BROOKINGS

CASE STUDY | APRIL 2025

AI IN THE FINANCE SECTOR

TRANSFORMING PRODUCTIVITY AND RISK MANAGEMENT

MARTIN NEIL BAILY AND AIDAN T. KANE

AUTHORS' NOTE

Martin Baily led the work on this case study. These case studies were written as part of a joint project with David M. Byrne and Paul E. Soto of the Federal Reserve Board. We are indebted to them for assistance and helpful comments. We would also like to thank Eli Schrag for his factchecking.

The Brookings Institution is committed to quality, independence, and impact. We are supported by a diverse array of funders. In line with our values and policies, each Brookings publication represents the sole views of its author(s).

1. Introduction

The rapid progress made in AI, notably the introduction of generative AI models, has brought a lot of excitement (and fear) about the potential consequences of this new technology. In the finance industry there was and still is hope that this technology will lead to much greater efficiency in an industry that has had a mixed record of productivity and performance.

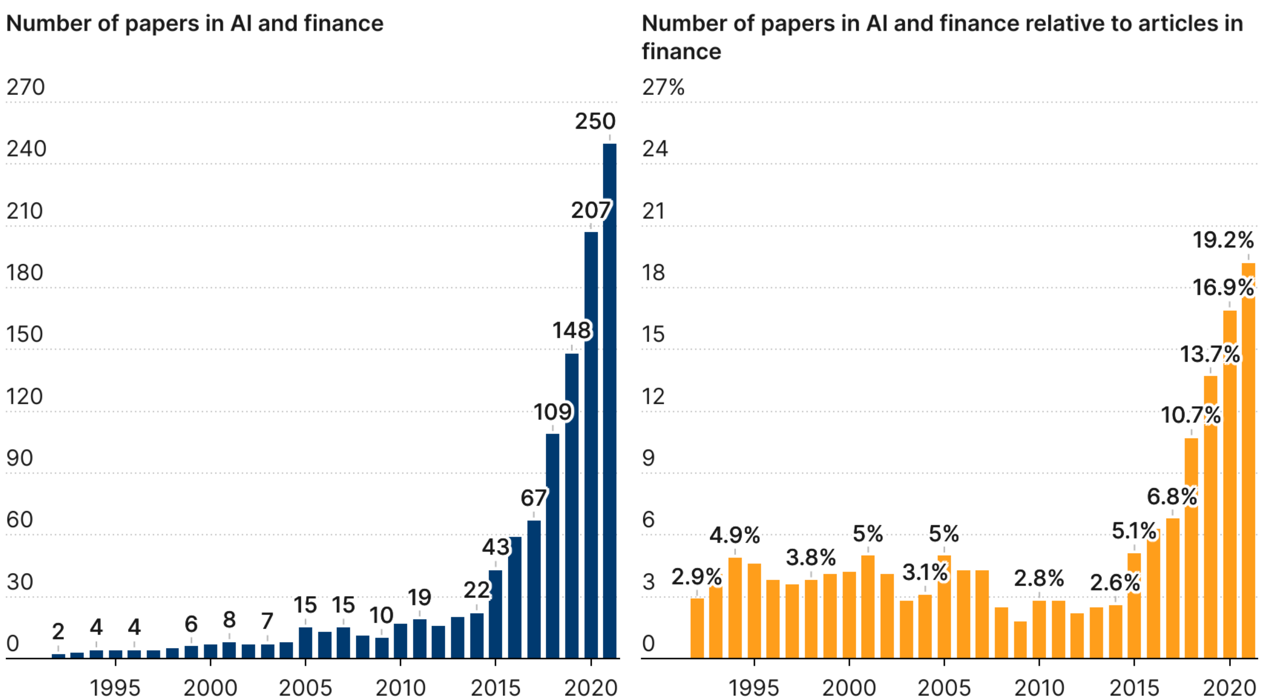
There has been an explosion of research interest in the use of AI in finance, illustrated by the number of articles written about it. There was a trickle of papers back in the 1990s and 2000s, but the number started to take off around 2015 and had jumped to 250 in 2021, approaching 20% of all articles in finance according to Bahoo et al. (2024). It is striking that the uptick in papers preceded ChatGPT and the AI boom. Perhaps the jump from 2016 to 17 was triggered by the arrival of the transformer architecture which enhanced forecasting of financial data (Lezmi and Xu 2023).

The largest U.S. bank, JP Morgan Chase, embraced AI early on and reported in March 2017 that they expected large productivity gains to come. To illustrate, the company said it had found a way to save 360,000 hours of the expensive time of lawyers and loan officers by using a new software called COIN, short for Contract Intelligence, to review and assess the bank's loan portfolio (Weiss 2017).

In this report on AI and finance we will examine some of the ways AI is being used in this industry and whether it will be able to make substantial gains in productivity.

FIGURE 1

The growth of papers on AI and finance



Source: Bahoo et al. (2024)

Center on Regulation and Markets at BROOKINGS

2. Bank productivity prior to AI

The U.S. Bureau of Labor Statistics reports labor productivity growth (output per hour worked) for the commercial banking sector, part of the finance industry, and recent growth data is shown in Table 1.

A distinctive feature of U.S. banking in the 1980s and early 90s was the high number of bank failures, particularly associated with the savings and loan crisis (Hanc 1998). These failures had dropped by the mid-1990s,[1] and it appears from Table 1 that the remaining industry was able to improve productivity at a substantial rate. If the less productive banks had disappeared, that would raise average productivity.

The passage of the Riegle-Neal Act in 1994 had a large impact on the industry. It allowed sound bank holding companies to acquire interstate subsidiaries starting in 1995 and then allowed bank mergers across state lines to be approved starting in 1997 (Medley 1994). After Riegle-Neal, stronger or bigger banks were able to take over smaller or weaker banks and take their business models nationwide. Bank consolidations likely contributed to the continuation of strong productivity growth from 1995-2007, although consolidating back-office functions and coordinating different computer systems reportedly took some time to work through and dragged on productivity (Calomiris 1999; Hunter et al. 1990; Nippani and Green 2002).

There were important changes in technology that contributed to the strong productivity growth from 1987 through 2007, such as the introduction of ATMs and the shift away from paper-based transactions towards electronic transactions. ATMs were introduced first by Barclays Bank in the U.K., while Citibank generated widespread usage in the U.S. when it instituted a $100 million program to make ATMs available everywhere starting in 1977 ("A History of ATM Innovation" 2021; Bellis 2019).

The U.S. banking industry was slow to adopt electronic funds transfer and continued to process very large numbers of paper checks.[2] Holland, for example, largely eliminated paper checks by the mid-1990s whereas U.S. check use continued to rise through 1995 (Baily and Zitzewitz 2001).[3] The U.S. still uses a lot of checks, as Figure 2 shows, although the number has fallen drastically, from a peak of 49.5 billion in 1995 down to 11.2 billion in 2021. Checks are being replaced by credit or debit cards, or by direct debits (when a bill is paid by providing bank information to the vendor).[4]

TABLE 1

Output per hour worked, commercial banks, annualized growth, percent per year

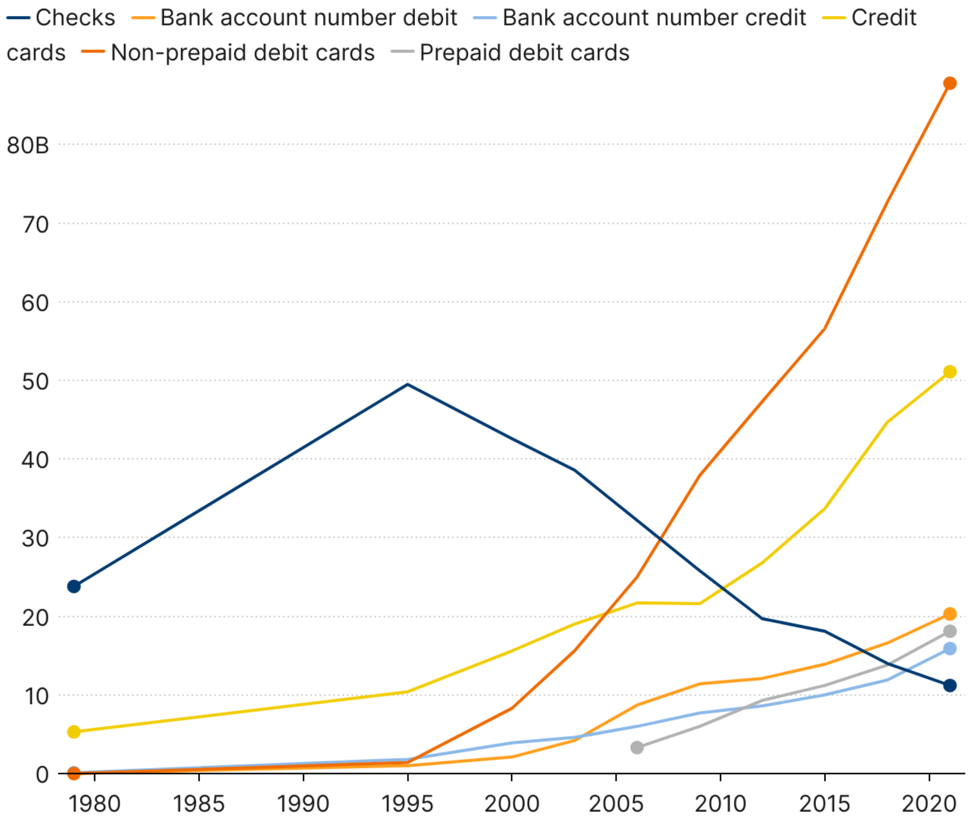
1987-1995	5.06%
1995-2007	3.90%
2007-2018	0.12%
2018-2023	1.05%

SOURCE: Bureau of Labor Statistics, Office of Productivity and Technology (2025)

FIGURE 2

Trends in number of noncash payments

Noncash payment methods for business and personal transactions, in billions



Source: Federal Reserve research (1979 and 1995), Federal Reserve Payments Study

B | Center on Regulation and Markets at BROOKINGS

The use of ATMs and shift to electronic funds transfers reduced the amount of time tellers and back-office personnel spent on routine transactions and contributed to strong bank productivity in the first two periods shown in Table 1.

The financial crisis of 2007-09 was another major influence on the financial industry (Weinberg 2013). The very slow growth of productivity from 2007-18 is not surprising as many banks faced losses in the period of mortgage weakness and became very conservative in their lending. Also, the economy grew slowly 2007-18. In the period 2018-23 one might have expected that banks would have worked through consolidation issues, cut costs in response to the financial crisis, and had strong productivity growth. We are not sure of the reason for the continued slow growth of productivity, although the COVID-19 pandemic is a likely explanation.

Is the arrival of AI to the banking and financial industry going to lead to a new era of rapid growth like that seen from 1987 through 2007? We hope so, but the payoff from AI may take quite some time to achieve. A second look at the story about JPMorgan Chase may help keep perspective. Saving 360,000 hours is actually very small set against total employment in the firm in 2017 of 252,540 workers (Statista Research Department 2024). The labor saving represented only about 0.07% of total hours worked.[5] It will take a lot of improvements like this one to make much difference to the firm’s overall productivity. Given its size and sophistication, JPMorgan Chase is probably ahead of other banks in the application of AI. Large-scale productivity gains across the sector won’t occur until other banks catch up.

On the other hand, 2017 was early in the development of AI for banks, so that bigger gains than the 0.07% touted by JPMorgan Chase could still come. The arrival of ChatGPT in the early 2020s renewed excitement around what AI could do for business. Over the past year or so, there has been more caution and even some disillusion, as applying AI productively in practice has proven difficult.

3. How is AI used in the finance industry?

Some of the main uses of AI in finance are as follows:[6]

3.1. ALGORITHMIC TRADING AND PORTFOLIO MANAGEMENT:

- High-frequency trading (HFT): AI algorithms execute trades at incredibly high speeds, taking advantage of minuscule price fluctuations.
- Quantitative analysis: AI models analyze vast datasets to identify patterns and predict market trends, informing investment decisions.
- Portfolio optimization: AI helps create diversified portfolios that optimize portfolios given risk preferences, , adapting to market changes dynamically.
- Risk management: AI assesses and mitigates various financial risks, including credit risk, market risk, and operational risk.

Machine learning has been used for algorithmic trading starting well before the latest generative AI technology was developed. The large investment banks, such as Goldman Sachs, JP Morgan Chase, and Morgan Stanley, employ teams of data scientists to try and predict market movements. Other less-regulated financial entities use AI for HFT, looking for market anomalies that can be exploited profitably. There are also specialist firms, such as Renaissance Technologies, that rely on machine learning algorithms to guide their trading. The detailed activities of these companies are not revealed in public documents.

AI is now being used to automate the development of portfolios for individual customers, reflecting the risk tolerance of the customer and goals. Blackrock and Vanguard do not rely purely on AI, but their asset managers integrate AI findings into their portfolio selections.[7] Blackrock has invested heavily in AI and fintech (financial technology). So-called Robo-advisors are used to provide individualized portfolio recommendations to smaller clients, and they also answer client questions. Companies using robo-advisers include Betterment and Wealthfront (“Betterment” n.d.; “Robo-advisor investing” n.d.).

Improving market efficiency can be helpful, but we are skeptical that adding AI to the mix will add much in terms of better market functioning. The market is already efficient in the sense that new information is incorporated into pricing decisions quickly. High-frequency traders use proprietary trading strategies to make trades in fractions of a second, and this has been the case for many years (Duhigg 2009). A concern about adding AI is that private distributional gains, in the form of advantaging one trader over another, will be greater than any increase in social gains in terms of market efficiency.

Forecasting the future price of stocks has been the holy grail of analysts since stock markets began operating. AI is now being used to make predictions in other economic activities such as predictive maintenance for equipment, so it is natural that it is being applied to predicting the stock market also. Does this make sense? As we noted, there is a widely held view among economists that the stock market is efficient (Malkiel 2007), so that attempting to second-guess the market is fruitless and that investors should simply hold index funds and not try to see the future.[8] It is certainly the case that ordinary investors without specialized knowledge are wise to avoid trying to forecast where the market is going or picking favorite stocks they think will outperform the market. Investors with special expertise may be able to do better (Warren Buffett is one example[9]), but even many professional investors fail to outperform the market. Buffett uses in-depth analysis of companies and not short-term trading.

3.2. FRAUD DETECTION AND PREVENTION:

- Anomaly detection: AI algorithms identify unusual transactions and patterns that might indicate fraudulent activity.
- Real-time monitoring: AI systems constantly monitor transactions and flag suspicious behavior in real-time.
- Predictive modeling: AI predicts future fraud attempts based on historical data and patterns.

AI can see patterns in data and companies make use of this ability to detect fraudulent transactions. JP Morgan Chase, American Express, Bank of America, Wells Fargo, PayPal, and Capital One are among those using AI in this role. The programs look at the history of transactions for individuals or organizations, checking the transaction amount, frequency, and location, looking for unusual patterns. This can be done instantaneously using AI. The companies can also send alerts to customers warning of possible problems. Human review is combined with results from AI.[10]

3.3. CUSTOMER SERVICE AND RELATIONSHIP MANAGEMENT:

- Chatbots and virtual assistants: AI-powered chatbots provide instant customer support, answering questions and resolving issues efficiently.

Few of us love getting a computer when we call up a financial company with a question, but providing personal service to all customers is very expensive indeed and would raise the cost of bank accounts or other financial products. In addition, even reaching a person on the phone can be frustrating if the question is complex. Trained chatbots are being used to answer routine inquiries and are also being used to train employees to help them answer questions.

3.4. REGULATORY COMPLIANCE AND REPORTING:

- Know Your Customer (KYC) and Anti-Money Laundering (AML) compliance: AI automates KYC/AML checks, reducing manual effort and improving accuracy.
- Regulatory reporting: AI assists in generating and submitting accurate regulatory reports efficiently.

Banks are using generative AI to analyze and summarize regulatory text to help them meet compliance requirements. They have been using machine learning to predict compliance risks. AI can also be used to carry out routine data collection and analysis to meet regulatory requirements, including risk assessment. The large national banks are using AI in these ways.

3.5. LOAN UNDERWRITING AND CREDIT SCORING:

- Credit risk assessment: AI analyzes applicant data to assess creditworthiness more accurately and efficiently.
- Loan approval automation: AI automates parts of the loan approval process, speeding up the process and reducing costs.

The major banks and some fintech companies are using AI to assist with loan underwriting and credit scoring. AI can do analysis on a wider range of data than is possible for most human employees, looking at payment history and social media to assess credit worthiness. AI is good at seeing patterns and determining the probability the borrower will default, or if the application is fraudulent. AI can also carry out routine paperwork associated with loans.

3.6. DATA ANALYTICS AND INSIGHTS:

- Predictive analytics: AI models predict future market conditions, customer behavior, and other relevant factors.
- Data mining: AI extracts valuable insights from large datasets, uncovering hidden patterns, and relationships.
- Business intelligence: AI provides actionable insights that support strategic decisionmaking.

As was the case even before the proliferation of modern generative AI models, all the major banks are using AI for these purposes. AI can be used for prediction, looking for estimates of market conditions based on market data, plus sentiment analysis, taken from company calls with shareholders, for example. AI has the capability to use very large financial and economic datasets. Data mining used to be considered unreliable (and it still can be), but with very large datasets it is possible for AI to pull out important patterns.

3.7. BACK-OFFICE OPERATIONS AND AUTOMATION:

- Process automation: AI automates repetitive tasks such as data entry, reconciliation, and document processing.
- Improving operational efficiency: AI streamlines processes and reduces manual errors.

AI is being used to review documents and provide summaries to staff, saving personnel time. It can check data entry for accuracy and validate findings and generate draft reports. These tasks are being automated by the major banks, as described in a study by Giovine et al. (2024), and substantial cost savings are being achieved or are expected. However, since individual companies do not wish to divulge the details of their operations, the exact magnitude of the savings have not been verified.

There are important limitations on the use of AI in financial institutions. For example, data analytics relies upon large data sets that reveal the important patterns, but if less complete data is used, this can create problems. For example, when AI makes assessments of loan applications it can be subject to biases that make it difficult for women and minorities to be approved for loans (Browne and Sigalos 2023).

One of the biggest failures of the financial system occurred in the financial crisis of 2007-09 when the risks of mortgage loan default was greatly underestimated. Even though AI was not as advanced at that time, sophisticated statistical tools were being used to assess the dangers. There was a mountain of data available, but it all came from a period when there had been relative stability in the housing market. There had been housing price declines in specific locations but never had the overall price of housing in the economy declined in the way that it did during the financial crisis. The analytics missed the danger in part because of incomplete data (Baily et al. 2008).[11]

Another concern about the use of AI in finance is that it is a “black box” approach, meaning that it is difficult or impossible to figure out how exactly the program reached its conclusions. The lack of explainability makes it frustrating to evaluate the conclusions. Further, we know that generative AI has a tendency to make up facts or citations when it is unable to find the references or data that would be needed to verify its conclusions. Financial companies cannot tolerate mistakes of this kind and have to verify the material being produced.

A report by Baig et al. (2024) examined the financial statements of 90 banks in the United States and evaluated their technology investments. The study did not focus exclusively on AI, but its findings are relevant to a broad range of technologies. They note that spending on technology increased by 9% per year in the past few years but that the net benefits to the institutions have been hard to quantify. One might have expected that the large banks would have had an advantage in their technology investments from returns to scale, but the study did not find that to be the case. Nor was it the case that large banks earned higher returns, on average. They suggest there is a complexity penalty that large institutions face, as well as greater regulatory burdens. The authors report that 50-60% of technology spending is for running bank operations, while 10-15% is for required mandatory activities. Discretionary changes account for 25-35% of spending. These authors judge that larger share of technology spending should be devoted to profit-oriented initiatives, although, from the economic perspective, if the spending on running the bank can be used to make operations more efficient and productive, that is valuable.

4. Some lessons on the effect of AI in finance using the focus of research

One way to assess the extent to which AI is being used in these different functions in finance is to look at where research is being done. Figure 1, above, showed the rapid increase in the number of research papers written on AI in finance, and the study by Bahoo et al. (2024) also examines the research topics studied in this literature.[12]

AI and stock market analysis. There are two main themes in the work on the market: the analysis of algorithmic trading and the use of AI to predict market movements. There is an argument that algorithmic trading improves the efficiency of the stock market by reducing the buy-sell spread, reducing adverse selection, and by providing price discovery.[13] Whether AI can help forecast the market is an open question since it relies on information that is widely available. Artificial Neural Networks (ANNs) are currently being used to make market forecasts, as is AI analysis of information about investor sentiment. We are skeptical of AI's ability to provide above-normal returns over an extended period. Even if certain AI programs were to succeed in the short-term, once the methodology became known, it will be copied and any advantage to the users of AI will disappear long-term.

As noted above, another tool that has been used to make predictions about the market is sentiment analysis. This is an approach that has been around for some time, used by Hollywood, for example, to assess the interest in a forthcoming movie or what people thought of the movie after it is released (Ramos-Santacruz 2019). The tools of sentiment analysis are being used to try and make stock predictions by scraping investor views from social media using natural language processing. News stories about a company have been found to have some predictive power on stock price for a few days or a few months depending on the nature of the stories (Heston and Sinha 2017). Another strategy was described in a slide presentation at the National Bureau of Economic Research Summer Institute in July 2024, which assessed the forecasting value of head and eye movements and voice pitch by the chair of the Federal Reserve or by CEOs (Alexopoulos et al. 2024). The value remains to be determined.

In summary, it is possible that the use of AI will lead to small improvements in the efficiency of the stock market, but we do not believe it can provide a sustained advantage to the broad spectrum of savers and investors—people looking to set aside funds for retirement, for example. Any success by AI in the stock market will mostly accrue to savvy users of the technology at the expense of other market participants. The gains will be distributional, not a net social benefit.

AI and Portfolio Management. Those using AI to predict the future of individual stocks have also extended their analysis to assess alternative stock portfolios, and it has been claimed that superior performance has been achieved (Zhao et al. 2018). The case for using AI here is stronger. Mutual funds that offer index-type funds, such as Vanguard or Fidelity, typically hold broader portfolios than just the S&P 500, and they screen companies to eliminate those that have a high probability of bankruptcy or weak performance. The use of AI to carry out such screening could well be helpful, although again, the impact is likely to be small relative to the screening already undertaken. However, AI could reduce the hours needed to carry out these risk assessments.

An important way in which AI can be helpful for investors is to match a portfolio to the specific preferences of the consumer. People differ in their willingness to tolerate risk and that will likely vary by the age of the household. People may choose to favor certain causes, such as avoiding fossil fuel companies or supporting companies seen as matching their political preferences. These individual differences can be accommodated by human intervention but at a cost. AI could reduce the personnel hours needed to manage such portfolios.

AI and Risk Assessment. The performance of financial companies is heavily impacted by the default and failure of loans to companies, real estate loans, or personal loans. As we have said, the financial crisis of 2007-09 was caused by severe failures in risk assessment by financial institutions.

To what extent can AI help resolve these difficulties? Predictive AI programs have been used for many years prior to the introduction of generative AI to predict mortgage and loan defaults. For example, the study by Chen et al. (2014) forecasts the price performance of real estate investment trusts (REITs). These authors use machine learning, ANNs, and so-called “grey theory” which is applied to situations without full information.[14] A REIT contains a portfolio of commercial mortgages, and its performance depends on the riskiness of each loan and the covariance across loans. Business loans are an important area for most banks, and the assessment of risk is more difficult. Much of the research effort using AI has been focused on predicting company failures, identifying distressed companies before they fail.[15]

Whether AI helps or hurts risk assessment in the long run depends on how it is used and the care that is taken by managers. The programs can be helpful even as they are constituted today, and there is a rapid pace of improvement that suggests they will get better at the task. The danger is that bankers will come to rely too heavily on the technology and lose their common sense. This was what happened in the financial crisis of 2007-09, as bankers were propelled by the ability to make money in the short run by minimizing the assessment of risks that will show up in the long run. The history of technological advances in financial markets has been very mixed. Long-term Capital Management (LTCM) was founded in 1994 by a group with strong technical expertise, and they hired the very best financial minds to assist them. They used the Nobel-prize-winning models developed by Black[16] and Scholes (1973) and by Merton (1973) to provide insight into asset market pricing, which they then used to identify pricing anomalies that they could profit from. They made money for several years but in 1998 they lost $4.6 billion, and the company went bankrupt, imposing losses on investors. The models worked well until a crisis triggered by events in Russia caused them to fail.[17]

5. CONCLUSIONS

As was found in the other industry case studies we have examined, the ability of AI to increase productivity in the finance industry is still very much at an early stage. There has been a lot of brainpower and technical expertise applied to finding ways to make money using mathematical and computer modeling of financial assets and portfolios. These efforts may have paid off for the users of these models, although the spectacular losses that were incurred in LTCM or, more broadly, in the financial crisis cast doubt as to whether any sustainable gains have been achieved. But even if there have been private gains, it is hard to describe these as productivity improvements. These gains are from one set of investors or analysists at the expense of another set of investors or of the broader market.

In the long run, the hope for AI in finance is that it allows banks, insurance companies, and other institutions to operate more efficiently and provide services at lower cost to consumers. There are avenues for this to happen. Handling paperwork and customer inquiries take a lot of time, time that can be reduced as AI becomes more capable and reliable.

References

“A History of ATM Innovation.” 2021. NCR Atleos. January 12, 2021. https://www.ncratleos.com/insights/a-history-of-atm-innovation.

Alexopoulos, Alex, Xinfen Han, Oleksiy Kryvtsov, and Xu Zhang. 2024. “Mixed Signals? How Media Distills Central Bank Messages.” Presented at the NBER Summer Institute 2024 Impulse and Propogation Mechanisms, Cambridge, MA, July 8. https://conference.nber.org/conf_papers/f208239.slides.pdf.

Bahoo, Salman, Marco Cucculelli, Xhoana Goga, and Jasmine Mondolo. 2024. “Artificial Intelligence in Finance: A Comprehensive Review through Bibliometric and Content Analysis.” SN Business & Economics 4 (2): 23. https://doi.org/10.1007/s43546-023-00618-x.

Baig, Aamer, Vik Sohoni, Xavier Lhuer, and Zane Williams. 2024. “Unlocking Value from Banking Technology Investment | McKinsey.” McKinsey & Company. October 23, 2024. https://www.mckinsey.com/industries/financial-services/our-insights/unlocking-value-from-technology-in-banking-an-investor-lens.

Baily, Martin Neil, Matthew S. Johnson, and Robert E. Litan. 2008. “The Origins of the Financial Crisis.” Brookings. November 24, 2008. https://www.brookings.edu/articles/the-origins-of-the-financial-crisis/.

Baily, Martin Neil, and Eric Zitzewitz. 2001. “Service Sector Productivity Comparisons: Lessons for Measurement.” In New Developments in Productivity Analysis, edited by Charles R. Hulten, Edwin R. Dean, and Michael J. Harper, 419–64. University of Chicago Press. https://www.nber.org/books-and-chapters/new-developments-productivity-analysis/service-sector-productivity-comparisons-lessons-measurement.

Bean, Randy. 2024. “How Vanguard Is Innovating With Data And AI In The Money Management Business.” Forbes. September 24, 2024. https://www.forbes.com/sites/randybean/2024/09/24/how-vanguard-is-innovating-with-data--ai-in-the-money-management-business/.

Bellis, Mary. 2019. “Why Inventing the ATM Was a Team Effort.” ThoughtCo. March 15, 2019. https://www.thoughtco.com/automatic-teller-machines-atm-1991236.

“Betterment.” n.d. Betterment. Accessed March 19, 2025. https://www.betterment.com.

Black, Fischer, and Myron Scholes. 1973. “The Pricing of Options and Corporate Liabilities.” Journal of Political Economy 81 (3): 637–54. https://doi.org/10.1086/260062.

Boivin, Jean, Wei Li, Raffaele Savi, Chris Weber, Nicholas Fawcett, Beata Gamharter, Veronika Roharova, and Adam Waltz. 2024. “AI’s Big Questions.” BlackRock Investment Institute. https://www.blackrock.com/corporate/literature/whitepaper/bii-megaforces-ai-november-2024.pdf.

Browne, Ryan, and MacKenzie Sigalos. 2023. “A.I. Has a Discrimination Problem. In Banking, the Consequences Can Be Severe.” CNBC. June 23, 2023. https://www.cnbc.com/2023/06/23/ai-has-a-discrimination-problem-in-banking-that-can-be-devastating.html.

Bureau of Labor Statistics, Office of Productivity and Technology. 2025. “Annual Labor Productivity and Costs: Detailed Industries.” https://www.bls.gov/productivity/tables/.

Calomiris, Charles W. 1999. “Gauging the Efficiency of Bank Consolidation during a Merger Wave.” Journal of Banking & Finance 23 (2–4): 615–21. https://doi.org/10.1016/S0378-4266(98)00096-X.

Chen, Jo-Hui, Ting-Tzu Chang, Chao-Rung Ho, and John Francis Diaz. 2014. “Grey Relational Analysis and Neural Network Forecasting of REIT Returns.” Quantitative Finance 14 (11): 2033–44. https://doi.org/10.1080/14697688.2013.816765.

Duhigg, Charles. 2009. “Stock Traders Find Speed Pays, in Milliseconds.” The New York Times, July 24, 2009, sec. Business. https://www.nytimes.com/2009/07/24/business/24trading.html.

“Eugene F. Fama - Facts.” 2025. NobelPrize.Org. March 13, 2025. https://www.nobelprize.org/prizes/economic-sciences/2013/fama/facts/.

Federal Deposit Insurance Corporation (FDIC). 2025. “Failures of All Institutions for the United States and Other Areas [BKFTTLA641N].” FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/BKFTTLA641N.

Ferguson, Niall. 2008. The Ascent of Money: A Financial History of the World. London: Allen Lane.

Gepp, Adrian, Kuldeep Kumar, and Sukanto Bhattacharya. 2010. “Business Failure Prediction Using Decision Trees.” Journal of Forecasting 29 (6): 536–55. https://doi.org/10.1002/for.1153.

Giovine, Carlo, Larry Lerner, Renny Thomas, Shwaitang Singh, Sudhakar Kakulavarapu, Violet Chung, and Yuvika Motwani. 2024. “Extracting Value from AI in Banking: Rewiring the Enterprise.” McKinsey & Company. https://www.mckinsey.com/industries/financial-services/our-insights/extracting-value-from-ai-in-banking-rewiring-the-enterprise#/.

Hanc, George. 1998. “The Banking Crises of the 1980s and Early 1990s: Summary and Implications.” FDIC Banking Review 11 (1): 55.

Hendershott, Terrence, Charles M. Jones, and Albert J. Menkveld. 2011. “Does Algorithmic Trading Improve Liquidity?” The Journal of Finance 66 (1): 1–33. https://doi.org/10.1111/j.1540-6261.2010.01624.x.

Heston, Steven L., and Nitish Ranjan Sinha. 2017. “News vs. Sentiment: Predicting Stock Returns from News Stories.” Financial Analysts Journal 73 (3): 67–83. https://doi.org/10.2469/faj.v73.n3.3.

Hunter, William C., Stephen G. Timme, and Won Keun Yang. 1990. “An Examination of Cost Subadditivity and Multiproduct Production in Large U.S. Banks.” Journal of Money, Credit and Banking 22 (4): 504. https://doi.org/10.2307/1992434.

Jones, Stewart, David Johnstone, and Roy Wilson. 2017. “Predicting Corporate Bankruptcy: An Evaluation of Alternative Statistical Frameworks.” Journal of Business Finance & Accounting 44 (1–2): 3–34. https://doi.org/10.1111/jbfa.12218.

Ju-Long, Deng. 1982. “Control Problems of Grey Systems.” Systems & Control Letters 1 (5): 288–94. https://doi.org/10.1016/S0167-6911(82)80025-X.

Lezmi, Edmond, and Jiali Xu. 2023. “Time Series Forecasting with Transformer Models and Application to Asset Management.” SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4375798.

Litzenberger, Robert, Jeff Castura, and Richard Gorelick. 2012. “The Impacts of Automation and High Frequency Trading on Market Quality.” Annual Review of Financial Economics 4 (1): 59–98. https://doi.org/10.1146/annurev-financial-110311-101744.

Malkiel, Burton G. 2007. A Random Walk down Wall Street: The Time-Tested Strategy for Successful Investing. Completely revised and Updated edition. New York London: W.W. Norton & Company.

Medley, Bill. 1994. “Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 | Federal Reserve History.” Federal Reserve History. September 1994. https://www.federalreservehistory.org/essays/riegle-neal-act-of-1994.

Merton, Robert C. 1973. “Theory of Rational Option Pricing.” The Bell Journal of Economics and Management Science 4 (1): 141. https://doi.org/10.2307/3003143.

Nippani, Srinivas, and Kenneth W Green. 2002. “The Banking Industry after the Riegle–Neal Act: Re-Structure and Overall Performance.” The Quarterly Review of Economics and Finance 42 (5): 901–9. https://doi.org/10.1016/S1062-9769(01)00106-5.

OECD. 2021. OECD Business and Finance Outlook 2021: AI in Business and Finance. OECD Business and Finance Outlook. OECD. https://doi.org/10.1787/ba682899-en.

Ramos-Santacruz, Mila. 2019. “Sentiment Analysis Captures Insights for the Entertainment Industry.” NetOwl (blog). March 22, 2019. https://www.netowl.com/sentiment-analysis-captures-insights-for-the-entertainment-industry.

“Robert J. Shiller - Facts.” 2025. NobelPrize.Org. March 14, 2025. https://www.nobelprize.org/prizes/economic-sciences/2013/shiller/facts/.

"Robo-Advisor Investing." n.d. Wealthfront. Accessed March 19, 2025. https://invest.wealthfront.com/robo-advisor-investing.

Sabău Popa, Diana Claudia, Dorina Nicoleta Popa, Victoria Bogdan, and Ramona Simut. 2021. "COMPOSITE FINANCIAL PERFORMANCE INDEX PREDICTION – A NEURAL NETWORKS APPROACH." Journal of Business Economics and Management 22 (2): 277–96. https://doi.org/10.3846/jbem.2021.14000.

Saibil, Jennifer. 2023. "You Won't Believe How Much More Warren Buffett Has Made Than the Market Since 1965." The Motley Fool. March 14, 2023. https://www.fool.com/investing/2023/03/14/you-wont-believe-how-much-more-warren-buffett-has/.

Statista Research Department. 2024. "JPMorgan Chase Number of Employees 2008-2023." https://www.statista.com/statistics/270610/employees-of-jp-morgan-since-2008/.

Weinberg, John. 2013. "The Great Recession and Its Aftermath." Federal Reserve History. November 22, 2013. https://www.federalreservehistory.org/essays/great-recession-and-its-aftermath.

Weiss, Debra Cassens. 2017. "JPMorgan Chase Uses Tech to Save 360,000 Hours of Annual Work by Lawyers and Loan Officers." ABA Journal. March 2, 2017. https://www.abajournal.com/news/article/jpmorgan_chase_uses_tech_to_save_360000_hours_of_annual_work_by_lawyers_and.

Zhao, Yang, Charalampos Stasinakis, Georgios Sermpinis, and Yukun Shi. 2018. "Neural Network Copula Portfolio Optimization for Exchange Traded Funds." Quantitative Finance 18 (5): 761–75. https://doi.org/10.1080/14697688.2017.1414505.

Endnotes

1 Data on bank failures from the Federal Deposit Insurance Corporation, reported FRED, the database from the St Louis Federal Reserve, https://fred.stlouisfed.org/series/BKFTTLA641N

2 Some of the processing of paper checks occurred and still occurs within facilities operated by the Federal Reserve System that, hence, do not impact measured bank productivity.

3 Many European banks were overstaffed and less productive overall than U.S. banks.

4 There are complicated reasons why the U.S. was a slow technology adopter. Banks make money earning interest on the time delay between the withdrawal of funds by the payor and the receipt of funds by the payee. Also, the physical processing of checks took place in Federal Reserve facilities using employees of the system whose jobs were threatened.

5 This assumes employees at the bank work 1,920 hours a year, so that 360,000 hours represents the work of 187.5 employee years. 187.5 divided by 252,539 equals 0.07 percent.

6 This section uses material developed with assistance from Google Cloud, Google Gemini and ChatGPT, accessed October 2024. The report on AI in finance by the OECD was also valuable (OECD 2021, 38).

7 BlackRock's use of AI is described in Boivin et al. (2024). Vanguard's use of AI is described in Bean (2024).

8 In 2013, Eugene Fama won the Nobel prize for his work showing the efficiency of financial markets, showing that the market is impossible to predict at least in the short run ("Eugene F. Fama – Facts" 2025). However, in the same year Robert Shiller won the Nobel prize for his work showing the stock market was not always efficient, in that it had predictable movements in the long run ("Robert J. Shiller – Facts" 2025).

9 According to Saibil (2023), $10,000 invested in Berkshire Hathaway in 1965 and held without withdrawals of principle or dividends would have been worth $355 million in 2022. The same amount invested and held in the S&P 500 would have been worth $2.4 million. Most of the differential gains, they find, occurred in the early years of Buffett's fund. Even Buffett finds it hard to beat the market today.

10 Personal experiences: A large order from a New Orleans restaurant to be shipped to Moscow was stopped. Correctly! An effort to pay for airline tickets for family was stopped. Incorrectly. A large but valid charge in France was approved without question. Surprisingly.

11 This report also identifies other serious problems with the mortgage system.

12 This section draws on Bahoo et al. (2014).

13 Discussed in Bahoo et al. (2024), the case for the benefit of algorithmic trading is made by Hendershott et al. (2011) and Litzenberger et al. (2012).

14 The unfortunately named theory has explored how to make predictions when there is a range of possibilities from full information (white) to no information (black). It was developed by Ju-Long (1982).

15 Jones et al. (2017) and Gepp et al. (2010) determine the probability of corporate default. Sabău Popa et al. (2021) look at business performance based on an index of financial variables.

16 Fischer Black died before he could receive the Nobel prize. His Ph.D. thesis was on artificial intelligence supervised by Marvin Minsky.

17 For a review of the LTCM story, see Ferguson (2008).