) that may significantly limit its efficiency. The financial sector can produce strong externalities within itself (due, for example, to the interconnectedness between financial institutions) and other sectors (in case of financial market crashes). Some financial intermediaries offer lending, but are able to avoid the traditional financial regulations affecting banks because they do not fund themselves with standard deposits. Also considering its considerable dimension ($50.9 trillion in 2018, that is 13.6% of total global financial assets, FSB 2020), these shadow-banking activities can be a source of systemic risk, as shown during the Great Financial Crisis that started in 2008.

Source: Author's own elaboration

1.2. Key actors at the global level and EU positioning

To identify the key countries that combine AI and the financial sector, one should consider three facts. First, AI is still an innovative technology in finance, which implies that funding AI applications is critical and not granted. Second, financial markets and services are already adopting AI solutions, but this is just one of the sectors interested in AI, and thus the presence in a country of a developed financial sector is important but not strictly necessary for the diffusion of AI. Third, the presence of a solid and vibrant AI industry helps facilitate the adoption of the technology in general and in the financial sector.

In terms of investments and number of start-ups on AI, the lion's share in the last five years is with the United States (US) primarily, followed by China (less than half of the investments in the US) and at some considerable distance other countries such as Canada, UK, Israel and few European countries such as France and Germany (Arnold 2020, Tech Nation 2020 report).

The presence in a country of a very developed financial sector such as in the US, UK, and some European countries, is not a precondition for the diffusion of AI. For example, the dramatic development in China of non-traditional investment platforms (crowdfunding and crowd-investment platforms) and digital payments relies more on a large population and complements a less developed banking sector. Also, the bank-centric financial sector of many European countries may impede to the extent that incumbent banks face legacy issues with the traditional technologies they currently use, making the transition to innovations more expensive. On the other hand, financial sectors that produce vast investment capacity of risk capital, such as venture and equity capital, like the US and the UK, are more apt to finance AI applications.

In addition to risk capital, the other crucial enabling factor for the diffusion of AI is a skilled workforce. According to O'Meara (2019), in 2018, the US was leading for numbers of researchers working in AI (28,000) over China (18,000), United Kingdom (UK) (7,000), Germany (9,000), and for top AI researchers (measured by the number of citations, 18% of them located in the US, 5% in China, 12% in Germany, 15% in the UK). The AI Index Report (2019) shows that the countries with the highest AI-related skills in the financial sector are the US and India, followed (with significantly lower index values) by France, Germany, UK, Canada, and China.

It is also instructive to observe in which AI applications the financial sector predominantly invests. The AI Index Report (2021) shows that the sectors receiving more investments for AI developments are autonomous vehicles (10%), drugs (6.1%), facial recognition (6%), video content (4.5%), and finance (4%). The World Economic Forum Report (2020) shows a stark difference between incumbent players and newcomers such as Fintech companies. Fintech companies use AI to offer new products and services, while incumbents predominantly adopt AI to reduce costs and improve existing products..

As it is known and these data confirm, the European Union (EU) is currently not in a leadership position in market applications of AI in general, and the financial sector is not an exception. The causes of this condition are, unfortunately, many and concomitant.

First, with few exceptions, the EU is lagging in terms of research on AI. Vibrant research environments are a crucial facilitating factor of AI spin-offs and early applications, such as finance. Second, the source of funding for innovations in the EU relies more on the banking sector and less so on risky capital such as venture and equity capital[5]. Since AI applications are still at the early stage and involve significant risks, the bank-centric EU source of funding is not ideal to invest in AI applications, in general, and for the financial sector. Third, the banking sector that dominates European financial markets is less prone to adopting disrupting innovations such as AI.

The exit of the UK from the EU is also problematic, as the UK has a vibrant financial centre and, at the same time, is one of the key players in AI research and applications.

Finally, although statistics comparing AI applications in the financial sector across countries are scant, the combination of our previous observations shows that the critical national players also in this case are the US, China, and the UK. Furthermore, there seem to be no significant changes in these conditions. Hence, one can expect to see these players dominate AI applications in finance for the next decade unless specific events and new policies emerge in the meanwhile.

1.3. Investments for developing AI

High investments and a significant risk of failure make the development of AI a complex task.

According to the AI Index Report (2019), in 2019, global private investment in AI was over $70 billion, mostly in terms of startup investments ($37 billion) and Mergers and Acquisitions ($34 billion). In 2010, the figure for startups was just $1.3 billion with average annual growth of more than 40% to have an idea of the trend. In 2019 (Statista 2020), the cumulative funding worldwide of AI applications went mostly on ML (45%), then to intelligent robots (around 10%) and similarly to NLP, recommender systems, and less (3-5%) to speech and video recognition.

[5] In 2017, 50% and 30% of the global venture capital went respectively to the US and China, whilst Europe just received 8% of it (OECD 2018).

The US has dominated the investments in AI at least since 2000, for the number of startups (more than 3000 in 2000-2016 that is 37% of the world total see Buchanan and Cao, 2018) and funding ($20.7 billion, that is 70% of world total). However, the leadership of the US has been challenged in the last 5-6 years by China that strongly increased both the number of startups, their funding, and the number of patents and research papers related to AI (CB Insights, 2018 and Wushen Institute Report, 2017). At a significant distance, there other countries such as the UK and Japan (interestingly, these two countries were among the top funding countries in the expert system era), followed by France, Canada, Germany, Singapore, India, and Israel. In 2017, European countries attracted about 8% of venture capital in AI worldwide, while the US and China respectively accounted for around 50% and 36% (OECD 2018). Overall, in 2018 the US and China combined accounted for 90% of global investment in AI (Statista, 2021).

Despite China's improvements, the US is still dominating with a robust financial sector that supports and funds AI market developments with venture capital and private equity funding. In general, the US is still leading in terms of research and development (R&D) spending in software and computer services spending three times more on R&D than China and the EU combined in 2019.

An interesting element in the US and China race for AI is that of cross-border deals on AI. In this case, since 2016, the number of US-based startup deals backed with Chinese private equity has been 50% higher than that of Chinese startups backed with US private equity capital.

The EU's venture and private equity funding are significantly smaller than the US but less so recently (in 2019, it was just 22% of the US funding) than in the past (13% in 2016). However, the number of deals and Mergers and Acquisitions in AI in Europe is smaller than in the US, with an increasing gap.

Funding for AI developments is not all private. There are public funds as well that are significantly impacting the sector. For example, in 2020, the US announced a plan of (non-military) public investments of more than 1 billion. Chinese local governments offer significant financial incentives for AI innovations, and in 2017 the China State Council planned private and public investments and actions aiming at becoming AI world leader in 2030. The case of European funds for AI will be extensively discussed in section 4.4, but also in this dimension, the European funds for AI are significantly lower than those planned in the US and China.

1.4. Applications of AI for the financial sector

Since the trading object in the financial sector is generally immaterial, AI's actual and potential applications are numerous. Here these applications are illustrated, referring to the most common services and activities of financial institutions.

1.4.1. Applications of AI for financial services

For financial services, AI is helpful in *front-office activities* that directly involve financial service customers (e.g., lending, investment management, and payment systems) and *back-office activities* (e.g., capital optimisation, risk management, and market analysis). This distinction is helpful because it identifies two groups of activities, accounting for the revenue and the cost stream of financial institutions[6].

Lending and credit risk prediction. Financial institutions typically have limited information about prospective borrowers and their riskiness, which can be a fundamental problem because asymmetric

[6] For examples of companies and their actual market applications of AI in the financial sector, see the report of the World Economic Forum (2018).

information leads to market inefficiencies and even market breakdown. Financial institutions have relied on credit scores typically based on borrowers' payment history to limit these problems. The advent of big data provides other sources of information, known as *alternative data*, such as social media, utility bills, telecom data, data from smartphones, or past purchases, that can be factored into richer models to predict risk class. The heterogeneity of these new data sources requires new tools to extract information about prospective borrowers, such as ML. The combination of alternative data and better prediction tools allows for quicker lending decisions and better predictions of individual risks with more refined segmentation/classification of potential borrowers[7]. The effect on the market is that one can have better and more profitable credit conditions and more borrowers receiving credit. Individuals who would have been considered non-bankable borrowers for insufficient information and inaccurate risk predictions (such as individuals with no payment history) may now receive credit and become a source of profit[8].

Credit risk prediction is also relevant in many other circumstances. For example, banks use it to internally assess the riskiness of their assets (the large banks that use the Internal Rating Based method), and on this assessment, they have to comply with the capital adequacy ratio. Better prediction of portfolio riskiness allows banks to save on capital requirements and associated costs (Aloso and Carbò, 2021).

Insurance. Financial institutions that provide insurance must identify the premia for different individuals and the level of risks. In this case, limited information is a problem and may induce insurance companies to ask such high premia that many individuals may remain uninsured. Combining ML with alternative data allows insurance companies to obtain more precise risk assessment, better personalisation of insurance contracts, and ultimately more access to insurance.

Payment systems. AI is already broadly adopted for processing payments, helping to detect fraud, fight money laundering, and making the payment networks more efficient, in fact, a mix of front-end and back-end activities. Fraudulent card payments have increased in the last years up to 1.8 billion in the Single Euro Payments Area (SEPA) and $14 billion globally[9]. It does not thus surprise then that financial institutions have started to implement AI solutions for automated and prompt fraud detection, with cost savings and better performances than human intervention. AI is also currently used to predict the amount of cash bank branches must hold to meet depositors' needs at the lowest possible cost.

Robo-advising and Virtual assistants. Robo-advisors are recommender systems (see box 2) designed to assist private investors in interacting with financial markets. They provide personalised recommendations in portfolio management. Some banks and big investment funds currently adopt them. In 2018 the US market reached $540 billion of assets managed with robo-advising, and this figure will possibly grow by more than 20% yearly (Statista 2020).

Virtual assistants or chatbots help customers to interact and operate with their financial institutions smoothly, in some cases substituting human interaction. Chatbots, in particular, are ML algorithms relying on NLP that provide financial service users with updated information, solicited but also

[7] See Onay and Öztürk (2018). Several papers have shown the superiority of AI algorithms (such as neural networks, support vector machines, decision trees, random forest,) for credit scoring with respect to logistic regressions traditionally used to this purpose, see for example Königstorfer and Thalmann (2020). It is important though to note that the superiority of AI algorithms tends to be specific to the environments and the data used.

[8] Banks could also use AI and alternative data for more personalised offers of deposits, although in this case the issue of asymmetric information is less relevant.

[9] The ECB report referring to the situation in 2016, see: https://www.ecb.europa.eu/pub/cardfraud/html/ecb.cardfraudreport201809.en.html.

unsolicited. They are also a relevant source of additional data for AI systems, thanks to their direct interactions with customers. Clients could soon use a virtual assistant to bargain with the financial institutions and negotiate financial transactions on the client's behalf.

As seen in Figure 1, in 2019 already 50% of European banks used AI for direct client interactions, and another third of them are preparing to do so.

Box 2: Recommender systems

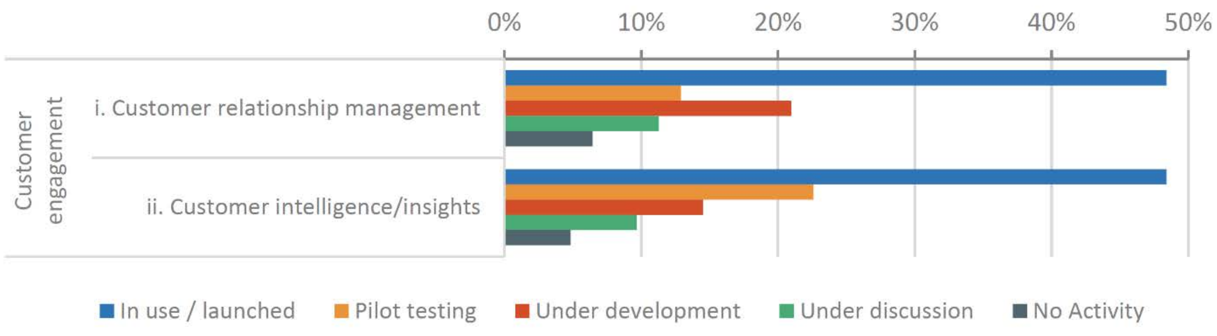
Robo-advisors are a specific application of a class of algorithms in the AI toolbox called Recommender systems. These algorithms are probably less known than others, and it is worth dedicating a few words to their functioning. Recommender systems are algorithms designed to predict ratings of users for given items, products, or services. Typical applications are videos, songs, books, but also financial assets as with Robo-advisors. The idea is that companies have some information on how much some individuals appreciated certain items that they have consumed. They should predict how much other individuals, who have not consumed these items, would appreciate them based on this information. Based on these predictions, the recommender systems show a personalised subset of items to each individual to help the individuals' decisions.

There are different approaches to address this prediction issue that are particularly effective in handling the enormous number of combinations of individuals and products, such as predicting the most preferred financial assets to invest across hundreds of thousands of different types of assets for possibly millions of clients.

These algorithms can dramatically simplify the search and decisions of users/consumers who may not even be aware of the available options. For this reason, they are also a potent tool for companies that can offer better services to their users and improve consumer retention. Since users rely on recommendations, there is a risk of manipulation of consumers' decisions.

Source: Author's own elaboration

Figure 1: AI and big data for customer interactions by European banks



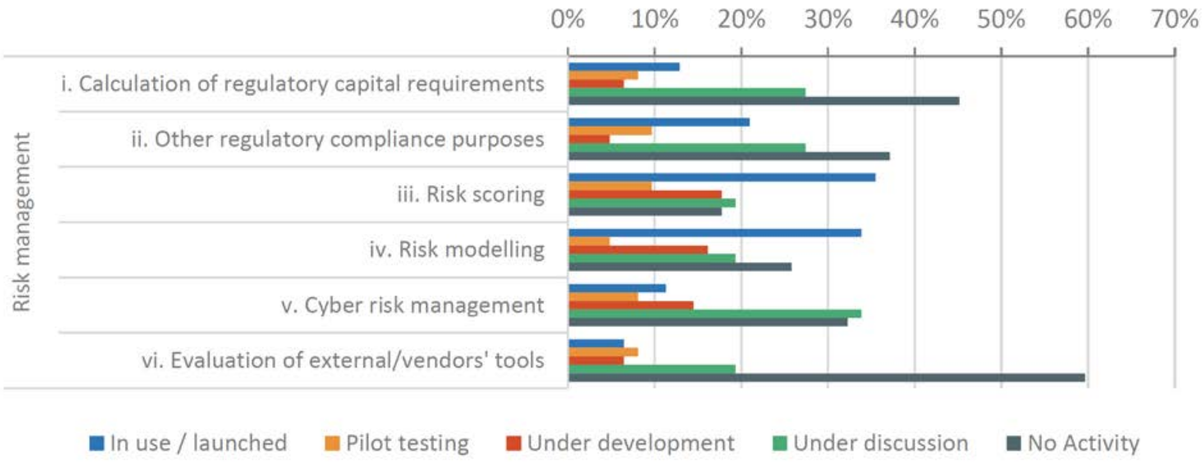
Source: European Banking Authority (EBA) risk assessment questionnaire (spring 2019).

Asset and risk management. An area where AI is becoming predominant in financial services is asset management with applications such as identifying assets to trade, portfolio optimisation, and automated trade execution. In 2018 according to BarclayHedge's Hedge Fund Sentiment Survey, more than 56% of hedge funds used AI in investment decisions with a yearly growth rate of more than 20%

in the previous three years[10]. Others (25%) were using AI to automate trade execution, and some funds are now entirely managed with AI (e.g., Numerai, Aidiyia Holdings, and Taaffeite Capital Management). In 2018, BlackRock, one of the largest asset management companies in the world, announced an AI lab that could count on a managed portfolio of $6.3 trillion. In some cases, the algorithms for these applications already factor in alternative data sources such as satellite imagery and social media.

AI also offers practical solutions for risk classification and consequent decisions for risk management. Automation here also plays an important role, like AI/ML tools combined with automated decision-making, allowing for a seamless process with feedback from the market and risk assessment. ML is also applied to internally assess traditional risk models used by financial institutions and identify extreme and unrealistic predictions (model validation). Figure 2 reports the different applications of AI and big data for risk management by European banks.

Figure 2: Risk management with AI and big data of European banks



Source: EBA risk assessment questionnaire (spring 2019).

The advantage of AI comparing with traditional asset and risk management techniques is the ability to feed data to the prediction algorithms that continuously adapt and autonomously reassesses, with the possibility of integrating automated trading decisions.

AI-related funds are today one of the sectors that hire most and the best AI-trained workforce, probably more than the Bigtech firms. These financial firms are so eager for these skills that a severe limit to their developments in the future will be the lack of a skilled workforce.

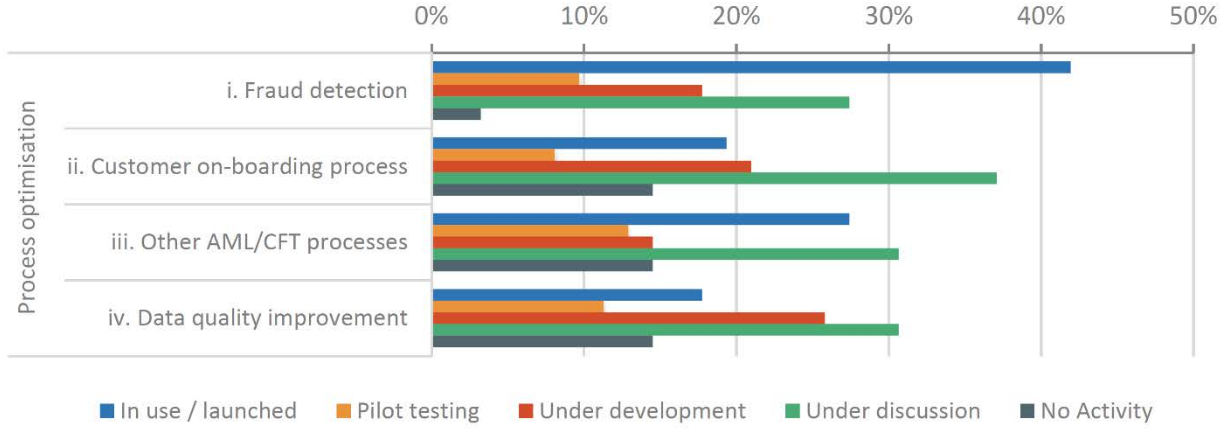
Algorithmic trading. Trading in structured financial markets has been among the first automated financial operations because these markets have work with precise and pre-specified rules. Early applications mainly focussed on increasing the ability of trading algorithms to trade and interact with the markets at a very high frequency. Algorithms competed to place orders faster than their rivals to gain small arbitrage margins on substantial orders. This process and the availability of a large amount of well-structured data naturally invited this sector of financial markets to delve into AI. ML can now help to assess portfolio positions, predicting market prices and risk exposure. These new algorithms for trading can identify the best actions and autonomously adjust risky or unprofitable positions.

Other applications. Other applications of important back-office activities of financial institutions can be successfully implemented or complemented with AI, with significant cost reductions. Financial institutions that trade in the organised market typically consider the market impact of their own (large)

[10] See https://www.barclayhedge.com/insider/majority-of-hedge-fund-pros-use-ai-machine-learning-in-investment-strategies.

marked orders. To avoid the negative impact of their own trading decisions, financial institutions manage the timing of their orders. This market impact analysis can benefit a lot from AI complementing traditional models using additional sources of information. Banks are also using AI to optimise the geographical networks of branches. Financial institutions have duties in detecting fraudulent transactions and must perform anti-money laundering and combat the financing of terrorism, i.e., Anti-money laundering and combat the financing of terrorism (AML/CFT) activities, on behalf of authorities. Trade venues (i.e., exchanges of tradable assets) use AI to monitor their market infrastructure and speed up transactions. Figure 3 shows the use of AI in other back-office applications by European banks.

Figure 3: Back-office applications of AI and big data of European banks



Source: EBA risk assessment questionnaire (spring 2019).

1.5. Evolution of algorithms for lending markets and financial flows

AI has had many phases with ups and downs and different types of algorithms and applications. The first significant market applications started in the eighties and relied on Expert systems. These tools were practical and widely adopted. One of the early and successful applications was an expert system for automated credit authorisation implement by the retailer Marks & Spencer in the UK. This retailer in 1991 automatically handled 90% of credit authorisations and controls with the expert system named *Behavioural Scoring*. Expert systems replicated what would have been complex processing and decision-making by humans, based on a possibly very detailed knowledge base. The type of data they used was mainly sector-specific. In the case of credit authorisation, in particular, they used data concerning personal demographics, problems with payments, and the flow of payments in the account. Expert systems were also used for investment decisions, retirement planning, and companies trading securities in financial markets frequently used these systems in the US and Japan. However, for the most complex operations like automated portfolio management, they remained prototypical.

With these early automated decision-making applications, the first cases of induced market instability appeared, such as a sudden reduction of the Dow Jones index in 1987 attributed to algorithms. Then the second winter of AI came in the nighties for applications in the financial sector too. These early approaches and their applications to finance remained limited and did not deliver as expected. In many cases, these applications were also abandoned because Expert systems were expensive to set up and maintain. The new developments witnessed since the last decade are the consequence of the factors discussed in section 1.1, namely reduced costs of calculations and data storage, the availability of significant and different data sources, and new types of algorithms. The critical technological advancement for the new wave of applications is the autonomous learning component of the algorithms, as contrasted with the hardcoded knowledge base of Expert systems.

The financial sector has some characteristics that make the advent of modern AI developments exciting and compelling. The first is the availability of a vast amount of good-quality data as compared with other sectors. Second, many of the markets in the financial sector have prespecified rules and are nowadays significantly automatised. Third, the enormous value at stake in the financial sector makes even the tiniest efficiency improvement extremely valuable and profitable. Digitalisation, market organisation, and the large financial values have produced an environment that fits very well with the adoption of algorithms in general and with AI solutions more recently.

As seen, AI applications in the financial sector vary substantially, and as a consequence, also the types of algorithms used. In some cases, the speed of processing and automation of decision-making is essential, such as trading in organised financial markets. In other cases, the ability to embed alternative data sources is important, such as using an algorithm in use at least from 2015 for lending decisions where the ultimate steps may remain in human hands. Since at least 2017, NLP is the standard approach for a virtual assistant for interacting with clients, shifting the balance from human relationships - a traditional banking model - to robot-client interactions. Since many of the data sources in financial service applications contain personal information, edge computing (also termed federated computing) is now seen as an approach to preserve privacy to sensible data. Recommender systems are in use for financial advising since at least 2016.

1.6. The AI tech added-value: experts vs. learning algorithms

The limitations of Expert systems in applications for financial operations should not be a surprise. Finance is an activity where building a knowledge base is particularly difficult. The population of individuals is vast and diverse, and the different applications vary considerably, so that the maintenance of Expert systems resulted being very expensive. The complex coding needed with rule-based Expert systems was particularly complicated.

What is more, the value of directly learning from the data, as in modern ML libraries, is substantial for financial services, and this explains the enthusiasm that welcomed the last wave of AI in financial markets. Another desirable feature of ML for financial markets is identifying unknown patterns and relations in environments where solid models and theories are not available, which is often the case in financial markets. In these cases, unsupervised learning approaches such as Reinforcement Learning are also effective for exploring and experimenting, collecting the following data, and autonomously identifying the best trading strategy.

In specific applications, such as predicting the price of financial assets, the flexibility of ML is an enabling factor. Financial time series are highly non-linear and noisy. Rather than using linear models, as in some traditional regression analyses, ML techniques such as deep learning models allow capturing the non-linear relationship between crucial variables with little prior knowledge from the data. As discussed next, this does not come without drawbacks, such as overfitting and the inability to identify fundamental structural breaks of the underlying economic conditions. Another advantage of modern AI for financial markets compared to previous “hard-coded” approaches like Expert systems is integrating with alternative data sources. There are already applications that factor-in textual information, such as financial news and reports and social networks (Chan and Chong, 2017).

AI systems used to predict prices of assets now often involve (at least) two modules. For example, one module or a random forest is trained on past data about related assets and then predicts asset price changes. This is often dubbed the market-model module. Then the predictions are passed to the trading module that implements the trading decisions based on the realisation of certain observed conditions. This is a common approach that has some limitations, however. The predictions transform into decisions that do not necessarily reflect the objective or current constraints (e.g., liquidity) of the trading entity. This approach can be improved using Reinforcement Learning, in which case the algorithm merges the learning of the model and the implementation of the decisions. This approach is also practical as it requires explicitly specifying the objective and the constraints of the trading entity[11].

[11] For recent applications of Reinforcement Learning in financial markets see Carta et al. (2021).

2. OPPORTUNITIES FOR AI AND APPLICATIONS TO THE FINANCIAL SECTOR

This chapter discusses the advantages and benefits of the applications discussed in chapter 1. Some "success stories" will be illustrated where AI shows its full potential. The next chapter instead considers the possible issues of these applications.

2.1. Efficiency for financial markets

AI applied to trading in organised financial markets (e.g., securities, derivatives, and commodities) has been one of the first comers in finance. The potential gains in terms of efficiency are significant and given a large amount of wealth traded in these markets, even the tiniest increase of earned margin can have a considerable impact on profitability. Thus, it is no surprise that these sectors are hiring intensively and the best AI experts, apparently more than Bigtech companies. And the windfall of AI is not only on the profitability of adopters, as more efficient financial markets transform into real growth.

AI applications for organised financial markets also have other sources of efficiencies. Compared to humans, AI algorithms do not experience fatigue, do not make computational errors, and are not subject to the multitude of human biases (Keynes' "animal spirits") that have been documented in the behavioural finance literature. AI algorithms are faster and can rely on many and alternative sources of data at the same time. Other efficiency gains also emerge with autonomous AI algorithms freeing humans from repetitive tasks, giving them the possibility to focus on higher-level tasks to develop the financial sector.

The margin of increase is vast as "quant funds" (that is, funds that rely on algorithms for predictions and trading) still manage a tiny fraction, slightly above 1%, of the global equity market ($72 trillion in 2019, see Shepherd, 2019). It has been estimated (Statista and PwC 2020) that this increase in productivity in the financial sector could account for up to 10% in terms of GDP in the next decade, although these are speculative estimates (see, for example, Beck et al. 2000).

In terms of performance, there is some (early) evidence that in recent years AI-managed hedge funds outperformed traditional funds by a significant margin, also considering risk-adjusted performance. A recent report (Cerulli, 2020) has shown that in 2016-2019 the return of hedge funds in Europe that were relying on AI was significantly higher than with traditional funds. There is also increasing academic literature that compares AI algorithms with traditional models to predict asset prices. For example, Chowdhury (2020) shows that "ensemble learning" AI algorithms based on multiple approaches outperform the traditional Black-Scholes method.

Currently, it is too early to assess the ability of AI algorithms for trading to make accurate predictions when an unexpected crisis realises, such that the one induced by the Covid-19 pandemic. However, some commentators (Cerulli, 2020) claim that AI can improve predictions in this event compared to traditional and human-based approaches. If confirmed, this could be the consequences of two ingredients of AI trading algorithms. First, they dynamically update their prediction modules to current events and continuously adapt to changing market conditions. Second, they rely not just on financial market data but also on alternative data sources. Some hedge funds actively use information from news articles and social media, and these alternative sources of data could have been effective in responding faster to an unforeseen and rare crisis like the Covid-19 pandemic.

2.2. Access to finance

Individuals and firms relatively less known to financial institutions and markets have difficulty accessing financial services, causing inefficiencies and is a source of inequality.

When only limited information is available on prospective borrowers, financial institutions cannot identify worthwhile projects (e.g. innovation with an Small and medium-sized enterprise or education with a household). Pooling several less-known projects together, good and bad projects, they can only offer average and unfavourable conditions. These conditions turn out to be particularly adverse for those who have good projects, which may then prefer to exit the financial market altogether, leaving only the bad projects. The Nobel prize George Akerlof proposed this vicious cycle to explain market failure due to lack of information in a famous paper in 1970 (Akerlof, 1970). Although the problem of "asymmetric information" is not specific to the financial sector (Akerlof's example was about the second-hand cars market), its consequences are dramatic when applied to finance. Not financed valuable projects mean wasted opportunities for individuals, firms and loss of growth.

According to the World Bank (2017), 1.7 billion adults (that is roughly one-third of the entire world population) were "unbanked" in 2016 and could not access even the minimal and essential bank services. Specifically, when considering the credit market, with traditional credit scoring rules, a potential borrower must have a sufficient amount of historical credit information so that a solid score can be calculated (in this case, the borrower is called "scorable"). When a score is not available, a potential creditworthy borrower is often excluded from the credit, which perpetuates the "unscorability" of the individual and hinders access to credit for the future.

Improving access to financial services is one of the most significant contributions one can expect from AI for the financial sector. AI has enormous potential in addressing this issue because it allows us to better extract information and from multiple sources of data. Some Fintech firms have started to leverage AI precisely to this end and can now target customers that traditional financial institutions, such as banks, would not serve because of lack of information.

The advantage of AI applied to financial services access is even more evident in economies, like less developed countries, where the financial sector is still incomplete. In these countries, many potential users who had no access to financial services, thus having "thin" financial history, are likely to remain excluded. For example, in China, an enormous market for credit, many borrowers do not have credit scores but are now served thanks to Fintech.

Fuster et al. (2021) show how ML can affect credit using a large dataset of 10 million mortgage loans issued between 2009 and 2013 in the US. The authors compare the predictions based on traditional statistical methods used for credit assessment (e.g., standard Logit models) with those that could be obtained with ML, such as Random forest. These authors observe that when deciding about a borrower's creditworthiness, ML benefits more those groups of individuals that are typically disadvantaged, thus granting more access to credit.

Gambacorta et al. (2019) study how AI can improve in estimating the probability of default on credit by a Fintech company in China, also using traditional and non-traditional variables. They also show that the more information is fed into the algorithms *via* a longer relationship with the credit institution, the better is the advantage of AI systems.

The possibility of leveraging alternative data sources, such as emails, purchase activity, and social media, is a significant advantage of AI algorithms. It can give sufficient information to "kick start" a creditor's history and give access to financial services. In computer science, this is often referred to as the "cold start" issue: when there is little or no information, predictions are imprecise or impossible[12].

Overall, AI can be a democratising tool for accessing financial services for individuals and firms that would have been otherwise excluded.

2.3. Fight against fraudulent and illegal exchanges

Fighting fraudulent financial transactions takes a considerable amount of resources in the financial sector and induces significant inefficiencies. Just considering credit card transactions on cards issued in the European payment system, the European Central Bank (ECB) (2020) shows that in 2018 the value of fraudulent transactions amounted to €1.80 billion in 2018. Financial institutions are responsible for monitoring and reporting illegal transactions, such as money laundering and financing terrorism. The FCA in UK reports that UK banks spend £5 billion yearly to address financial crime, and the figure rockets to $70 billion for compliance expenditures by US banks (Buchanan, 2019). The World Economic Forum (2018) survey in 2014-2016 shows that most financial institutions reported increased costs in fighting fraudulent and illegal activities and an increase of 246% in global credit card fraud loss from 2012–2017. Failing to meet financial crime requirements, US financial institutions were fined $12 billion in 2009–2015.

The advantages of AI in fraud detection are twofold. First, AI tools, in this case in particular ML classifiers, can quickly detect suspicious transactions. This ability relies on real-time analysis of vast amounts of transaction data, millions of transactions in fact, in a short time frame. Fast processing is fundamental as transactions require real-time approval, especially with cards and POS. Second, the quality of predictions obtained with ML allows to better control the two typical errors in identifying fraudulent financial transactions: false negatives and false-positive cases. In the former cases, the problem is that the system wrongly classifies a fraudulent transaction as non-fraudulent. In the latter, instead, a non-fraudulent transaction is classified as fraudulent and then wrongfully denied. Both types of errors are costly for the banks and the clients. The less obvious false negative is responsible for $118 billion losses in retail worldwide in 2015 for wrongly declined transactions (Javelin, 2015). Thanks to the large amount of historical data, credit card transaction monitoring with AI tools is already quite common and successful in detecting fraud. ML instead allows speed-up the process, performing it in real-time with self-adjusting rules that automatically adapt to new data and identify hidden correlations.

Anti-money laundering has proven more challenging to apply AI due to the relatively limited amount of data to train ML algorithms so that many financial institutions still rely on traditional methods. However, recent academic research (Zhang and Turbey, 2017) has recently shown some successful applications of AI algorithms (in particular Artificial neural networks (ANN), support vector machines, and random forests) that outperform classical logistic regression models, at least when training data contains a relatively high frequency of illegal activities.

Interestingly, ML helps predict fraud by managers, such as stock market manipulations (Hoberg and Lewis 2017 and Cecchini et al. 2010).

Overall, AI can significantly improve financial market integrity and strengthen trust, a vital ingredient of the financial sector.

[12] Interestingly the flow of information can be two ways, between financial institutions and players in other sectors. For example, Barclays and Amazon have setup a partnership with the intention to merge data in order to have better tools to predict decisions for credit approval and consumers' needs.

2.4. Customised services

Customisation and personalisation of financial services, as in any other activity, creates value for clients, individuals, and corporations, and financial intermediaries as well. However, until recently, the personalisation of financial services has been an option only for clients with large portfolios and wealth. The reason for this is straightforward from an economic viewpoint. Personalising financial services implies relatively high fixed costs associated with the necessity to learn about customers' preferences, their actual conditions, and needs. These fixed costs prevented the possibility to offer customisation of financial services at large, thus excluding SMEs, individuals, and households with relatively small savings.

AI is about to change all this as some of the AI tools, particularly ML and Recommender systems, are very effective in identifying individual preferences and contingent needs. With AI, the fixed cost for predictions moves from an individual client-level to the fixed cost of developing the AI systems that are then used for predictions on many clients. The possibility of sharing the fixed costs of developing AI systems over many clients opens up an unprecedented opportunity to offer customised financial services that were in precedence reserved to the wealthiest.

A notable example is Robo-advising for asset management. Financial advising performed by humans is a time-consuming and labour-intensive activity. Asset management, in particular, involves asset allocation identifying the target assets, cost-effective implementation, regular rebalancing the portfolio, "behavioural coaching" (e.g., advising to avoid emotion-driven decisions), and tax planning. These activities can be addressed with AI tools, combining ML and Recommender systems. Some of the currently most successful Robo-advising platforms offer their services with €0 account minimum balance, meaning that they are accessible to any individual, and some of them have their base service offered for free (earning some fees on more advanced services).

Another potential advantage of Robo-advising compared to human asset management is the fiduciary relationships between the investor and the advisor. Cases of asset managers' misconduct abound, such as financial advisors appropriating clients' funds or steering investments towards those granting the advisors with higher commissions and unauthorised trading decisions. In principle, a Robo-advisor may be immune from this type of conduct. As discussed in the next chapter, Robo-advising is not free of risks either, but what matters here is the comparison with humans.

The entire industry of asset management can thus benefit from Robo-advising, building, and in some cases restoring trust with clients.

2.5. Fintech developments and market structure

The Financial Stability Board (FSB) defines Fintech as "*technologically enabled financial innovation that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services*"[13]. Fintech players have been expanding in recent years in payments, lending, asset management, and insurance. The current success of Fintech is due to its ability to exploit AI technology and Bigdata, reducing fixed costs, search and matching costs, and increasing the quality of their predictions.

It is currently unclear which trajectory Fintech players are taking and their impact on the financial industry in the long run (see Barba Navaretti et al. 2017). For the present report, it is instructive to observe that Fintech companies currently use a pure-intermediation activity, leaving most of the risks

[13] See https://www.fsb.org/work-of-the-fsb/financial-innovation-and-structural-change/fintech/.

with the trading parties. For example, in the case of lending, Fintech often uses the "agency" model (or broker model), according to which they only perform the matching between borrowers and lenders, receiving a commission, but take no risk for the loans that they originate. All risks then remain with the investors and not with the Fintech.

Another notable development that Fintech players are actively pursuing with their technologies is dealing with "soft information". Typically, financial intermediation relies on two types of information. "Hard information", e.g., clients' payments, transactions, and assets, is codifiable and easily digitalised. This type of information can be seamlessly shared across departments within financial institutions and analysed. However, financial intermediation relies on "soft information" that cannot be easily digitalised and is yet very important. For example, a bank branch manager typically would be able to assess the creditworthiness of a client owner of a local SME. Based on experience and personal interactions, the bank's manager can subjectively assess that the SME's owner is a "good entrepreneur" and should then have access to credit. This type of soft information is the basis of "relationship banking". It is not codifiable and less so transferrable in its entirety. Some Fintech firms are developing NLP tools that rely on alternative datasets to transform soft information into hard information. The effect on the cost structure of financial intermediation of this transformation can be significant, reducing the fixed costs of personal interactions between the intermediary and their clients.

The lean approach for financial intermediation of Fintech, together with the mentioned reduction of fixed costs, are the two key factors facilitating Fintech development in the financial sector. This process is valuable not only for the new opportunities that will offer to clients and the efficiency gains but also for the change in market structure that it may induce. Philippon (2016) has convincingly illustrated that the financial sector has remained expensive for its clients, with fees that, adjusting for quality of services, remained surprisingly unchanged over the last century both in the US and Europe. The heavy regulation of the sector has undoubtedly contributed to freezing the financial sector's market structure with very few new players and unchanged competition. Fintech could be instead a critical novelty that can make the financial sectors more efficient and more competitive. With this respect, it is instructive to see that most traditional banks, with few exceptions, have been relatively very slow in adopting AI. One could say that at the moment, these traditional players have been forced into AI, more as a necessity to cope with the arrival of entrants, than willingly embracing the technological innovations offered by AI.

The arrival of Fintech and the associated pressure on all the financial sector is a unique opportunity to move the sector to a more efficient and competitive status with possible substantial benefits for its clients.

2.6. Regulatory compliance

Financial institutions are subject to many regulations with high compliance costs. Financial sector regulations include rules aiming to protect consumers from fraud, discrimination, and abuse, reducing the risk of failure of single institutions and promoting the financial system's stability (see Box 1).

For example, one could consider the set of standards identified by the Basel accords as a simple (yet imperfect) measure of the intensity and extent of regulation in the banking sector. These rules went from the 60 pages of Basel I in 1988 to the 616 pages of Basel III in 2010. Härle et al. (2010) calculate that to comply with Basel III, a medium-sized bank would need from 100 to 200 more workers. Dahl et al. (2016) show that regulatory compliance accounts for 8% of all (non-interest) costs for small-sized banks and 3% for medium banks. These are billions of euros.

Although some regulation of the financial sector is necessary, the regulatory burden on financial institutions is heavy, both in terms of systematic assessment of own activities and fines incurred for non-compliance. The highest regulatory costs on the side of institutions are operating costs, costs incurred to comply with the regulations, and opportunity costs [European Systemic Risk Board (ESRB), 2019]. The most relevant operating cost is skilled staff trained explicitly to review procedures and applications to the regulators. On the side of authorities, there are substantial costs too in supervising financial institutions to assess to what extent they comply with the regulations. Opportunity costs are instead the costs of business opportunities that are foregone because of the regulations. Regulations may make certain activities comparatively more expensive for the financial institutions, preferring to avoid them and move to less expensive but possibly less valuable ones. These regulatory costs may also affect the market structure of the financial sector. For example, shadow banks (and, to some extent, Fintech companies) can profitably operate in certain activities (e.g., peer-to-peer lending) because they are not subject to the same regulatory burden on these activities as traditional banks.

Regulators and supervisors of financial institutions are generally aware of the regulatory burden and avoid overburdening with regulations. AI and automation offer novel possibilities for regulators to put financial institutions in the conditions to comply with financial regulations at a lower cost. Interestingly, AI can significantly help this, with developments in regulation and supervision, named Regulatory Technology (Regtech) and Supervisory Technology (Suptech) (Ehrentraud, 2020), and that involve the use of innovative technology, notably AI and big data analytics.

With Regtech, regulators can frame and implement regulations so that compliance on the side of the financial institutions can be standardised and automated and, similarly, for supervisors who can then automate the verification of compliance. A simple yet effective example is the standardisation of information collection into prespecified templates that financial institutions can populate over time with automated routines and that supervisors could access through properly designed API interfaces. The FCA in the UK explores the possibility of machine-readable regulatory handbooks that could allow financial institutions to interpret and execute regulations (Citi, 2018) automatically.

With Suptech, authorities can effectively perform supervision, for example, using ML to detect anomalous patterns in market outcomes that may signal misconduct and excessive risks. AI offers the possibility to design "screening algorithms" that systematically and continuously monitor financial markets identifying risks and manipulations, with a better balance between false positive and false negative than humans. The Netherlands Bank, for example, uses automated analysis of orders and executions of banks to identify funds transferred to the same recipients via different routes in high-risk jurisdictions. The ECB has set up a Suptech Hub connecting many stakeholders and national supervisors and developing an NLP project for unstructured information analysis. The Division of Economic and Risk Analysis of the SEC in the US and the Monetary Authority of Singapore study ML "screens" to detect misconduct and frauds in stock markets[14]. In these applications, a two-stage approach is often adopted. With a first activity regularly taking place, unsupervised AI algorithms scan markets looking for general patterns. Once anomalous patterns are flagged out, supervised ML algorithms step in to predict actual risks.

2.7. New opportunities and jobs

The question about the impact of AI in labour markets has ancient roots. It goes back to the old debate of the possibility to substitute human labour with machines (possibly beginning with Plato's Phaedrus, ca. 370 BC, where it was claimed that writing would have displaced human memory). It is undoubtedly

[14] For other examples of Regtech and Suptech applications see Ehrentraud et al. (2020).

the case that automation can and will substitute human labour in certain activities, and this will also happen for the automation associated with AI. This substitution process will be dramatic for the displaced workers and must thus be managed with suitable policies. For example, Grennan and Michaeli (2020) study the effect of AI on the financial labour market, in particular on sell-side equity analysts, a job increasingly taken over by AI. They show the following: AI intensity used in the analysts' company negatively correlates with analysts' employment, analysts are more likely to drop the analysis of stocks with high AI intensity, the best analysts either move to stocks less covered by AI or leave the profession. At the same time, AI will demand new jobs and create job vacancies at a rate that currently AI education may not be able to fill.

The financial sector, in particular, is labour-intensive, and the impact of AI on its labour force can be strong but difficult to predict. On the one hand, AI and automation will substitute the typically repetitive and time-consuming tasks in financial services, such as screening and monitoring customers and their accounts, complying with regulations, assessing markets, and performing transactions. Also, very labour-intensive activities, such as those associated with "relationship banking" and soft information, will be soon performed by AI. For example, GIS-Liquid Strategies and asset management company was managing assets worth $13 billion with just twelve employees in 2016; the financial market analysis company Kensho, established in 2013 and then acquired by Standard &Poor's, was founded with the precise intention of completely substituting human analysts (Buchanan 2019). On the other hand, AI is already creating new services and new companies and attracting new customers, and all these new activities are expected to create new jobs.

The overall and net effect of AI on jobs in the financial sector is currently unclear, and estimates are speculative at the moment. Although in our opinion, the most likely scenario for the next 5-10 years is an approximately zero net effect[15], it is important to emphasise again that a significant number of workers will be displaced from the financial sector, and appropriate policies are in order.

[15] Buchanan (2019) reports estimates for the financial sector with 230,000 job reduction worldwide by 2025, especially in asset management. However, these estimates apparently do not to account for job creation and seems thus significantly biased. The report on AI by Statista 2019 indicates a plausible close to zero net effect on labour force in financial services.

3. CHALLENGES

As already evident in some of the cases analysed in chapter 2, AI will inevitably bring significant challenges for the financial sector in parallel with benefits. When an AI algorithm goes from the status of academic research to market applications, new issues emerge that were absent in the abstract research environment. Two factors tend to make these issues possibly more challenging. First, some of the issues are novel because AI technology and its applications are relatively new. Second, solutions generally require a combination of AI-specific skills and sector-specific ones.

3.1. Adoption hurdles

The fact that AI is already available as a technology for the financial sector does not imply that effectively adopting AI for market applications is simple. The survey of the World Economic Forum (2020) clearly shows that two main problems stand in-between AI and market application, according to the majority (80%) of interviewed. The first is the lack of adequate data, both in terms of quality and amount. The second is the lack of AI-related skills for fast-growing labour demand. Other potential issues such as cost of hardware/software, market uncertainty, and (at least for the moment) the regulatory burden seem less relevant.

The performance of AI applications in finance, in particular, relies on data that in the financial sector tend to be more available than in others. However, as seen, the full potential of many AI applications also relies on the combination with alternative data sources that remain relatively scarce and not well integrated with standard financial data. Then we know that the proper choice of the algorithm is essential, and here the diversity of financial applications and tasks require a thorough screening of the best options (Onay and Öztürk, 2018). Finally, the skills of the staff working on the AI systems and their familiarity with the financial applications are determinant (Aziz and Dowling, 2019). The scarcity of AI-related skills is a global phenomenon, but the situation in Europe is worse than in other countries, both for training and in retaining young people with AI skills. Bruegel (2020) shows that Europe lags in terms of the number of AI-related bachelor's and postgraduate degrees, and the gap with the US has increased.

Overall, combining rich data with good algorithms and staff turns out to be complex, and the risk of falling short of expectations is significant.

Another hurdle comes with the difficulty that traditional financial businesses have in adopting AI approaches and integrate or substitute them with pre-existing solutions. Even if the changes seem relatively limited and confined to the algorithm to use, such as moving to ML algorithms for credit card fraud detection, the new process may require different skills and significant re-organisations.[16] When AI also implies the automation of tasks and substitution of the human workforce, the resistance to transformation can be so strong that either traditional financial institutions fail to adopt AI or adopt it with external acquisitions. This is one explanation of the many Mergers and Acquisitions of small AI-focussed startups observed in the last 5-10 years by traditional financial institutions such as banks and hedge funds.

Finally, although specific regulations of AI applications are rare at the moment, financial institutions must already ensure that their AI systems comply with the many sector-specific regulations, as discussed in the following sections. For this purpose, a financial institution that decides to adopt an AI system must monitor it, grant some minimal transparency and documentation of the system's activity,

[16] For the difficulties with this specific case see Butaru et al. (2016).

which may be difficult in the case of AI. This hurdle will most likely increase with the advent of horizontal regulations of AI.

3.2. Unfairness and discrimination

ML algorithms based on specific datasets may lead to decisions that can be considered unfair and discriminatory. In financial markets, this has been shown, for example, with lending decisions. Applying AI tools to the US mortgage market, Fuster et al. (2018) have shown unequal treatment across different groups of potential borrowers. AI-powered algorithms predicted a higher probability of default for minority racial groups than more traditional logistic models. In the case of pricing, this prediction would imply charging higher interest rates to these categories. Furthermore, this result occurs with AI algorithms that strictly comply with anti-discrimination laws and do not use sensitive variables such as gender, ethnicity, or religion of the borrowers. The AI algorithms were de facto able, using non-linear combinations of other variables such as income, credit scores, and loan-to-value ratios to recover the information that a given borrower belonged to one of these protected minorities.

The careful reader has indeed noted that these authors were already discussed in section 2.4. On that occasion, it has been emphasised that the AI systems increased these minority groups' probability of access to mortgages. This is a clear example of the complicated trade-off associated with AI systems in financial applications. The AI system offers more access to some financial services than traditional approaches but at discriminatory conditions. The policy assessment of this outcome is not trivial, as further discussed below.

Unfair decisions can also emerge because they are already contained in the dataset that the AI algorithms used for training. This possibility is even more relevant when considering that AI in financial applications often factor in non-financial information from alternative datasets. For example, in peer-to-peer Fintech credit platforms, a higher probability of credit is granted when some unverifiable information is made available on the platform, such as a photo of the loan seeker (Duarte et al., 2012) or specific friendships (Lin et al. 2013). However, the market has not remained inactive with these discriminatory and unfair outcomes. For example, Zest Finance, one of the top startups embracing AI for financial markets, has developed a tool that helps borrowers identify and exclude from their credit applications signals that concur with biased credit decisions.

3.3. Market interactions of AI systems

When discussing AI systems, one tends to neglect that these systems need to interact with humans, a possibly tricky partnership, but they typically interact with each other. Interactions between autonomous machines are currently the subject of one of the most recent research fields on AI, multiagent systems. If dealing with an autonomous AI system is complicated, having many of them interacting and learning is more so, with possibly unexpected outcomes. This is even more relevant for the financial sector, where interactions between different players are the norm, as discussed previously.

A critical case in financial markets where this type of interaction certainly takes place is pricing and trading. Organised markets have seen early applications of algorithmic decision-making. An AI trading algorithm is specifically designed to set the price for the trader in some environments together with desired quantities to trade, and the market responds with market-clearing exchanges. In normal competitive conditions, sellers should try to attract buyers with competitive and lower prices. However, sellers may prefer to avoid this competition that erodes their profits and instead agree to collude, not reducing their prices. Although collusion between human traders has been largely documented in financial (and other) markets, it is not an easy outcome to organize[17]. Each seller has a unilateral incentive to renege the collusive agreement and secretly undercut others' offers. This intrinsic instability of cartels makes them fragile and requires typically that colluding firms explicitly exchange (coveted) proposals and promises to establish and maintain the agreements. These explicit collusive interactions are also what authorities typically gather as evidence against colluding firms in antitrust cases.

In recent research, Calvano et al. (2020a, 2020b, 2021a) have studied the outcome of market interactions of AI pricing algorithms that autonomously learn what pricing strategy to use. Interestingly, these authors have shown a stubborn ability of Reinforcement Learning algorithms to learn to charge high prices. What is more, they have also shown that sophisticated pricing strategies support these high prices. The strategies that the algorithms autonomously learn contain implicit and tacit threats of punishment that make the decision to undercut rivals unprofitable. It is as if the strategies learned by these algorithms contained announcements of the type "*I'm ready to charge a high price if you also do so, but the moment you undercut me, I'll punish you with a price drop. So watch out, and let's avoid price wars*."

Notably, this robust collusive scheme is obtained by algorithms autonomously and with no explicit communication so that market authorities would have no evidence of agreement at all. The fact that the algorithms arrive at the collusive agreement autonomously and silently may imply that the companies using these algorithms (and their programmers) could not be considered responsible for the collusive outcome, at least under the current legal environment.

3.4. Explainability of AI

A general challenge for humans with AI is to keep up with its increasing sophistication. AI tools such as Deep Neural Networks or Reinforcement learning algorithms are complicated pieces of software. Coders themselves may fail to understand the actual functioning once the algorithms have autonomously learned from data and experience. This is called the black-box or explainability issue of AI and refers to the ultimate difficulty to explain the predictions that an AI system reaches[18].

According to Bloomberg (2017), hedge funds that already use autonomous AI algorithms for trading are concerned with deploying them in actual markets for the difficulty they may face with explaining the trading decisions to their clients. Lack of explainability can thus also be an issue for adopting AI systems in the financial sector.

The credit market is another environment in which the explainability of autonomous algorithmic decisions is essential. When financial institutions use AI algorithms to make credit decisions, they may fail to explain to their customers, external auditors, and financial authorities. Butaru et al. (2016) illustrate how the adoption of AI algorithms for credit allocation can make the entire process non-transparent and potentially unsustainable.

Overall, for the financial sector, the lack of explainability is not only a problem per se. It can be ultimately so relevant to become a source of lack of trust in AI and consequently limited adoption.

[17] On the Forex cartel, see https://ec.europa.eu/competition/elojade/isef/case_details.cfm?proc_code=1_40135.

[18] There is a subtle distinction between *explainability* which refers to the possibility to understand how an algorithm works and *interpretability* which instead refers to the ability to understand why certain specific decisions have been taken by the algorithm in a given case.

3.5. Privacy concerns and public acceptance

Leveraging alternative datasets is particularly effective for financial applications of AI. However, personal data is often contained in these sources of data, and the fact that individuals may be unaware of these different data sources being pooled together raise privacy concerns.

For example, virtual assistants in use with financial intermediaries rely on a significant amount of information collected with written chats, emails, and verbal conversations. If customers of financial services were aware, they would prefer to have this type and amount of personal information kept private or not even recorded. The trade-off to address here is between the efficiency and profitability of the AI systems and the large amount of data they use to obtain superior predictive performance. Also, the lack of trust in how financial institutions handle such vast amounts of personal data may constrain AI developments in financial services. Public acceptance of AI may remain limited as long as AI systems in finance are non-transparent in the data they use and in their functioning.

3.6. Changing relations with customers and regulators

Some services in the financial sector, notably those offered by banks to their customers, still rely on traditional approaches. Relationship banking is the term that refers to relations between clients and banks that rely on proximity, personal knowledge, and informally shared information. Especially for clients such as depositors, small investors, and SMEs, these relations are likely to remain important for at least the next 10-20 years. After this period, almost all of the banks' clients will be "digital natives" and ready to interact with digital technologies. However, in the meanwhile, the process of adopting AI systems and the substitution of human interactions will occur. The contemporaneous presence of older generations of clients and the substitution of traditional services with more evolved AI services may induce a significant mismatch and relegate some clients to downgraded financial services. The market may respond with small banks focusing on relationship banking and proximity services. However, it has been observed that with the arrival of AI in financial services, small banks may become acquisition targets for larger banks (Barba et al., 2017).

On the other side of the demographic spectrum, there is the risk that younger generations interacting with AI systems will not be completely aware of the functioning of AI systems. It could be a substantial risk, for example, when relying too much on the recommendation of Robo-advisor. Recommender systems, for example, may increase the homogeneity of decisions, which in financial market applications could imply a concentration of risks (Calvano et al. 2021b). The demarcation between practical recommendations and manipulation is, in fact, a thin line.

Interactions could be more complicated also between financial institutions adopting AI solutions and their financial regulators and supervisors. Many competent national authorities have started to develop their Regtech and Suptech tools (BIS, 2020). The risk here is an increase of fragmentation with different and possibly incompatible solutions for the same problems. Lack of international coordination of regulation in the financial services is problematic, and it has been a significant issue in the past. Institutions such as the Bank for International Settlements and the complicated process of the European Banking Union testify to the difficulty and importance of dealing with international coordination on financial sector regulation. The fast and uncoordinated adoption of the Regtech and Suptech tools may take international coordination a step back. This risk is currently real, and Europe should pay great attention and profit from the (uncommon) opportunity to start coordinating this regulatory process at its inception, that is now.

3.7. Risk for stability

Stability is a general concern in the financial industry, and many of the regulations of the sector are designed to increase and maintain stability at the level of a single financial institution and the macro level. Bodies such as the European Systemic Risk Board, the FSB, and the Basel Committee of Banking Supervision have been established to improve financial market stability.

The impact of technologies on financial market (in-)stability is not new and not necessarily related to AI. High-frequency trading has increased financial market instability, as documented by the "flash crashes" of the New York Stock Exchange in 2010 and 2015. In these episodes, stock markets lost trillions of dollars in a matter of seconds as trading decisions were delegated to super-fast algorithms. Interestingly, in some cases (for example, in the 2010 flash crash), the trading algorithms observed unexpected market conditions that they were not designed to deal with and, consequently, reacted erratically.

Financial markets are also quickly reacting to the news with a speed of reaction that with algorithmic trading can become excessive. For example, in 2013, the Twitter account of a famous press agency was hacked and used to report an attack on the White House falsely. The moment this fake news leaked out, high-frequency trading algorithms reacted in a matter of minutes, trading shares for millions of dollars based on manipulated information and taking the Dow Jones Industrial Average index down by 150 points [19].

In addition to the consequence of fast automation, AI systems applied to financial markets can further contribute to instability. These specific sources of risks are a new category and have been noted by financial market authorities (e.g., FSB, 2017). First, most AI systems for financial applications are currently untested for financial crises scenario. Testing in the market can be expensive and itself a source of instability [20]. The relatively limited information and lack of data about AI applications for financial markets in stressed conditions remain a source of concern.

Model testing is essential with AI, especially when trying to address the problem of overfitting. Sophisticated deep learning models contain thousands or even millions of parameters that have to be tuned-in (estimated) with time - and energy - consuming learning sessions that their users may want to avoid. A large amount of parameters and the associated non-linearity in the deep learning models is a mixed blessing. On the one hand, they are responsible for the superiority over traditional methods in fitting non-linear relationships between relevant variables (the so-called Universal Approximation Theorem). On the other hand, this flexibility can lead to the problem of "overfitting". This large number of parameters is determined in the learning phase to fit the market conditions described by the data of the training set. However, these parameters may be unfit for changed market conditions generated by an unexpected, persistent shock. The model then poorly adapts to the new and modified conditions. Overfitting is a well-known issue in computer science and is partially addressed with regularization techniques. However, the problem remains when the novel market conditions differ significantly from those observed in the past. If this happens, the model should be retrained, an expensive process that financial firms using these algorithms may prefer to delay.

Coordinated behaviour may be another source of instability. Herding can occur with AI on different dimensions. For example, it could be the consequence of adopting similar types of algorithms that

19 See https://www.theguardian.com/business/2013/apr/23/ap-tweet-hack-wall-street-freefall.

20 For example, the fund Knight Capital in 2012 deployed in the market an untested trading algorithm that was responsible of a loss worth $440 million to the fund, in just 45 minutes. See https://www.bloomberg.com/news/articles/2012-08-02/knight-shows-how-to-lose-440-million-in-30-minutes.

would then identify common patterns in the explanatory variables used for prediction. This common modelling issue may occur with financial institutions that outsource their AI systems to the same third parties. Or it may be the consequence of the algorithms being trained on the very same data. Overall, this algorithmic herding and the implied model uniformity of predictions and behaviour can produce a new type of interconnectedness in financial markets (Gensler and Bailey, 2020)[21].

AI-specific regulations can become a source of homogeneity as well, to the extent that regulations impose some common characteristics to the AI systems in financial markets and inadvertently lead to model uniformity.

Homogeneity is not only an issue for large traders in organised financial markets. It can also become an issue in other environments, such as when Robo-advisors rely on the same algorithms and the same data sources. Advising uniformly to many, possibly millions of individuals, Robo-advising may create market imbalances that are reminiscent of the phenomenon of route congestion when AI mapping algorithms contemporaneously suggest the same driving directions to many drivers. Whether this is a real risk remains to be verified, as the available results are mixed. Calvano et al. 2021 show that recommender systems in a general environment may increase homogeneity. Using data for asset management in the US, D'Acunto et al. (2019) and Rossi and Utkus (2021) show that Robo-advisor improves risk-adjusted portfolio returns and diversification, in some cases reducing the typical home-bias in portfolio decisions.

A novel source of instability specific to AI systems in financial markets is the so-called feedback loop between the data and the algorithm. AI systems are designed to learn from the data and adapt autonomously. When AI algorithms populate financial markets massively, financial data will incorporate the algorithms' decisions, which will use these data to learn and update their predictions and decision. This is problematic because it creates an endogeneity issue where models generate data used to update models in a cycle that may behave erratically. This issue is just now under the radar of academic research, and little is known at this stage. For example, Malik (2020) has studied ML algorithms that are already used to predict the value and pricing of properties. He has shown that the feedback loop between data and an updating ML algorithm creates a "self-fulfilling prophecy": the ML system overestimates its prediction accuracy, and its (human) users over-rely on the system predictions. The risk of generating bubbles in this way is concrete.

Finally, a particular reference is for shadow-banking intermediaries adopting AI systems representing a specific source of concerns. Shadow-banking activities are very significant (see FSB 2020) but avoid (most of) traditional bank regulations because they do not take deposits. The Great Financial Crisis that started in 2008, has shown that interconnectedness within shadow banking and the links with traditional and regulated banking sector can be a significant source of systemic risk. The adoption of AI in shadow banking should then be explicitly handled. AI systems could be used in shadow banking, both on the side of lending (e.g., assessing the creditworthiness of borrowers) and that of the sources of funding (e.g., designing and issuing collateralised financial credit). One particular source of concern is that, differently from traditional banks, shadow banks are not subject to regulations, and the increase in risk due to AI systems would go unnoticed in this case.

3.8. Cyber-risks

Automated systems in the financial sector expose to risks of external malicious and unobserved manipulation. Some AI-related and specific issues may occur, especially with the manipulation of data.

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[21] The attitude to collude of algorithmic pricing systems discussed in section 3.3 is another example of algorithmic coordination that may lead to interconnectedness.

The academic literature on adversarial ML has shown that ML algorithms can be relatively easily manipulated by altering (or "poisoning") the data that fed into the algorithms. For example, image recognition is a workhorse and well-studied environment in ML, and yet it has been possible to fool sophisticated ML algorithms with data manipulation. In a famous experiment, an ML algorithm that in normal conditions had a minimal error rate (lower than that of humans) was induced to interpret a stop sign as a speed limit sign by simply altering few pixels of the original image and in a way that would go unnoticed to human eyes[22]. The implications of data poisoning for the financial sectors are many and should be kept under scrutiny. This is especially the case when considering that many financial institutions rely more and more on third-party services and they can thus become a target of interest for malicious manipulations.

This type of manipulation is relevant not only for market players, but it may also concern the recent developments of Regtech and Suptech.

3.9. Changing and concentrated market structure

Although prominent players in the financial sector are developing their AI systems in-house (or in acquired and controlled companies), many small and medium players will rely on third-party services. This is a sensible approach that allows these smaller companies to leverage common developments of AI systems and share the associated fixed costs. Fintech companies, for example, often rely on external non-financial providers to perform data analytics. These external companies provide the infrastructure, design and maintain the algorithms, process and store data for many financial and non-financial institutions. In addition to AI systems, third-parties relationships may also involve data-sharing, as in the case of Business-to-Government, Government-to-Business, and Business-to-Business agreements[23].

However, relying on third-parties is a source of risk, as already discussed in sections 3.7 and 3.8, and it is also a source of specific concern. The vertical unbundling or outsourcing of essential tech services makes monitoring and supervision of regulated entities more complicate. Regulations explicitly addressing outsourcing of some activities by financial institutions already exist[24], but problems persist. For example, in the well-known Wirecard case, many subsidiaries of the holding companies relied on third-party operations for AI-related services (see Barba et al. 2020). This structure complicated the supervision of the group, as national authorities could only oversee operations outsourced to third-parties that were incorporated in the same country as the regulator but not in other countries. Although extending regulatory reach can fix this specific problem, the example shows the complications of the changing market organization that AI systems are inducing.

As discussed in chapter 2, AI applications are inducing changes in the market structure of the financial sector that are also desirable. The majority of economists would agree that increasing competition is a desirable fact in general. As seen, the financial sector has been criticised for its limited competition and

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[22] See https://spectrum.ieee.org/cars-that-think/transportation/sensors/slight-street-sign-modifications-can-fool-machine-learning-algorithms.

[23] See Bertin and Néstor (2020). The European Commission has developed an European data strategy that contemplates, among other data sharing between the different actors, see https://ec.europa.eu/info/strategy/priorities-2019-2024/europe-fit-digital-age/european-data-strategy_en.

[24] See the proposal for regulation prepared by the Commission to the EU Parliament and the Council, about digital operational resilience in the financial sector (European Commission, 2020), EBA's guidelines for banks' cloud services outsourcing https://www.eba.europa.eu/sites/default/documents/files/documents/10180/2551996/38c80601-f5d7-4855-8ba3-702423665479/EBA%20revised%20Guidelines%20on%20outsourcing%20arrangements.pdf?retry=1 in the US the FDIC: Guidance for Managing Third-Party Risk (FIL)-44-2008, https://www.fdic.gov/news/financial-institution-letters/2008/fil08044.html and OCC Bulletin 2013-29, OCC Bulletin 2020-10.

staggering costs. However, one should handle with care sudden market structure changes in finance. For example, it is known that increasing competition and reducing profitability in the banking sector may increase banks' failures[25].

Bigtech companies are also ready to enter the financial sector, or they have already done so, as in China, where the Ant Group moved from e-commerce and now offers payment solutions all over the country. The advantages of Bigtech over traditional financial operators are at least three. Bigtech can leverage a large amount of data amassed in different activities such as e-commerce, social networks, and search engines. They already have experience with AI technologies that they have developed in their non-financial markets. Finally, they can rely on significant amounts of funds for their investments in the financial sector. The entry of these new players in not dynamic markets is desirable. However, different from Fintech, Bigtech may induce high market concentration and market power. It is known that digitalised markets tend to concentrate (the tipping-market effect or the winner-take-all issue), and competition authorities have recently started to take action, as with the Digital Market Act and the Digital Service Act of the European Union that address the large platforms or "gatekeepers"[26]. The risk here is that Bigtech players replicate the path of concentration in some financial sector activities.

The impact on concentration and market power of AI developments in the financial sector can also percolate in other sectors, as shown in Begenau et al. (2018). AI analytics in financial markets reduce the cost of capital for large firms more than for small firms, which generates a self-reinforcing mechanism. Cheaper funding enables large firms to grow larger and thus generate more data about their activities. More data, in turn, imply that the financial sector becomes better and better able to predict the returns of large firms than those of smaller firms, thus offering even cheaper financing to the already growing large firms. This is a virtuous cycle for large firms, of course, but ultimately leads to heavy concentration in the real economy.

3.10. Funding AI for the financial sector and in general

Developing AI market applications is currently an activity with an uncertain outcome, thus financially risky. In parallel to success stories, there are many (more) failures.

Financing startups and early-stage companies with high growth potential but high risks require specific sources of funding. A developed stock market can provide some of it but is typically not sufficient and not the best way to finance less known and transparent AI-related startups. Private equity funding, particularly venture capital, is a better approach as few and specialised investors accept the risks because they get involved in developing early-stage activities in exchange for equity.

Another common approach for the growth of AI-related companies is acquisition. Large companies, such as Bigtech, often acquire small tech companies and provide the funding for full development. An example of this approach is the AI startup Deepmind acquired in 2014 by Google and has become one of the most advanced and well-funded companies developing advanced AI applications.

Considering these sources of funding, Europe is not well placed. The equity market in Europe is notoriously under-developed, the market for risk capital is also insufficient, as was discussed in section 1.3, and Europe has no Bigtech companies. For these concomitant factors, Europe is currently in a second line for developing AI applications, as concluded in chapter 1. This situation is not per se a source of risk, but it is undoubtedly a key challenge for the developments and applications of AI in financial markets.

[25] See for example Vives (2010).

[26] For the proposal of the Digital Market Act, see EC (2020).

4. POLICY IMPLICATIONS

In chapters 2 and 3, the benefits and the challenges of AI systems in the financial sector have been discussed. After a background on the regulation of AI in Europe, this chapter discusses the incentives on AI adoption for the financial sector, and draws implications for policies and some recommendations.

An outright ban of AI from the financial service is already unfeasible and would relegate Europe to a marginal role in global financial markets, still exposing European citizens to risks of AI applications managed abroad. Our opinion is that the benefits of developing AI in the financial sector outweigh, and by far, the risks. Once the risks are controlled, which does not mean they are eliminated, AI development in the financial sector should be accepted and incentivised.

It is important to recap a few general points about the financial sector covered in the previous pages. First, the financial sector is a global industry with highly integrated and interdependent markets. Second, it is a heavily regulated industry (see Box 1). Third, some prominent players in the financial sector can count on vast amounts of funds for developing AI applications and innovations. Finally, higher efficiency of financial markets with AI developments generates higher growth, but this does not necessarily imply that all those affected will be better off.

4.1. The regulatory background for AI in Europe

Regulations that can explicitly and directly affect AI applications with consequences for the financial sectors are rare.

In Europe, some pieces of regulation already affect AI applications for the financial sector.

The European Markets in Financial Instruments Directive (Directive 2014/65/EC (MIFID II) prescribes that any financial institution that adopts algorithmic trading must notify the competent authority of its member state and the trading venue[27]. The home member state authority may require details of the algorithms and a description of the underlying strategies implemented with algorithms. The firm must also keep a record of the algorithms that have been used in specific transactions and allow the authority to monitor compliance. For financial asset trading, the exchanges where transactions occur (or trading venues) must fulfil requirements to guarantee the market infrastructure's resilience and cooperate with traders to test their algorithms in simulated environments and provide self-assessment. Also, the European Securities and Markets Authority (ESMA, 2020) has recently launched a public consultation about algorithmic trading[28].

Other regulations that already affect AI in Europe pertain to the use and sharing of data, both personal and non-personal data. First, the General Data Protection Regulation (GDPR) prescribes that individuals in Europe "*have the right to receive an explanation for decisions based solely on automatic processing, such as automatic refusal of an online credit application*". Second, the European strategy for data contains broader regulations or proposals that may affect AI applications for the financial sector, particularly for what pertains to data sharing. Notably, the Open Data Directive, substantially amended in 2019, mandates that data held by public sector bodies must be made available for commercial and non-commercial uses. In particular, the "high-value dataset" (Article 13(1) of the directive), such as geospatial and meteorological data, data about companies, and mobility, are of great interest for many

[27] The European Directive 2014/65/EU, also known as MiFID II (and associated regulation MiFIR) entered into forces in 2014 and are fully operative since 2017. It addressed and harmonised the regulation for investment services, increasing competition, investor protection and levelling the playing field.

[28] See https://www.esma.europa.eu/press-news/esma-news/esma-consults-impact-algorithmic-trading.

applications, including the alternative data set used in finance, as seen in the previous pages[29]. The European Commission is promoting the sharing of data, in particular non-personal data and between companies (e.g. the so called business-to-business data), which would profoundly impact the use of these data for AI applications in finance and other sectors. During the preparation of this paper, the European Commission has released (April 21st, 2021) its new proposal for broad and horizontal regulation of AI, EC (2021), which is the outcome of a series of steps and analyses of the European institutions representing a unicum in the policy of AI[30].

The Commission's proposal is important and innovative. Although this is not the place where to give a complete review, the most relevant implications for the financial sector will be discussed.

The proposal relies on a risk-assessment approach according to which AI applications should be regulated to the extent they generate risks. It intends to introduce a list of banned AI applications, another open list of high-risk applications that are subject to significant new regulations, and other AI applications about whom the proposal encourages the use of codes of conduct.

In the case of high-risk applications, the regulation requires that AI users must guarantee (i) adequate risk assessment and mitigation systems; (ii) high quality of the datasets; (iii) logging of activity to ensure traceability of results; (iv) detailed documentation for authorities to assess compliance; (v) clear and adequate information to the user; (vi) appropriate human oversight measures to minimize risk; (vii) high level of robustness, security and accuracy.

The proposal explicitly touches upon the financial sector on three dimensions. The first reference to the financial sector identifies creditworthiness as a high-risk AI application because of a significant risk of unfair treatment (Recital 37) and Annex III 5b to Article 6(2)). The proposal also contemplates a waiver on regulations for activities performed by "*small scale providers for their own use*" (Annex III 5b to Article 6(2)), where the reason for this exemption is the small scale of these providers and the presence of some market alternatives.

Second, the proposal acknowledges the complication and need to coordinate with the financial sector regulations and supervisory activities. In particular, it specifies that when AI systems perform regulated financial services (for lending but not only), the competent authority for the AI regulation should be the financial sector supervisor (Recital (80)). The compliance procedure of AI regulation must integrate into those of financial market regulations (e.g., the European Directive 2013/36/EU on credit institutions and investment firms). Third, to avoid duplications, the proposal allows derogating on some of its requirements for high-risk AI applications when they would be in any case satisfied because of existing financial sector regulations (Recital (80)).

Finally, relevant for the financial sector is the reference of chatbots, virtual assistants, as an application that poses a limited risk and is subject to transparency obligations guaranteeing that users become aware they are interacting with an AI system and can decide to back off.

4.2. Incentivising innovation of AI for financial markets

Public intervention in markets, especially if involving public money and regulations, should always be justified either by the presence of some market inefficiency or by market outcomes that systematically

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[29] Directive (EU) 2019/1024 on open data and the re-use of public sector information. Also the proposed Data Governance Act (EC 2020) aims at extending the Open Data Directive to data subject to protection restraints such as third-party intellectual property rights.

[30] This proposal is part of the European Strategy on Artificial Intelligence that contemplates other documents. The European Commission, issued a "White Paper on Artificial Intelligence - A European approach to excellence and trust", in Feb. 2nd, 2020; in April 2019 the European Commission published its Ethics Guidelines for Trustworthy Artificial Intelligence and in June 2019, a "Policy and investment recommendations for trustworthy Artificial Intelligence"; the EU Commission's High Level Expert Group on Artificial Intelligence issued several reports, see https://digital-strategy.ec.europa.eu/en/policies/expert-group-ai.

and substantially diverge from those preferred by the society. Incentives for AI innovation and its applications should not be an exception.

As seen in the previous chapters, in Europe, the funds for developing AI market applications are limited, mainly because risk capital, such as equity and venture capital, is underdeveloped in the EU. It is not possible to discuss here all the concurrent reasons conducing to this outcome. Two are most relevant for our purposes. First, the high transaction costs associated with corporate failure make risk capital too expensive. Second, pension funds, very active in providing risk capital in other countries like the US, have limited participation in the EU. Addressing these issues with appropriate incentives is possible, but such discussion would take us too far for the aim of the present study. Instead, a more direct and pertinent initiative should further incentivize and mobilize private risk capital for AI by expanding public risk capital to be used for public guarantees and public-private partnerships. The European Union has many such initiatives, such as those run by the European Investment Fund (EIF). This possibility will be discussed in section 4.4, which is devoted to best practices. The point here is that more public risk funds should be made available.

Another essential factor that is particularly scarce in Europe and that should be incentivised is the combination of skills and knowledge about computer science and the financial sector. These are skills in high demand globally, and the European higher education system is providing too few graduates with these skills. The difficulty here could be that individuals may lack information on the job opportunities in these sectors and a general problem of access to a higher education degree. Incentivizing programs providing these skills and enrolment would be thus important, although not sufficient.

The relatively limited supply with the requested skills is composed of highly mobile workers attracted to the countries offering the best conditions, currently the US and the UK. It would thus not be enough to expand higher education programs on AI and finance in Europe. It would be necessary to complement this plan with incentives to intercept this highly educated workforce and creating the best conditions to help them start their enterprises in Europe. It is not an easy task as small financial startups find it difficult to compete in hiring talents with large financial institutions that can offer high salaries and count on funds for long-term and ambitious research projects.

Sandboxing and development hubs for AI market applications are also effective and should expand, as foreseen in the recent Commission's proposal. Pilot programs and experiments overseen by competent financial market authorities should also be promoted[31]. Some interesting proposals for sandboxing and hubs will be discussed in section 4.4.

AI algorithms voraciously rely on data. Fostering access to data is thus fundamental to develop AI applications in the financial sector. The Payment Service Directive II (PSD2) offers an early example of sharing relevant transaction data with simple API interfaces. However, only banks are currently subject to this data accessibility requirement, and nowadays, the financial sector is populated by many new types of players, such as Fintech and Bigtech. None of these players is currently subject to equivalent disclosure requirements. A level playing field approach should be implemented, according to the principle "same activity, same risks, same rules". Data portability is essential in the financial sector, and open access to data should be enforced and expanded (with GDPR privacy compliance) to harness the full potentiality of AI applications in the financial sector.

[31] The proposal of an European Digital lab has been articulated in particular by the French Autorité des marchés financiers in 2020 (AMF, 2020).

The European Union is already promoting competition and innovation in the financial sector and its technological developments[32]. In the case of AI applications, section 3 has illustrated that the impact on the competition of the financial industry is in principle ambiguous. Competent authorities should then closely monitor how the market of AI services for the financial sector evolves, particularly third-party services and cloud computing. Another highly concentrated marker should be avoided, as it happened with many digital markets.

Finally, adequately designed regulations of AI can incentivize its adoption, particularly for AI applications in the financial sector. This sector and its services are relatively complex for its customers, and transparency is often limited. To increase public acceptance of sophisticated AI applications in finance, it is essential to enhance transparency, disclosure, robustness, safety, and security of AI applications in the financial sector. Users' awareness should be obtained, clarifying the strengths of AI systems, their weaknesses, and the efforts to mitigate biases. The presence of AI systems open to an independent assessment of AI applications is one of the most promising approaches to increasing acceptance, as described in section 4.4.

4.3. Recommendations to improve regulatory impact

Here some recommendations are provided that could inform regulation of AI applications. These recommendations are organised with a first group being pertinent for the financial sector applications and a second group relevant for the financial institutions that adopt AI systems. The last group refers to the existing regulations of risk in the financial sector.

4.3.1. General recommendations for AI regulations and the financial sector

1. Regulation of AI applications in the financial sector should consider the characteristics and market failures specific to financial markets. This is further developed in the following list of recommendations concerning financial sector regulations.
2. Regulation of specific AI applications for the financial sector should account for the many sector-specific regulations of the financial market. It is crucial to identify the interactions between the two types of regulations on the financial sector and AI, systematically eliminating fragmentation, inconsistencies, and duplications. Assessing the consistency of these different regulations requires interdisciplinary skills that competent authorities may need to acquire.
3. Related to the previous point, financial market regulators must keep up with AI developments and their applications in the financial sector. This also requires involving new experts with knowledge and skills both in financial markets and AI.
4. Financial regulations generally rely on high transparency and openness with customers and supervisors to the extent that they may clash with the black-box issue of some AI tools and their applications. The way to address this is not by relaxing the standards of financial regulations, which would create a clash between regulations, but granting that AI applications comply and adapt to these higher standards.
5. Encouraging new players in the financial sector should be a priority of any regulation that affects the financial sector, including those related to AI. The financial sector is concentrated with staggering costs of quality-adjusted services (Philippon, 2016). The entry of new players is then a critical modernization factor that should be incentivised and accounted for by

[32] See the Digital Finance Package presented in September 2020, with a strategy for digital finance and crypto-assets.

regulations affecting the financial sector. In particular, AI regulations should avoid stifling entry of new players such as Fintech.

6. Regulations of AI applications in the financial sector should account for the new risks and ultimately rely on a cost-benefit analysis. This analysis is essential for two reasons. First, the alternatives to AI systems in finance are not perfect solutions either (e.g., human biases in creditworthiness assessment are possible, as discussed in the previous pages). Second, the financial sector comprises global markets, and regulations may stifle financial firms' competitiveness. As further discussed below, the financial sector is already subject to effective stability risk and consumer protection oversight, especially in Europe with the development of the Banking Union. It may now be the occasion to push more on innovation, competition which ultimately will benefit financial service customers.
7. When regulating AI in general and for applications in the financial sector, one should constantly assess the incentives to innovate and develop AI market applications, such as measuring the increased costs for AI applications. This assessment is critical during the current phase of experimentation of AI applications for the financial sector.
8. The core set of broadly emerging principles for horizontal regulation of AI (human oversight, robustness and safety, data protection and privacy, fairness, transparency, accountability)[33] is consistent and compatible with the proper functioning of the financial sector and its sector-specific regulations. However, given the complexity of the financial sector and its regulations, financial market competent authorities should be ultimately responsible for assessing to what extent financial sector regulations effectively cope with these principles and how they could embed in sectoral regulations. Such an assessment should be systematic, and it is urgent.
9. As discussed in section 3.7, shadow-banking activities adopting AI represent specific concerns for systemic risk. Since these intermediaries mostly avoid traditional banking regulation and supervision, they cannot be assessed following the proposal of the previous points 5-8. Under the EU framework for financial supervision, the financial market authority for assessing the use of AI for shadow-banking is best suited with the activities of EBA, also because of EBA's responsibilities on shadow-banking and on AI for banking institutions, together with monitoring by the European Systemic Risk Board (ESRB) that monitors the shadow-banking sector in the EU.[34] Specifying the organization of these responsibilities is also urgent.
10. Market applications of AI are still in the phase of development and experimentation, and there must be a substantial degree of flexibility of regulations to adapt to market changes and further innovations. It is also crucial to produce a retrospective analysis of the effects of regulations on AI on the financial sector at a relatively high frequency for a prompt adjustment when adverse and unexpected effects occur.

4.3.2. Specific recommendations for activities of financial institutions adopting AI

1. For financial institutions adopting AI systems, a standalone AI framework seems appropriate where it would be possible to efficiently insulate the functioning of AI tools in case of

[33] See for example in the reports of the OECD see https://www.oecd.org/going-digital/ai/principles/ and those of the European Commission's AI High Level Experts Group, https://digital-strategy.ec.europa.eu/en/policies/expert-group-ai.

[34] EBA (2016) issued new guidelines to limit individual exposures to shadow-banking. The European Commission's Digital Finance Strategy, 24 September 2020, assigns new responsibilities to EBA in particular in relation to AI, digital financial intermediaries and Regtech and Suptech. See https://www.eba.europa.eu/financial-innovation-and-fintech. See also the ESRB 2018 report of shadow-banking in the EU, https://www.esrb.europa.eu/pub/pdf/reports/esrb.report180910_shadow_banking.en.pdf.

malfunctioning. This is essential to grant continuity of essential financial services, especially for payments, lending, and financial markets.

2. AI adopting financial institutions should provide sector regulators with complete documentation of the development process of AI systems for their financial market applications, explicitly reporting information about: *data* (collection, storage, and data preparation including exploration, cleaning, and transformations such as normalizations), *analytics* (in particular model training, tuning, validating, and selection among different models), *operations* (deployment, testing, monitoring, updating).

3. Algorithms should be rigorously tested before being deployed in financial markets (off-market testing), and once deployed in markets, they must be monitored especially checking their learning process and their adaptation to changing market conditions (in-market testing). Specific techniques for AI applications to financial markets should be considered, such as back-testing and dynamic testing[35]. Testing must contemplate: (i) stressed market conditions, (ii) "adversarial" conditions, and (iii) compliance with market regulations. When third parties perform testing, one must account that AI applications are the outcome of significant investments, and developing companies need to protect their intellectual property rights[36].

4. External auditing and testing of AI applications should guarantee three conditions: independence, no conflict of interest, and specific financial market and computer science skills. These are general principles for auditing but are essential in the case of the financial sector, given the substantial economic interests around it. Section 4.4 discusses as this could be done by presenting some practical and relevant cases.

5. When relying on third-party AI services, financial institutions should, in any case, remain responsible for some activities. In particular, they should guarantee due diligence about data (legitimacy of sources, quality, and biases), transparency and explanations to customers, some control over the AI service, and also guarantee some control on the side of financial service customers (for example, opt-out options). Third-party should be responsible for testing and monitoring the algorithms are discussed in the previous points.

6. Financial institutions adopting AI should be active in disclosing their AI applications to their service customers, also improving clients' awareness and knowledge about AI applications. They must consider the information needs of their clients and effectively communicate about AI in line, for example, with credit risk disclosure and investment advice services.

7. When imposing and requiring ex-ante explainability of AI applications for the financial sector, it is necessary to consider that these restrictions may substantially impair the possibility of effectively using AI algorithms for financial applications, especially with self-learning algorithms. Instead, it seems preferable for these applications to require post-hoc explainability, monitoring and assessing outcomes and performances of the algorithms ex-post.

8. Some elements of the internal governance of AI applications should be requested of users in the financial sector, particularly a clear definition of roles, adequacy of skills, and accountability

[35] Back-testing (already in use with quantitative finance) is based on the idea of repeatedly testing the prediction model (for example measuring some prediction error) by retraining it with a portion of the currently available data and test it on the rest of the data that has not been used for training. Another approach is dynamic testing that is meant to validate the application by simulating the use and functioning of the algorithms as it could work in actual applications.

[36] Interesting developments for testing may exploit the idea of Zero-knowledge proofs, a method for verifying some properties of the algorithms without disclosing too many (possibly zero) of its details.

in the decision process. In the case of third-party services and standard due diligence, financial sector institutions must fully understand the terms of conditions with their AI providers and must monitor and internally assess the external AI services they purchase.

4.3.3. Specific recommendations for financial sector regulations of risk

Activities in the financial sector are subject to two broad types of risks: micro or firm-level risk and macro or systemic risks. Accordingly, regulations in the financial sectors can be organised into two groups addressing these two risks, leading respectively to micro-prudential policies and macro-prudential policies. Applications of AI in the financial sectors may have implications for both types of risks and policies.

1. Buffer regulations of financial institutions, such as capital adequacy rules, are designed to absorb shocks and reduce the risk of bank runs. When some relevant decisions in a financial institution are delegated to AI systems with impact on buffers (e.g., using ML for a bank's assets risk assessment in the Internal Ratings Based approach), the systems' robustness should be checked, also benchmarking with other more traditional methods. In the alternative, it may be helpful to consider adjusting the buffers and other micro-prudential regulations for those financial institutions that adopt these AI systems.
2. Related to the previous point, risk models used by financial institutions are often subject to regulatory oversight. This activity should begin incorporating the diffusion of AI applications for risk modelling and address explainability. Currently, the assessment of risk models is based on the description and documentation of the models adopted. With AI models, it seems better to move from this formalistic approach to assessing the outcomes. This is undoubtedly a significant change in the micro-prudential approach that requires collaboration between supervisors and financial institutions. Traditional models for risk assessment could still be used to guarantee benchmarking and backup.
3. For the first years of adopting AI systems, regulations could contemplate redundant and backup systems ready to enter in use if principal AI systems fail to deliver the expected outcome (which could happen for errors and or adversarial attacks, for example). Financial institutions, especially if they provide system-wide infrastructure, should ensure reliable AI systems. Safeguards and redundancy of AI could operate similarly to those for information and communication technologies (ICT) in the financial sector[37].
4. When financial institutions deeply engage in AI applications, they should prepare and share with regulators the "internal mapping" of their AI applications. These mappings should identify interdependencies within the organization that emerge with datasets and algorithms for different applications.
5. Concerning macro-prudential regulations, financial institutions should also provide "external maps" of their use of AI, including descriptions of their dependencies on external sources such as datasets, algorithms, and externally acquired AI and cloud services.

[37] See European Commission Financial services – improving resilience against cyberattacks (new rules). https://ec.europa.eu/info/law/better-regulation/have-your-say/initiatives/12090-Financial-services-improving-resilience-against-cyberattacks-new-rules-. Also the ECB currently sees ICT and cyber risk as a priority one of its key Supervisory Priorities for 2020. The ECB specifically carries out IT on-site inspections and requires some significant banks and operators providing payment systems and infrastructure to report cyber incidents. See a summary of ECB priorities at https://assets.kpmg/content/dam/kpmg/xx/pdf/2019/12/ssm-supervisory-priorities-2020.pdf.

6. Putting together the external maps of AI, competent financial market regulators should build a view of the systemic interconnections of financial activities related to AI applications. They should publicly report on these system-wide dependencies due to AI and, if needed, adapt existing macro-prudential policies accordingly.
7. To avoid model uniformity and its risks (see section 3.7), regulators should propose and allow multiple approaches to comply with regulations.
8. Although Regtech and Suptech initiatives should be welcome, the risk of uncoordinated developments is real, as well as its costs. Some minimal international coordination should be considered, beginning with harmonised definitions and shared knowledge of techniques and approaches (e.g., setting a common standard for machine-readable documentation).

4.4. Examples of best practices

Policies explicitly designed for AI and the financial markets are scant in Europe and the rest of the world. Nevertheless, three examples of policies are illustrated to be considered best practices to follow and further develop.

4.4.1. Supporting factors for AI in the financial sector.

As previously discussed, the scarce factors for developing AI and market applications in finance are the skilled workforce and the capital for investment. Some initiatives are now illustrated that were successful in fostering the availability of these scarce factors.

The endemic limitation of risk capital in Europe is a problem for developing AI market applications, and policy interventions should address it. The European Commission has also emphasised this with the mid-term review (EC (2017)) of the Capital Market Union (CMU). There are already some successful initiatives that should further expand. The efforts in the CMU towards a single European capital market of the European Commission would undoubtedly help increase the availability of risk capital in Europe.

The European Investment Fund (EIF) is a part of the European Investment Bank group and is designed to offer risk capital, guarantees, and lending to support SMEs in Europe[38]. The fund already manages €100 million for AI activities with venture debt contracts[39]. In 2020 the fund launched a new initiative specific to AI (worth €150 million) of co-investments in partnership with private equity funds. This has quickly attracted attention to the setup of 6 new venture capital funds specifically for AI and private equity funds from Austria, Finland, Germany, Luxembourg, and the Netherlands, at an expected overall investment capacity of €700 million.

It is a success story, but it does not surprise that these activities attracted attention, and they are certainly welcome. The lack of private equity funding in Europe is endemic, and markets are eager to finance innovation in AI. The success of this initiative, however, is limited by the dimension of the fund. The estimate is that it would help finance 20-30 SMEs in Europe at the current amount[40]. This is not enough to significantly impact and help Europe regain leadership in AI and market applications. The

[38] See https://www.eif.org/what_we_do/the-eif-in-2020/index.htm.

[39] Venture debt is a type of debt that is granted typically to purchase equipment, even if the company does not currently show significant cash flows nor has assets to be used for collaterals. This debt contract often contemplates warrants on the equipment or the right to acquire equity, in order to compensate for the high risk.

[40] See the press release of the European Commission, March 2021, https://digital-strategy.ec.europa.eu/en/news/new-eu-financing-instrument-eu150-million-support-european-artificial-intelligence-companies.

EIF has a broad mandate, probably too vast, and focusing more of its resources on AI-related activities seems worth considering.

There are other few relevant initiatives to support risk capital at the country level that could help develop AI, such as the German 'High Tech Gründerfonds' and the 'Austria Wirtschaftsservice Gesellschaft'. The German fund, for example, was established in 2005, counting on €900 million. It invested in more than 550 operations (although not specifically on AI), attracting additional private investments for €2 billion.

The other scarce factor for market applications of AI is a skilled workforce. European universities have excellent educational programs in computer science and finance, but, as explained previously, they are insufficient. Education is another case in which public-private partnerships could be effective. An exemplar case is the new Schwarzman College of Computing at Massachusetts Institute of Technology co-financed by the Schwarzman investment fund. Partnerships between universities and the financial industry on AI applications should be explored in Europe as well.

4.4.2. Experimenting with AI in financial markets

Especially in this early phase of market adoption of AI in financial markets, sector authorities should guide with assessments[41]. Some financial market authorities have already issued position papers on AI. It has already been mentioned some in the previous pages, such as the FSB (2019) and the Bank of England (2019)[42]. The European Supervisory Authorities, ESMA, EBA, and EIOPA, issued an early joint paper in 2018 on big data and AI in the financial sector (ESA, 2018).

Although these position papers were important, they should be updated because AI and its financial market applications are quickly evolving. Furthermore, the information they could provide and the guidance would be more significant if they were prepared to collaborate with subjects with specific AI knowledge. This type of partnership between financial sector authorities and centres specialised in AI has fruitfully taken place, such as the collaboration between the FCA and the Alain Turing Institute for AI in the UK[43].

Another interesting case of regulators' engagement is with the idea of sandboxes. Although they spread quickly worldwide (UNSGSA, 2020 and European Parliament, 2020), a clear assessment of these many and diverse initiatives is not available. The success cases are typically those where the authorities also provided a significant amount of resources to monitor the sandbox developments effectively and provide regular guidance and advice. In terms of firms that have entered the sandbox, one of the most successful cases is that of FCA in the UK.

The sandboxing approach relies on the idea of assessing in a controlled environment the consequences of waiving some of the regulations that firms would otherwise be subject to. The sandboxing approach has been spelt out with details in the European Commission's proposal (EC 2021, Articles 53 and 54). A related but different approach is described in De Andrade and Kontschieder (2021), although not explicitly designed for the financial sector. The idea is to testbed specific new regulations about AI and assess their market implications and costs of implementation by directly involving the firms that should live with them. Although the current implementation of this idea has been so far limited to a case study

[41] These reports are useful to the extent they are independent and organically generated by authorities. Delegating the preparation of these reports to external subjects seems much less useful both for the readers and for the authorities themselves in developing internal skills.

[42] See also the earlier paper by the Monetary Authority of Singapore (2018).

[43] See https://www.turing.ac.uk/news/ai-transparency-financial-services.

where only the firms' view was relevant, this is a promising and novel approach that could be extended, including the view of other stakeholders.

4.4.3. Independent assessment of AI

Authorities should play a role in facilitating interactions and the exchange of ideas. The Federal Trade Commission in the US (FTC), for example, organizes showcase meetings for applications and developments about AI, data security, and privacy[44]. During these events, researchers have the opportunity to illustrate to a broad audience some of the issues, for example, on AI and discrimination and possible solutions in specific market applications. These events are helpful on several dimensions. They increase awareness about AI and its market applications by providing "real-life" examples. They help companies use AI to identify specific issues with independent vetting of their activities and propose solutions. Finally, they allow authorities to remain updated about cutting-edge applications of AI.

Independent assessment of AI applications should be incentivised and certainly not opposed. Academic researchers can play a crucial role in this and should access AI systems deployed in the market to test them. In 2020 a federal court in the US had ruled that "*independent research aimed at uncovering whether online algorithms result in racial, gender, or other discrimination does not violate the Computer Fraud and Abuse Act*". These decisions will encourage independent testing of AI algorithms and their interaction with customers in the financial sector[45]. Companies that use AI should consider the benefits of engaging with a transparent and independent assessment of their use of AI. Research centres and universities can play a prominent role in these auditing activities requiring independence and specific skills[46]. Researchers have the expertise for this type of assessment and a reputation at stake. Instead, the typical commercial auditing and consulting solutions may not be adequate for AI applications for the financial markets.

44 See PrivacyCon 2020 https://www.ftc.gov/news-events/events-calendar/privacycon-2020.

45 See https://www.aclu.org/press-releases/federal-court-rules-big-data-discrimination-studies-do-not-violate-federal-anti

46 An interesting example of independent assessment of an AI algorithm initiated by a private company for job market matching is in Wilson et al. (2021).

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This paper studies the transformation that Artificial Intelligence (AI) is bringing to the financial sector and how this sector can contribute to developments of AI applications. The study addresses the contribution of AI to a more efficient, open, and inclusive financial sector and the challenges of the AI transformation, and it provides recommendations for policies and regulations of AI and financial services.

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