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The Economic Impact by AI on Job Displacement in The Finance Sector

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Master in Business Administration

Supervisor:

PhD, Diptes Chandrakante Prabhudas Bhimjee,

Invited Assistant Professor

Iscte – Instituto Universitário de Lisboa

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BUSINESS
SCHOOL

Department of Marketing, Operations and General
Management

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Resumo

Esta dissertação examina empiricamente o impacto económico da adoção da inteligência artificial (IA) na substituição de empregos no setor financeiro, com foco nas variações entre subsetores, tamanhos de empresas e regiões. Os rápidos avanços da IA, particularmente em aprendizagem automática, processamento de linguagem natural e automação de processos robóticos, estão a transformar os serviços financeiros, automatizando tarefas rotineiras e, ao mesmo tempo, criando demanda por novas funções que exigem habilidades mais qualificadas. Utilizando dados de painel ao nível das empresas de 152 empresas financeiras cotadas em bolsa na América do Norte e Europa entre 2015 e 2023, esta dissertação emprega modelos de regressão de efeitos fixos com ativos intangíveis e despesas de capital como proxies para a adoção da IA. A hipótese de que a adoção da IA reduz o emprego, particularmente em funções rotineiras, não é validada. Em vez disso, os resultados mostram que os ativos intangíveis, refletindo as capacidades digitais e a integração do capital humano, estão positivamente associados ao crescimento do emprego, enquanto as despesas de capital não mostram nenhum efeito significativo. A heterogeneidade do subsetor, regional e do tamanho das empresas indica ainda que a adoção da IA complementou a mão de obra na maioria dos contextos, apoiando a transformação organizacional e a atualização de competências, em vez de uma substituição generalizada. Estas conclusões contribuem para o debate sobre a IA e o emprego, reformulando a narrativa de uma substituição inevitável para uma adaptação diferenciada, destacando a importância dos investimentos complementares e do contexto institucional na definição dos resultados do mercado de trabalho.

Palavra-chave: Inteligência Artificial, Setor Financeiro, Emprego, Substituição de Empregos, Ativos Intangíveis, Análise de Dados de Painel

Classificação JEL: J23, J24, O33, G20

Abstract

This Dissertation empirically examines the economic impact of artificial intelligence (AI) adoption on job displacement within the finance sector, focusing on variations across sub-sectors, firm sizes, and regions. Rapid AI advancements, particularly in machine learning, natural language processing, and robotic process automation, are transforming financial services by automating routine tasks while also creating demand for new higher-skilled roles. Using firm-level panel data from 152 publicly listed financial companies across North America and Europe from 2015 to 2023, this Dissertation employs fixed effects regression models with intangible assets and capital expenditures as proxies for AI adoption. The hypothesis that AI adoption reduces employment particularly in routine roles, is not validated. Instead, the findings show that intangible assets, reflecting digital capabilities and human capital integration, are positively associated with employment growth, while capital expenditures show no significant effect. Sub-sector, regional, and firm-size heterogeneity further indicate that AI adoption has complemented labour in most contexts, supporting organisational transformation and skill upgrading rather than widespread substitution. These findings contribute to the debate on AI and employment by reframing the narrative from inevitable displacement to differentiated adaptation, highlighting the importance of complementary investments and institutional context in shaping labour market outcomes.

Keywords: Artificial Intelligence, Finance Sector, Employment, Job Displacement, Intangible Assets, Panel Data Analysis

JEL Classification: J23, J24, O33, G20

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Glossary

- **AI (Artificial Intelligence)** – Computational methods that perform tasks requiring human-like cognition (learning, reasoning, perception).
- **ML (Machine Learning)** – Subfield of AI where models learn patterns from data to make predictions/decisions.
- **NLP (Natural Language Processing)** – AI techniques for understanding and generating human language.
- **RPA (Robotic Process Automation)** – Software “bots” that automate repetitive, rule-based tasks.
- **GPT (General-Purpose Technology)** – Broader innovations (e.g., AI) whose productivity effects require complementary investment.
- **Intangible Assets** – Identifiable non-monetary assets without physical substance, for example computer software, licences and patents, that are recognised on the balance sheet if they meet accounting standards (e.g. IFRS requirements of identifiability, control, future benefit and reliable measurement).
- **CapEx (Capital Expenditure)** – Spending on physical infrastructure and long-term assets, including IT systems that support AI adoption when capitalised under applicable accounting rules.
- **Panel Data** – Dataset that tracks multiple firms over time, allowing analysis of within-firm changes
- **Fixed Effects (FE)** – Statistical method that controls for time-invariant firm characteristics using within-firm variation.
- **Hausman Test** – A specification test used to decide between Fixed Effects and Random Effects estimators.
- **Elasticity** – in log-log regressions, the percentage change in the dependent variable resulting from a 1% change in an explanatory variable.

1. Introduction

1.1. Contextualisation

The rise of artificial intelligence (AI) marks a new epoch in technological advancement with important implications for organisational transformation and how labour markets will evolve. AI systems have increasingly demonstrated their capabilities in cognitive tasks where AI technologies are being rapidly adopted in order to (i) optimise decision-making, (ii) streamline operations, and (iii) increase efficiency. The finance sector, long known for its reliance on data-intensive, cognitive work, is particularly exposed to the disruptive potential of AI technologies. As these technologies evolve, so do concerns about the shifting nature of work and the economic consequences of AI-driven automation.

The growing integration of *machine learning*, *natural language processing*, and *robotic process automation* into financial operations needs a critical assessment of their effects on workforce dynamics. The demand for AI-related skills has increased tenfold between 2010 and 2019, with the finance sector being one of the most affected (Alekseeva et al., 2021). On the one hand, AI has been proven to present opportunities for productivity gains and new forms of high-skilled labour. On the other, AI carries the risk of workforce automation, heightening job insecurity for employees engaged in both routine and repetitive work. AI systems are beginning to routinise tasks such as analytical reasoning and professional client interaction, which are core functions in many finance roles (Choi & Leigh, 2024). The finance sector has long been at the forefront of technological adoption, (i) leveraging innovations to streamline processes, (ii) reduce costs, and (iii) enhance competitiveness. As machines increasingly replicate human cognitive functions, the roles and responsibilities of financial professionals are being redefined.

This shift raises important economic and societal questions regarding the quantity and quality of jobs in finance, work inequality, and skill transformation. Understanding the effects of AI on employment in finance is essential not only for anticipating future labour market trends but also for informing education, policy, and organisational strategy.

Despite significant scholarly attention towards AI and employment, empirical research specifically focused on the finance sector remains limited. This Dissertation will offer significant potential for new insights into a highly topical issue. Existing academic literature primarily provides assessments of AI's impact without thoroughly addressing sector-specific nuances, such as differences between banking, insurance, investment management, etc. The aim of this Dissertation is to address this important gap by analysing the economic impact of AI-driven job displacement, focusing on variations across subsectors within the finance industry.

1.2 Research problem

The rapid advancement of artificial intelligence (AI) and machine learning technologies is reshaping different industries all over the world. Companies within the financial sector are increasingly adopting AI-driven technologies to (i) enhance efficiency, (ii) reduce costs, and (iii) improve decision-making processes. While AI might initially displace some jobs in the finance sector, it has the potential to create new opportunities in the long term (Kande, M. & Sonmez, M., 2020). According to McKinsey (Manyika et al., 2017), administrative support tasks and transaction-based roles in finance are most susceptible to automation. The authors project that by 2030, automation could displace around 30% of work activities globally, with the finance sector being notably affected. AI will shift job demands significantly over the next five years, particularly in repetitive and transaction-based positions that rely on manual data processing, such as customer support, data entry, and payroll management (World Economic Forum, 2023).

However, while AI adoption by companies brings clear economic advantages, it also poses significant risks for the human workforce within the financial industry. AI adoption can create problems such as workforce inequality. Those who lack access to specialised training and education in high-demand skilled job roles risk being left behind as the job market evolves (Autor & Dorn, 2013). This creates a future challenge for workers, policymakers, and businesses, who need to balance the benefits of automation with the need to sustain a skilled, adaptable workforce. By studying the economic impacts and developing strategies to address this issue, this research can provide valuable insights for business leaders and educational institutions in order to mitigate the adverse effects of job displacement while maximising the benefits of AI in finance.

In recent years, artificial intelligence has experienced remarkable growth, becoming a widely discussed and increasingly normalised topic both in professional circles and popular media. Reflecting this rising interest, the search term “AI” experienced an increase of 350% in Google search queries from early 2022 to early 2024 (Google Trends, 2024). This surge in attention highlights the widespread awareness of AI’s transformative potential and suggests a growing recognition of both its opportunities and challenges. Understanding how this rapid proliferation of AI impacts specific sectors, particularly finance, becomes not only academically relevant but also essential for businesses and the workforce to proactively adapt to the rapidly evolving technological environment.

1.3. Research Aim

The aim of this research is to empirically analyse the economic impact of AI-driven job displacement within the finance sector, identifying whether AI technologies primarily create, replace, or displace jobs. This Dissertation will assess the effects of AI adoption on employment levels, wage structures,

and skill requirements across different subsectors of the finance industry using econometric analysis. The outcomes aim to provide insights for both professional and educational use.

1.4. Research Question

To examine the economic impact of AI on job displacement in the finance sector, the present document will explore whether AI leads to job displacement, creates new opportunities, transforms existing roles by changing skill demand, and affects wages and productivity by questioning:

- *“How does AI adoption influence employment outcomes and job displacement across sub-sectors, firm sizes, and regions within the finance sector?”*

1.5. Research Objectives

To address the research problem, this Dissertation will begin by gathering valuable insights from existing literature on AI-driven automation, job displacement, labour demand, job creation, and AI technological trends in the finance sector. The goal is to define key concepts and identify current trends, development, and automation practices within the industry. This academic literature review will provide the basis for understanding how AI in this sector is influencing job structures and economic dynamics.

Accordingly, the research conducts an empirical analysis to assess the economic impact of AI-driven job displacement with a focus on employment levels across firms in the finance sector. The analysis examines how AI adoption influences workforce sizes with the consideration of variations across sub-sectors, regions, and firm sizes. By the end of the Dissertation, these objectives are expected to be met, providing evidence-based conclusions on AI’s labour market impact in finance.

1.6. Expected Results

This research expects to unveil significant insights into how AI adoption affects employment trends within finance, revealing which roles and sub-sectors face the greatest risks of displacement and unfolding the evolving skill demands and wage patterns correlated to artificial intelligence technologies. The findings of this Dissertation are expected to inform strategies for workforce adaptation, giving knowledge to the decision-makers within the industry to better navigate the economic impacts of AI on employment and mitigate adverse outcomes for workers.

2. Literature review

2.1. Introduction to AI and Automation in the Workforce

Artificial intelligence and automation have become transformative forces in the workforce. Automation is defined as the replacement of human labour input by machine input in some tasks within economic processes (Sostero, 2020, p. 3). AI is defined as the ability of a machine to mimic intelligent human behaviour, seeking to use human-inspired *algorithms* to solve problems (Salehi & Burgueño, 2018). AI includes a wide range of technologies that replicate human cognitive functions, including (i) learning, (ii) problem-solving, and (iii) decision-making, giving machines the ability to undertake complex tasks once performed by humans (IBM, 2023).

For the workforce, AI offers several benefits, such as automation of repetitive tasks, faster insights from data analysis, reduced human errors, improved decision-making, 24/7 operational availability, and minimised physical risks for employees. Automation leverages scientific and technological methods to perform business tasks that were previously conducted by humans (Mamede et al., 2023). Contemporary AI uses advanced computation to automate specific tasks at or above human cognitive capacity. Powered by *machine learning*, recent AI breakthroughs are achieving human-comparable results across an expanding range of human tasks (Tyson & Zysman, 2022).

2.2. Overview of AI Technologies in Financial Services

AI-driven automation in financial services is reshaping the industry by enabling data-driven insights, optimising processes, and improving decision-making capabilities. AI technologies such as machine learning (ML), natural language processing (NLP), and robotic process automation (RPA) have become essential drivers of transformation within the industry.

Directly underneath AI, which will be our primary focus due to its relevance, is machine learning (ML), a core component that enables AI systems to improve their performance based on experience and data analysis. It can be used for tasks such as fraud detection, risk assessment, and predictive analytics. Machine learning is the type of algorithms that is particularly critical in workforce automation. It allows systems to analyse exceptionally large varieties of datasets, detect patterns, and make data-driven decisions more accurately and efficiently than traditional programming allows. (Jordan & Mitchell, 2015). This has been possible through the explosion of development of new learning *algorithms*.

2.2.1. Machine learning

In machine learning, an algorithm constitutes a core mechanism that enables systems to learn from data by searching through a range of potential solutions to find the one that best optimises performance. These algorithms use structured methods, such as optimisation or evolutionary processes, to refine predictions and improve outcomes based on past data (Jordan & Mitchell, 2015). Algorithms in machine learning are fundamental for applications across fields like language processing and automation.

2.2.2. Natural Language Processing

Natural Language Processing (NLP) allows AI computers to understand and interpret human language. NLP approaches can extract economically meaningful information from various sources, such as corporate annual reports, news articles, and X (Twitter) posts (Bartram et al., 2020). Financial institutions use NLP for various applications, including chatbots, virtual assistants that provide customer support, and as a financial analytical tool. The most common example of an NLP today is the Generative Pre-trained Transformer 4 (GPT-4), a multimodal large language model created by OpenAI (Taecharungroj, 2023).

2.2.3. Robotic Process Automation

Robotic Process Automation (RPA) involves the use of software robots to oversee repetitive, rule-based tasks automatically. RPA is used as an automation tool because it delivers quick results and does not involve changing the existing underlying computer systems inside organisations (Mamede et al., 2023). In the finance sector, RPA is being used for tasks such as data entry, account reconciliation, and compliance reporting. Automating these routine processes allows financial institutions to allocate human resources to more complex, value-added work.

2.3. Impact of AI on employment in the finance sector

AI-driven automation has been enabling financial institutions to streamline complex, data-intensive tasks, such as risk assessment, credit scoring, fraud detection, and algorithmic trading, which previously required manual effort and extensive human oversight. This technological shift enhances operational efficiency and reduces costs, which is the biggest upside of the AI wave. Yet it also raises concerns about job displacement, particularly for roles focused on repetitive and data-heavy tasks, which are highly susceptible to AI automation (Dwivedi et al., 2021). While some positions may become redundant, the demand for new, higher-skilled roles is expected to grow. This includes roles with a stronger focus on AI oversight, data science, and cybersecurity. For finance professionals, this shift

highlights the increasing need to combine traditional financial expertise with technical knowledge in AI and data analysis to adapt to an evolving technological landscape.

AI technology in finance creates new labour demand (Choi & Leigh, 2024). They analyse the labour demand creation effect, showing that the invention and adoption of AI technology, especially in metropolitan statistical areas (MSA) in the US, areas rich in innovation, have fuelled the demand for AI-skilled workers across multiple sectors, especially in finance (Choi & Leigh, 2024). As AI skill adoption increases, the job displacement effect of AI tends to affect non-routine cognitive tasks previously deemed less vulnerable to automation, suggesting that AI technologies are encroaching on tasks that we once considered resistant to automation (Choi & Leigh, 2024). While AI-driven automation is transforming the finance sector by optimising operational processes, it simultaneously challenges the stability of traditional job functions, emphasising the need for workers to acquire advanced technical and analytical skills to remain competitive.

Additionally, there is a framework called “Productivity Paradox” that highlights a recurring phenomenon in technological transition, where rapid adoption of technologies or innovations like AI does not immediately translate to measurable gains (Brynjolfsson et al., 2019). As a result, improvements in productivity and employment tend to come up slowly, often unevenly, and can be difficult to detect in the early stages.

According to their broader framework, in early phases of AI diffusion, only a share of firms, typically larger ones, are positioned to make such investments. For this reason, AI adoption may initially increase productivity and performance dispersion among firms rather than raising output for the whole industry. This dynamic creates a “winner-take-most” effect where a small group of “frontier firms” capture disproportionate benefits in productivity, while others lag behind or fail to realise returns altogether (Brynjolfsson et al., 2019). Such patterns have direct implications for both labour market outcomes and inter-firm inequality, particularly in a highly technological sector like finance.

In the end, one of the most influential frameworks for interpreting these divergent effects is the Skill-Biased Technological Change (SBTC) theory. The SBTC theory explains that technological advancements, especially those involving automation or digital tools, tend to increase the productivity and demand for high-skilled labour (Autor et al., 2003). In the context of AI, this means that technologies are more likely to complement professionals engaged in cognitive tasks than workers performing repetitive or rules-based functions. As a result, AI adoption in sectors like finance may not reduce the employment overall but rather increase the demand for skills and adaptability for more digitalised roles.

2.4. Extent of Job Displacement by AI technologies

In the academic literature, there are several reviews on the workforce impact of technologies, both within and outside the finance sector. The review of Filippi et al. (2023) systematically analyses how automation technologies impact employment across various levels, including industry and occupational levels. Their findings suggest that while automation leads to a reduction in routine and manual jobs, it also creates demand for high-skilled roles, particularly in areas that require advanced technical skills. The research points out that automation's effects are not purely displacement-orientated; it has the potential to improve productivity and generate new opportunities, especially in sectors well-suited for elevated levels of human-AI collaboration (Filippi et al., 2023).

Automation and AI technologies often displace routine, repetitive roles but simultaneously create new job categories that require specialised technical skills, shifting the demand towards higher-skill positions (Cascio & Montealegre, 2016). This trend reflects the complex nature of AI's impact on employment, as job displacement varies significantly based on the level of routine involved in tasks and an industry's ability to adapt to modern technologies (Cascio & Montealegre, 2016). The areas most impacted by AI technologies are those that demand digital fluency and adaptability to new tools. Therefore, eventual job displacement from AI is uneven, influenced by each position's capacity to integrate with advancing technology.

Both articles emphasise that the risk of job displacement is inevitable. To succeed amid technological disruption, companies should focus on workforce agility and strategic planning to equip employees to work alongside advanced technologies (Cascio & Montealegre, 2016). Technology will continue to transform work, and the organisations that prepare their employees to engage with innovative approaches will be better equipped to thrive in a digitally driven environment (Cascio & Montealegre, 2016). After all, effects of automation vary widely across industries and regions, which shows the importance of considering industry-specific and regional factors in studying job displacement (Filippi et al., 2023). The extent of job displacement caused by AI technologies is not entirely uniform but rather contingent on the types of tasks and depends on the region's ability to adopt and integrate modern technologies.

The labour market effects of AI adoption are highly heterogeneous across regions, industries, and firm sizes (OECD, 2023). Countries with more flexible labour markets and dynamic innovation ecosystems, such as the United States, are better positioned to capture the employment benefits from AI adoption due to their greater capacity for organisational restructuring and labour reallocation. In contrast, European countries, with stricter labour market regulations and a slower digital infrastructure roll-out, may experience more gradual labour market adjustments as AI technologies are introduced (OECD, 2023). The OECD also notes that larger firms tend to benefit disproportionately

from AI adoption, as they have greater financial resources and organisational capabilities to invest in complementary assets, which means widening productivity gaps between existing firms (OECD, 2023). These structural differences are critical in explaining the cross-country and firm-level variations in AI's labour market effects.

2.5. AI-Driven Automation in Financial Services

From credit scoring and fraud detection in banking to algorithmic trading and portfolio management in asset management, AI is expanding its reach, automating routine tasks in the different sectors in the finance industry. Not only is it improving efficiency but also driving innovation and significantly reshaping the workforce. In this section, this academic literature review delves into the existing applications of AI-driven automation across different areas in the industry.

Artificial intelligence can also be understood as a General-Purpose Technology (GPT). GPT is a class of transformative innovations, like electricity or the internet, that reshape multiple industries through widespread adoption and complementary organisational change (Brynjolfsson et al., 2019). In financial services, GPTs based on AI do not provide productivity or labour advantages by themselves. Instead, their effectiveness depends on complementary investments by firms in software, human capital, data infrastructure, etc. Without these, AI investments may fail to translate into measurable economic gains even in sectors that have a high automation potential.

2.5.1. Applications of AI-driven Automation in Key Banking Areas

AI-driven automation is transforming banking by enhancing efficiency, accuracy, and personalisation in financial services. AI tools can optimise credit scoring, lending, fraud detection, and customer recommendations by analysing vast datasets in real-time. These advancements not only streamline operations but also enable banks to provide customers with tailored services that are responsive while meeting the demand of a tech-driven marketplace (Doumpos et al., 2023).

Financial services in banking where AI-driven automation is used are primarily for tasks that enhance efficiency and decision-making. AI techniques, such as machine learning, improve credit scoring accuracy and optimise lending decisions by analysing a combination of financial and non-financial data, including insights from social networks and mobile devices, going beyond traditional data sources (Doumpos et al., 2023). ML models also help banks by recommending tailored financial products based on customer history and preferences, increasing customer engagement, and managing customer relationships more easily (Doumpos et al., 2023).

As for risk management, AI can manage and predict financial threats using *machine learning models* and *Bayesian networks*. Bayesian networks use probabilistic models that map and analyse

relationships between various risk factors, helping to forecast outcomes like default risk based on previous patterns (Doumpos et al., 2023). Some studies have employed the Bayesian networks model to analyse liquidity and operational risks (Sanford & Moosa, 2015). Deep learning models detect potential fraud by examining data patterns within transactions and quickly flagging suspicious activity to reduce fraud-related losses (Doumpos et al., 2023).

For financial planning and robo-advisors, machine learning and big data are used to develop robo-advisors that can incorporate user preferences and financial data to provide tailored advice (Doumpos et al., 2023). Not only is it more effective and accessible to retail investors, but it also reduces biases inherent in traditional advisory services.

2.5.2. AI-driven Asset Management

Asset management is a significant segment of the global financial sector. As of June 2024, the global asset management industry managed approximately \$132 trillion (€123.3 trillion) in assets (McKinsey, 2024). This represents a substantial portion of the global financial assets, which include banking assets, insurance assets, and capital markets. Bartram et al. (2020) breaks down AI's role in various financial services in asset management.

As for portfolio management, AI algorithms, including *neural networks* and *genetic algorithms*, support complex asset allocation by predicting returns and assessing risks more accurately than traditional models. For instance, neural networks optimise portfolios to enhance metrics like the Sharpe ratio and can even replicate benchmark portfolios with fewer assets for lower costs (Bartram et al. 2020). ML models have also helped in transforming raw data into relevant variables for asset return prediction and portfolio optimisation.

In trading, AI automates algorithmic trading processes, from pre-trade analysis to execution and post-trade analysis. In pre-trade, for example, AI models forecast asset performance, estimate risks, and form trade lists, while in trade execution, algorithms select optimal timing and pricing—AI's speed and analytical power allow for complex high-frequency trading strategies that traditional methods cannot manage (Bartram et al., 2020).

AI automation in risk management has enhanced market risk modelling by integrating diverse data sources, including news and social media, to forecast variables like bankruptcy probability and market volatility. ML models backtest predictions, providing benchmarks that highlight discrepancies and trigger risk alerts to support a more reliable decision-making (Bartram et al., 2020).

AI and ML have enabled the development of personalised investment advisors, customising portfolios to align with individual investors risk preferences and goals. *Natural language processing* (NLP) and big data allow robo-advisors to incorporate user inputs and financial data, making investment

management accessible and personalised (Bartram et al., 2020), remarkably like the robo-advisors earlier mentioned in Doumpos et al. (2023). Robo-advisors make financial advice more accessible for retail investors and reduce human biases in investment decisions, offering a cost-effective alternative to traditional financial advisors.

2.5.3. AI-Driven Automation in Accounting Services

AI is transforming accounting by using ML and natural language processing (NLP) techniques to analyse complex financial data with greater accuracy and efficiency. For example, AI helps auditors assess the integrity of financial reports by automating the review of large datasets from regulatory filings and corporate disclosures (Cao et al., 2021). ML algorithms process and analyse large datasets to identify patterns and anomalies to improve financial analysis. By learning typical transaction behaviour and flagging anything unusual, ML models can detect irregularities in financial transactions. By using deep learning models and other leading image recognition algorithms in neural networks, AI can improve accuracy by identifying complex, hidden patterns that simple algorithms might miss (Cao et al., 2021), making the automation not only effective but also dependable.

With ML, AI can streamline tasks like data entry and transaction processing, allowing accountants to focus more on analysis and decision-making rather than manual work. These systems learn from past actions and can be programmed to manage structured data, automating high-volume processes that previously required manual input (Cao et al., 2021).

NLP and big data analytics enhance real-time reporting for fiscal management by generating real-time financial reports that capture the latest financial data and insights. The AI relies on structured data such as accounting entries and inventory updates and unstructured data like news feeds, social media, and economic indicators (Cao et al., 2021). NLP models extract insight from text data sources like earnings reports, press releases, and financial news to interpret relevant information. This way AI can support dynamic fiscal management and faster decision-making, which are essential in today's fast-paced market environment.

2.5.4. AI-Driven Automation in Insurance Services

The integration of AI into financial insurance services is transforming the industry by enabling advanced analytics, enhanced fraud detection, and more accurate risk assessment. Recent developments in modern AI techniques such as deep learning and machine learning are reshaping the financial insurance landscape by enabling insurers to predict risks, automate complex processes, and offer more personalised services to their customers (Cao et al., 2021).

The incorporation of AI-driven automation in the insurance industry has shown significant economic benefits when strategically optimised. A decision model grounded in maximising the present value of cash flows, advocating an adaptable strategy for automation decisions (Braunwarth et al., 2010). Their research indicates that neither fully automated nor entirely manual insurance processes yield optimal economic outcomes. Instead, dynamically adjusting automation levels based on real-time capacity, workload variations, and process complexities significantly enhances profitability (Braunwarth et al., 2010). For instance, a case study in their research demonstrated substantial financial advantages when automation was adapted dynamically according to workload conditions, such as increasing manual oversight during periods of low workload and maximising automation during periods of high demand (Braunwarth et al., 2010).

Furthermore, integrating blockchain technology with AI enhances data security, transparency, and real-time decision-making, significantly reducing fraud and ensuring more efficient, secure insurance operations (Dhieb et al., 2020). Using advanced ML algorithms and online incremental learning, insurers can dynamically detect fraud with greater accuracy and adapt their risk management strategies in real time. These AI innovations, strategically integrated with economic optimisation principles, enable insurers to balance automated and manual processes effectively, leading to improvements in cost efficiency and profitability (Braunwarth et al., 2010)

2.6. Economic consequences of job displacement

Job displacement, defined as involuntary job loss due to (i) economic downturns, (ii) technological innovation, or (iii) structural shifts in the economy, imposes substantial economic costs both on individuals and society. Displaced workers often face significant declines in lifetime earnings and increased risks of long-term unemployment, factors that adversely affect overall economic security and welfare (Stevens, 1997; Ruhm, 1991). Beyond immediate income loss, displaced workers experience depreciation of firm-specific human capital, reduced re-employment probabilities, and potential exclusion from the labour force, especially among older demographics (Tatsiramos, 2010). Older displaced workers' transitions into retirement or re-employment are heavily influenced by institutional factors such as unemployment benefits and early retirement schemes, which in turn shape broader economic outcomes such as public expenditures and labour market efficiency (Tatsiramos, 2010).

The economic consequences of job displacement extend well beyond immediate unemployment, significantly impacting workers' long-term economic prospects, job quality, and career trajectories. Displaced workers typically face persistent earnings losses, prolonged employment instability, and increased risks of long-term unemployment, which can alter their socio-economic status substantially. Displaced households are about 2.5 times more likely to file for bankruptcy in the year

immediately following job loss compared to those not displaced (Keys, 2010). The heightened bankruptcy risk remains elevated for two to three years after displacement, highlighting a lasting economic consequence of unemployment. Even short-term unemployment spells can have long-lasting negative effects on household creditworthiness, financial stability, and access to future credit. Furthermore, technological displacement, notably through automation and robotics, aggravates these economic consequences by not only displacing workers but also degrading job quality and intensifying wage inequality, which reshapes the structural characteristics of labour markets (Guarascio et al., 2023).

2.7 Technological and Economic Forces Reshaping Human Capital

Human capital plays a crucial role in economic and technological advancements, as it encompasses the knowledge, skills, and health that individuals acquire through education, training, and experience. According to Becker (1993), human capital refers to investments in individuals, such as schooling, medical care, and job training, which enhance productivity and potential earnings. Unlike physical or financial capital, human capital is inseparable from the person possessing it (Becker, 1993). As technological and economic forces continue to evolve, the demands on human capital are shifting, requiring continuous adaptation to new skills, education, and knowledge.

Technological advancements, particularly in AI, are significantly transforming labour market dynamics by increasing demand for specialised skills. There is a dramatic rise in the demand for AI skills across various sectors, with IT, management, scientific, and engineering fields experiencing particularly intense growth (Alekseeva et al., 2021). Such technology-driven shifts have created wage premiums, with postings requiring AI skills offering an 11% higher wage within the same firm and a 5% higher wage within the same job title. The wage premium for AI skills is notably highest in managerial occupations, emphasising AI's critical role in broader organisational transformations rather than isolated technical functions (Alekseeva et al., 2021). The growing need for these technological competencies signals an economic shift, with firms that are financially strong, large-scale, and heavily invested in R&D leading in AI adoption and thus reshaping their workforce towards more technological and skilled human capital.

Specific human capital acquired through experience and on-the-job training, as well as general human capital derived from formal education, significantly reduces job turnover rates, particularly in high-tech industries (Silva et al. 2017). Silva et al. (2017) used longitudinal matched employer-employee data to analyse and reveal that higher technological intensity strengthens the positive correlation between skill levels and job duration. Such evidence underlines the economic value firms place on skilled human capital in increasingly technology-driven environments, for example, in finance.

2.8 Ethical implications of AI integration

The integration of artificial intelligence within the financial sector presents substantial ethical implications and accountability challenges that prompt good governance and responsible management. To achieve responsible AI integration, it is crucial to develop strong governance structures, clear accountability frameworks, and practical ethical guidelines that align technological progress with societal values (Kazim & Koshiyama, 2021). Ethical governance of AI must address complexities arising from technology's rapid advancement, particularly regarding accountability, transparency, privacy, and fairness (Kazim & Koshiyama, 2021; Tóth & Blut, 2024). Addressing these ethical implications requires an understanding of both theoretical and practical aspects of ethical AI, from corporate responsibilities to regulatory oversight, and from philosophical considerations to professional accountability.

2.8.1 Human-centric AI

AI ethics is an interdisciplinary domain, merging insights from philosophy, computer science, law, and social sciences to address the complex ethical challenges posed by AI technologies. Central to these considerations is the concept of “human-centric AI”, which prioritises the enhancement and safeguarding of human well-being, autonomy, and dignity within AI development and implementation (Kazim & Koshiyama, 2021). Building upon this foundational concept, human-centric AI also advocates for transparency in AI operations, ensuring that users clearly understand how decisions are made and how their personal data is managed. Additionally, fairness is emphasised to guarantee equitable outcomes, uphold trust, and minimise bias within financial systems.

The concept of human-centric AI is grounded within three philosophical ethical frameworks that are provided as practical guidance and a deeper justification. *Utilitarianism* draws attention to the importance of maximising societal benefits through efficient, accessible, and broadly beneficial AI systems, thereby promoting overall public welfare. *Rights-based ethics* highlights the necessity of protecting individual entitlements such as privacy, autonomy, and equitable treatment, reinforcing the critical role of transparency and fairness. Finally, *virtue ethics* underscores developing an ethical organisational culture, advocating that AI development should be guided by virtues like honesty, integrity, and accountability. Collectively, these integrated ethical perspectives make sure that human-centric AI aligns with broader societal values and ethical standards, effectively safeguarding human dignity and well-being.

2.8.2 Principle-Based Ethical Frameworks and Their Limitations

Kazim and Koshiyama (2021) identify several foundational ethical principles crucial for guiding AI development and deployment. These principles include *transparency*, *fairness*, *accountability*, and *privacy*, each serving as an essential component to ensure responsible and ethically sound integration of AI technologies.

Transparency emphasises clarity in AI processes, ensuring users and stakeholders understand how AI-driven decisions are made, thus enabling informed trust and reducing uncertainty. *Fairness* is directed at preventing discrimination and bias and advocating for equitable and just outcomes across diverse user groups. *Accountability* is about creating clear frameworks for attributing responsibility and establishing mechanisms to hold developers and institutions answerable for the impacts of AI systems. *Privacy* emphasises safeguarding personal data and maintaining user autonomy, thereby ensuring AI applications respect individual rights and freedoms. Collectively these ethical principles aim to strengthen trust, equity, and responsibility in AI applications, particularly within sensitive areas such as financial services.

On the other hand, there are critical limitations of relying solely on principle-based approaches, arguing that ethical principles alone cannot guarantee the ethical deployment of AI. Principles often face practical implementation challenges due to their inherent abstractness, ambiguity, and variability across context (Mittelstadt, 2019). Effective ethical governance requires complementary structures, including clearly defined fiduciary responsibilities, solid professional norms, and empirically validated methods for translating principles into specific, actionable guidelines (Kazim & Koshiyama, 2021). There is a need for enforceable legal and professional accountability mechanisms to ensure principles are not just aspirational statements but genuinely guide real-world behaviour (Mittelstadt, 2019). It becomes clear that while ethical principles are indispensable for providing normative guidance, their effectiveness critically depends on detailed contextualisation and structural reinforcement.

Recognising the limitations of these principles underlines the need for concrete governance structures and regulatory frameworks that proactively address the economic disruption AI may cause. By incorporating practical measures alongside ethical principles, financial institutions and policymakers can effectively anticipate and mitigate negative impacts of AI, such as unequal distribution of benefits or disproportionate job losses. It's important to ensure that AI integration promotes not only efficiency and competitiveness but also socio-economic resilience to protect both economic stability and ethical standards amid workforce transformations.

2.8.3 Corporate Digital Responsibility in the Financial Sector

Corporate Digital Responsibility (CDR) is a strategic framework emphasising corporate accountability for the ethical, social, and environmental impacts associated with digital technologies, including AI. This strategic approach broadens traditional corporate responsibility by focusing on digital ethics concerns, including transparency in data usage, fairness in algorithmic decision-making, strict privacy protection, and active prevention of digital harms. This ensures technological innovations align with societal values and expectations (Tóth and Blut, 2024) “CDR is of particular importance in financial services given the nature of the service and its impact on people’s lives” (Tóth and Blut, 2024). They further explain that AI algorithms can have adverse consequences and undercut individuals’ rights and dignity.

CDR requires not just ethical guidelines but the creation and implementation of strong governance structures, including internal ethical policies, specialised oversight roles such as CDR representatives, and comprehensive ethical review boards. Effective implementation demands an organisational culture deeply embedded with ethical awareness and continuous reflection on evolving digital practices. Such an approach not only mitigates risks associated with digital innovation such as AI but also enhances consumer trust, regulatory compliance, and overall organisational reputation.

In the context of the financial sector, adopting CDR becomes particularly crucial due to the significant socio-economic implications arising from AI-driven job displacement. Financial institutions face ethical responsibilities towards affected employees and show the necessity for clear communication, equitable treatment, and substantial investments in workforce retraining and re-skilling initiatives. Institutions that proactively embrace CDR ethically manage these workforce transitions, balancing technological efficiency with socio-economic stability (Tóth and Blut, 2024). Transparent and responsible decision-making should be prioritised by financial institutions to not only address the immediate ethical challenges but also to contribute to long-term societal resilience and trust in digital innovations by the stakeholders.

3. Methodology

3.1. Research Context

This research is grounded in the context of the ongoing transformation brought about by AI-driven automation within the financial sector. The finance industry is undergoing rapid technological advancement, creating uncertainties for existing workers in the industry. These AI technologies are not only optimising efficiency and accuracy but also influencing employment structures by automating routine and data-intensive tasks.

The focus of the research is on the economic consequences of job displacement caused by AI adoption in the financial sector, with a particular emphasis on financial services such as banking, asset management, accounting services, and insurance services. For context, the finance sector was selected due to its extensive reliance on data-driven decision-making and its early adoption of AI technologies, making it an excellent industry for examining the effects of automation on employment. I have referred to “The Future of Jobs Report” (2023) by the World Economic Forum and “The Impact of Artificial Intelligence on the Future of Workforces in the European Union and the United States” by the White House (2022) to highlight the finance sector’s heightened susceptibility to AI-induced job displacement. These reports provide good insights on the effect of automation as well as the impact of AI on various industries, helping to contextualise its transformative effects on the labour market.

Table 1.1 AI Impact across Financial Sub-sectors

Aspect	Banking (Doumpos et al., 2023; Sanford & Moosa, 2015)	Asset Management (Bartram et al., 2020; Doumpos et al., 2023)	Insurance (Braunwarth et al., 2010; Cao et al., 2021; Dhieb et al., 2020)	Accounting (Cao et al., 2021)
Focus	Transaction processing, customer services, risk assessment	Portfolio management, analysis, forecasting	Claims processing, risk evaluation, customer service	Financial reporting, audit, compliance, transaction process
Typical tasks	Rule-based transactions, customer interactions, regulatory compliance	Investment analysis, portfolio optimisation, data-driven forecasting	Problem-solving, advisory	Bookkeeping, financial statement preparation, audit testing, compliance monitoring

Impact of AI/Automation	High (automation of transactions, risk modelling, customer interfaces)	Medium-High (use of AI for analytical and predictive capabilities)	High (significant use in claims automation, fraud detection, chatbots)	High (Automated bookkeeping, transaction matching, anomaly detection, predictive audit analytics, fraud detection).
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3.2. Research design

As mentioned earlier, the topic of this thesis is about AI-driven job displacement in the finance sector with an emphasis on its economic impact. The research of this topic is contextualised within a literature review to provide evidence-based insights; this research will then conduct an empirical econometric analysis. This approach is highly suitable for identifying and quantifying the relationship between AI adoption and workforce changes within the financial industry. The analysis will aim at isolating the effects of AI adoption on job displacement and transformation by applying relevant statistical models. As for the automation technologies related to AI automation, the ones that do not aim to replace human labour with machines are excluded from this analysis.

3.3. Data Collection

The data used in this study were sourced from Eikon DataStream, a comprehensive financial and economic database widely used in academic and industry research. Initially, as a first preliminary research step, the sample consists of publicly listed US and European financial firms across various sub-sectors, including banking, insurance, asset management, and accounting/audit. The main variables collected for each firm include the number of employees, capital expenditures (CapEx), intangible assets, and market value.

While data was initially collected for the period 2010-2023, it was determined that retaining observations prior to 2015 would not be meaningful because AI had limited influence on capital expenditures and intangible assets during those years. The final sample period of 2015-2023 was therefore chosen deliberately. Intangible investment became significantly more important from the mid-2010s onward (Corrado et al., 2016). As AI adoption in finance is closely tied to these intangibles, starting in 2015 makes sure that the analysis captures the period when AI-related investments became economically meaningful (Corrado et al., 2016). The end year 2023 reflects the most recent available data and covers both the pre-pandemic expansion, the COVID-19 shock, and the early recovery.

Considering that the dataset reported financial figures in various local currencies, all monetary values were converted to US dollars for consistency and comparability across firms. To maintain accuracy over time, historical yearly exchange rates were used for each corresponding year.

3.3.1 Banking

For transaction-based roles, this data analysis focuses exclusively on banks located in the United States and Europe to ensure consistency in data availability, regulatory frameworks, and comparability in technology adoption. Both regions represent mature financial markets with high levels of AI adoption and robust public disclosure standards, which ensures reliable reporting of employment, CapEx, intangible assets, and other financial indicators. Moreover, the US and European banking sectors are among the earliest adopters of AI-driven automation technologies, making them ideal for studying the economic impact of AI on job displacement.

A total of 65 banks were selected based on size, geographic distribution, and operational type, enabling meaningful segmentation and comparative analysis. The sample includes 21 banks from the United States and 44 from Europe, covering both large multinational financial institutions and mid-sized regional banks. This segmentation allows us to analyse how AI adoption may differentially impact banks depending on their scale and market focus. The banks were chosen primarily from publicly listed institutions due to their transparent and standardised financial disclosures, particularly regarding staffing levels, investment activities, and AI-related expenditures (often captured through CapEx, or intangible assets). Including a mix of commercial and regional banks also helps with investigating into whether smaller, regional banks experience the effect of automation differently than larger global institutions. This cross-sectional coverage strengthens the validity of the econometric analysis, particularly when we are going to examine the trends in transaction-based job displacement driven by AI.

3.3.2 Asset Management

For the asset management segment of the analysis, this research will focus on firms based again in the US and Europe. These two regions not only represent the largest and most mature global asset management markets but also show high levels of AI integration and data transparency. The firms selected span a mix of traditional asset managers, investment banks with asset management divisions, and alternative asset managers. These companies were selected for their market relevance, transparency in financial and employment data, and for us to assess the impact of AI adoption in portfolio optimisation, algorithmic trading, and automated client services.

A total of 39 asset management firms were included in the analysis, consisting of almost equal representation from North America (20) and Europe (19). The sample includes globally dominant firms such as BlackRock, Vanguard, Amundi, and Allianz, alongside mid-sized firms to allow for segmentation by size and structure. It also included both independent asset managers and those affiliated with larger banking or insurance groups for us to understand how AI adoption interacts with

organisational models and operating scales. This approach to the sample allows for consistent data quality while providing a representative view of the broader industry's structural and technological transformations.

3.3.3 Insurance

Within the insurance sub-sector of finance, I collected a structured sample of 45 publicly traded insurance companies, where 18 are from North America and 27 are from Europe. These companies were specifically selected for several reasons. Publicly traded status helps with transparency and availability of data necessary for an analysis. Market capitalisation was also considered, as selecting firms of varying sizes provides insights into how AI adoption affects companies differently based on their scale and resources. In the sample there is a mix of various types of insurance, including health, life, property and casualty, multiline, speciality insurance, and reinsurance.

The insurance sector was identified as a critical area for analysing the impact of AI because of its increasing exposure to automation, ML, and AI-driven analytical processes. Insurers progressively use AI for tasks such as claims processing, fraud detection, risk assessment, customer interaction, and underwriting, all areas characterised by labour-intensive activities. The decision to include both European and US-based insurers is to help the analysis with being able to compare AI impact across regulatory environments and market structures. The data set aligns with the thesis's aim to quantify and explore the technological adoption that affects employment dynamics in the insurance industry.

3.3.4 Accounting

The accounting sub-sector is included as a distinct category in this Dissertation, even though it represents the smallest sample (6) among the financial sub-sectors analysed. 4 of the companies are from North America, while 2 are from Europe. The global accounting and audit industry is dominated by the "Big 4" firms (Deloitte, PwC, EY, and KPMG), which account for the majority of global audit and professional services revenues. However, these leading firms are organised as private partnerships rather than publicly listed corporations, meaning that they are not required to disclose detailed, standardised annual financial data. As a result, historical and consistent firm-level information on variables needed for the analysis is not sufficient or available for these accounting firms.

Due to these data limitations, the accounting sample in this Dissertation consists exclusively of publicly traded accounting and professional services firms for which standardised panel data could be collected. They operate within the same sector and are subject to similar technological pressures, such as adopting new automation technologies and AI-driven solutions in their operations.

The inclusion of the accounting sub-sector is not merely justified but necessary given its critical position at the intersection of finance and technological change. Accounting is among the most affected areas in the financial sector when it comes to the automation of standardised and repetitive tasks, due to the highly codified and rules-based nature of much of its work. Excluding the accounting sub-sector would therefore risk overlooking some of the most pronounced and illustrative examples of job displacement and evolving skill demands brought about by AI adoption in finance. By keeping this sub-sector in the empirical analysis, the Dissertation can capture the full spectrum of economic impact arising from AI-driven change across the industry.

3.4. Conceptual Framework

The conceptual framework outlines the relationships between the key elements of the study: (i) AI adoption, (ii) job displacement and transformation, and (iii) economic impacts.

3.4.1. AI Adoption

AI adoption refers to the integration of advanced technologies such as machine learning (ML), natural language processing (NLP), and robotic process automation (RPA) into financial processes. These technologies are particularly relevant to finance roles, as they automate complex tasks, enhance operational efficiency, and support improved decision-making within firms. Key applications are

- ML: Fraud detection, predictive analytics, credit scoring
- NLP: Chatbots, robo-advisors, text-based financial analysis
- RPA: Automation of repetitive tasks like data entry.

The drivers of the AI adoption will be pressure to reduce operational costs, demand for real-time decision-making and data-driven insights, and competitive advantage through personalised financial services. Adoption can range from incremental process improvements to comprehensive organisational transformations. However, firms face substantial barriers, including regulatory compliance issues, data privacy concerns, significant implementation costs, resistance to change, and a workforce skill gap.

3.4.2. Proxies for AI adoption

Measuring firm-level AI adoption directly is difficult due to the limited availability of granular data capturing specific AI investments. To overcome this challenge, this research follows established literature that employs financial proxies reflecting the complementary investments typically associated with AI adoption. Specifically, two proxies are being used: *intangible assets* and *capital expenditures* (CapEx).

Intangible assets have been widely recognised as a reliable proxy for AI adoption or technological investment. Intangible capital, such as organisational know-how, proprietary software, databases, data processing infrastructure, and firm-specific human capital, represents the foundation for modern technology-driven production processes (Corrado et al., 2005; 2009). AI technologies rely heavily on these intangible inputs, as they require extensive data accumulation, algorithm development, internal system integration, and human expertise to be effectively implemented. AI is a general-purpose technology that demands substantial complementary investments in data architecture, employee training, process reorganisation, and management adaptation, which all fall under the category of intangible assets (Brynjolfsson et al., 2021). Without such complementary investments, AI adoption cannot generate meaningful productivity gains or business transformation. Intangible assets increasingly dominate production in the digital economy, particularly for advanced technologies like AI that are embedded in data-driven, algorithmic decision-making and complex service delivery processes such as those prevalent in the financial sector (Haskel & Westlake, 2018).

In parallel, capital expenditures serve as a second proxy, capturing the physical infrastructure investments often required to support AI integration. These include expenditures on servers, data centres, high-performance computing hardware, networking equipment, and other specialised physical assets essential for the operation of AI systems. Automation technologies, including AI, typically necessitate significant capital deepening through investment in physical and computing infrastructure (Acemoglu & Restrepo, 2018). Capital expenditures associated with IT infrastructure can reflect the physical backbone required for digital and algorithmic technologies to function effectively (Bloom et al., 2012). In sectors such as finance, where AI-driven applications such as algorithmic trading, risk analytics, and personalised financial advising depend on real-time data processing and large-scale computational capacity, capital expenditures often directly embody these AI-enabling investments.

Recent empirical work further validates the combined use of intangible assets and capital expenditures as proxies for AI adoption. AI investment is not solely captured through R&D but also materialises through complementary organisational investments, infrastructure spending, and software development, which are all reflected in financial reporting of intangibles and capital assets (Babina et al. 2020). Investments in ICT (information and communications technology) infrastructure, which are frequently reported as capital expenditures, are critical enablers of AI adoption, especially in sectors reliant on intensive data processing and advanced analytics (DeStefano et al., 2020). ICT capital facilitates the deployment of complementary data-intensive technologies such as advanced analytics, machine learning, and predictive modelling, which link ICT CapEx directly to AI-relevant investments (DeStefano et al., 2020).

The use of intangible assets and CapEx for AI adoption is grounded in the GPT framework, which states that the value of technologies like AI arises only when paired with complementary organisational capabilities (Brynjolfsson et al., 2019). Physical investment alone without strategic and human-centred transformation is unlikely to yield meaningful impacts on labour or productivity outcomes.

3.4.3 Proxy Limitations and Considerations

While R&D expenditure is widely recognised as a theoretically strong proxy for AI adoption due to its direct connection to innovation, algorithm development, and internal technological advancement (Brynjolfsson et al., 2019), its practical use in this research is limited by significant data constraints. Many publicly listed financial firms either do not report R&D expenditures separately in their financial statements or aggregate them into broader operating expenses without standardised disclosure. This inconsistency in reporting in the financial sector makes it difficult to rely on firm-level R&D datasets across the full sample.

As a result, while R&D spending would ideally capture AI-related internal development activities such as model building, algorithm refinement, and software engineering, its exclusion in this analysis reflects the reality of insufficient and incomplete data coverage, rather than a theoretical weakness of the variable itself. Therefore, this research will instead rely on the proxies' intangible assets and capital expenditures, as they are both theoretically grounded and consistently available across financial firms.

In addition, even for intangible assets and capital expenditures, some measurement limitations remain. Intangible assets often lack fully standardised valuation methodologies and may involve some level of managerial discretion in reporting. Similarly, capital expenditures may include broader physical infrastructure investments not exclusively linked to AI adoption. Furthermore, implementation lags may exist between when investments are made and when corresponding productivity effects take shape, potentially complicating the interpretation of empirical results.

Despite these limitations, the use of intangible assets and capital expenditures remains the most practical and empirically manageable approach to approximate AI adoption at the firm level within the finance sector, particularly when working with large panel datasets of publicly listed companies. These proxies capture the essential complementary investments, both organisational and infrastructural, that enable firms to deploy AI technologies, even when specific AI expenditure items are not separately disclosed. As such, they provide a theoretically grounded and widely accepted basis for empirical analysis of AI's labour market impacts in financial services.

3.4.4 Dependent Variable

The dependent variable in this study is the total number of employees reported by each financial company on an annual basis, serving as a direct indicator of financial workforce size. Employment is thus used to capture the labour dimension most susceptible to transformation or displacement as a result of AI adoption in the finance industry. This variable reflects the full scope of a company's internal workforce, including both high- and low-skilled roles across departments. Given the nature of the research question, employment is the most appropriate outcome variable to assess whether AI-related investments are associated with reductions, stability, or increases in labour demand. Given that the total number of employees serves as the key measure of labour demand, it is necessary to contextualise how AI adoption can influence employment outcomes. The following subsection outlines the main channel through which AI may drive either displacement or transformation of jobs in the finance sector, thereby directly affecting the dependent variable.

3.4.5. Job Displacement and Transformation

One of the most immediate consequences of the rise of AI in the finance sector is job displacement. Tasks reliant on manual data processing are particularly vulnerable and are being increasingly automated by AI systems, such as robotic process automation (RPA) and machine learning algorithms. For instance, major banks like JPMorgan Chase deployed an AI tool called COiN (Contract Intelligence) back in 2017 to review thousands of legal documents in seconds, a task that previously consumed 360,000 hours of lawyers and loan officers time annually (Son, 2017).

On the other hand, this wave of automation is accompanied by a transformation of roles rather than their outright elimination. AI has created demand for roles that combine domain-specific financial knowledge with AI technologies that increase automation and effectiveness.

For theoretical context, like any other automation tools, AI impacts human tasks through three broad effects: (i) *displacement effect*, (ii) *productivity effect*, and (iii) *reinstatement effect* (Tyson & Zysman, 2022).

- Displacement effect: reflects a decrease in demand for labour in tasks that are automated.
- Productivity effect: reflects an increase in the demand for labour in non-automated tasks.
- Reinstatement effect: reflects the creation of new tasks for labour.

3.4.6. Economic impact

The economic consequences of AI-driven job displacement in the finance sector are multifaceted, with implications for employment levels, wage structures, skill demand, and productivity. Technological change of this nature often exhibits both displacement and productivity-enhancing

effects that unfold over different time horizons (Acemoglu & Restrepo, 2019), a pattern also observed by Tyson and Zysman (2022) in their analysis of AI's broader economic implications. While high-skill roles may expand in the long run due to increased demand for AI-complementary labour, this shift contributes to persistent labour market polarisation. Anchoring the analysis on firm-level employment trends enables interpretation of broader economic dynamics such as wage polarisation, organisational restructuring, and the pace of skill transformation triggered by AI.

3.4.7. Framework Relationship

In this Dissertation's conceptual framework, AI adoption is proxied by firm-level CapEx, and intangible assets, which represent the key investments required to integrate advanced technologies into core financial processes. These investments are expected to influence workforce dynamics by enabling automation and efficiency improvements within the industry. The nature of this impact depends on how AI interacts with different categories of work, potentially displacing routine tasks while augmenting or creating roles that require increased skill levels (Tyson & Zysman, 2022; Brynjolfsson et al., 2019)

From the perspective of General-Purpose Technology (GPT) theory, the magnitude and direction of employment effects vary according to the presence of complementary investments in human capital, restructuring in the organisations, and digital infrastructure. These conditions vary across sub-sectors, firm-sizes, and regions, which helps explain the heterogeneous impacts observed in the empirical analysis.

This framework serves as the basis for the research hypothesis, which guides the selection of variables, informing the analysis models, and linking the theoretical foundations established in the literature review with the empirical tests that follow.

3.5. Research Hypothesis

The primary research hypothesis is that higher levels of AI adoption, proxied by firm-level CapEx and intangible assets expenditure, are associated with a reduction in employment. This hypothesis reflects the notion that automation and intelligent systems are more likely to substitute routine-based or repetitive financial tasks, which are often concentrated in lower-skilled positions.

H1: Higher levels of AI adoption, proxied by capital and intangible asset expenditure, are associated with a decrease in employment in the finance sector, particularly in lower-skilled roles.

H0: AI adoption has no significant impact on employment levels or skill composition in the finance sector.

To test this hypothesis, the research examines a panel dataset comprising 65 banks, 45 insurance companies, 39 asset management companies, and 6 accounting companies. from both the US and

Europe over a defined time of 10 years. By comparing these sub-sectors comprising the global finance industry, the analysis seeks to identify whether the impact of AI adoption on employment is uniform across the industry or more acute in certain segments (e.g., such as banking), where customer-facing and back-office operations are more vulnerable to automation.

The null hypothesis states that AI adoption has no significant effect on employment levels or workforce composition by skill. This assumption will be tested using a fixed effects panel data regression model, which controls for firm-specific and time-invariant characteristics. Digitalisation intensity is proxied through intangible/tangible asset ratios or IT/software spending where available. The results will provide empirical evidence on whether AI adoption in finance is indeed labour-replacing and whether its effects vary significantly across sub-sectors.

4. Empirical Analysis

4.1 Model specification

To assess the relationship between AI-related investments and employment in the financial sector, a fixed-effect panel regression model using firm-level data from 2015 to 2023 is estimated. All key continuous variables in the analysis are log-transformed prior to estimation to improve interpretability, comparability, and model fit.

First, log-transforming both the dependent and independent variables allows the estimated coefficients to be interpreted as elasticities. For example, a coefficient of 0.1 on CapEx implies that a 1% increase in capital expenditure is associated with a 0.1% change in employment. Second, variables like capital expenditures and market value vary widely across firms and time. Therefore, logging helps reduce skewness and brings variables measured in different units onto a comparable scale. Third and last, many economic relationships are multiplicative rather than additive, and the log-log functional form is better suited to capture these complex dynamics, particularly when effects diminish proportionally with firm size.

$$\begin{aligned} \log(\text{employees}_{it}) \\ &= \beta_1 \log(\text{CapEx}_{it}) + \beta_2 \log(\text{Intangibles}_{it}) + \beta_3 \log(\text{MarketValue}_{it}) + \gamma_t \\ &+ \alpha_i + \varepsilon_{it} \end{aligned}$$

In this specification, the dependent variable $\log(\text{employees}_{it})$ is the natural logarithm of employees at firm i in year t , representing the financial firm's labour size. The main explanatory variables are $\log(\text{CapEx}_{it})$, which captures log-transformed capital expenditures and serves as a proxy for AI-related and technological infrastructure investment, and $\log(\text{Intangibles}_{it})$, which reflects log-transformed intangible assets such as software, algorithms, and intellectual property related to AI capabilities. The $\log(\text{MarketValue}_{it})$ is included as a control for investor-perceived market valuation, which may also reflect innovation and intangible capital.

The model also includes year fixed effects, γ_t , to account for time-specific shocks such as macroeconomic changes, technological trends, or regulatory shifts that affect all firms simultaneously, such as the Covid-19 pandemic in 2020. Firm fixed effects, α_i , control for time-invariant firm characteristics like business model, industry position, and location. At the end of the equation, we have

ε_{it} that denotes the idiosyncratic error term. This model structure allows the estimation to focus on within-firm changes over time, isolating the effect of changes in AI-related investment on employment.

4.1.1 Choice of Estimator

Panel data estimation can be conducted using either Fixed Effects (FE) or Random Effects (RE). The FE estimator controls for all time-invariant firm-specific characteristics, while RE assumes that these unobserved effects are uncorrelated with the explanatory variables.

To determine the appropriate approach, a Hausman specification test was conducted using the model described above. The null hypothesis (H_0) is that RE is consistent and efficient; the alternative hypothesis (H_1) is that RE is inconsistent and FE is preferred. The test strongly rejected H_0 ($X^2(11) = 69.728, p < 0.001$), indicating that the explanatory variables are correlated with unobserved firm-specific effects (see **Annex Table A1** for full test output).

Based on this result, all regressions in this analysis are estimated using a Fixed Effects (within) estimator with firm and year effects, and standard errors clustered at the firm level to address potential heteroskedasticity and autocorrelation.

Interpretation: The null hypothesis that the random effects estimator is consistent is rejected at the 1% significance level ($p < 0.001$). This supports the use of fixed effects estimation for all core models in the analysis.

4.2. Results of the One-Way Fixed Effects Panel Regression

This section presents the results from the one-way (individual) fixed effects regression, estimated using the within transformation on an unbalanced panel dataset. The final analytical sample comprises 152 financial sector firms observed over a period ranging from 1 to 9 years ($T = 1-9$), resulting in a total of 1,346 firm-year observations ($N = 1,346$) spanning the 2015-2023 period.

All main explanatory variables are entered in log-transformed form (using $\log(x + 1)$), allowing coefficients to be interpreted as elasticities. The percentage change in firm employment associated with a 1% change in each predictor, holding other factors constant. Model residuals are symmetrically distributed around zero, with a minimum of -0.677 and a maximum of 0.667, and a median near 0.

The estimated coefficient for intangible assets ($\log\text{Intangibles}$) is 0.085 ($p < 0.001$), indicating a significant positive association with employment. Market value ($\log\text{MarketValue}$) is also significant and positive (0.020, $p < 0.001$). In contrast, CapEx ($\log\text{CapEx}$) shows no statistically significant effect (-0.0003, $p = 0.92$). Among year fixed effects, only 2019 through 2023 display significant positive

coefficients relative to the base year 2015, suggesting increased employment in recent years (**Annex Table B1**).

The model achieves an R-squared of 0.2317, meaning approximately 23% of the within-firm variation in employment is explained by the included predictors. The adjusted R-squared is 0.1265, which reflects the model's explanatory power after accounting for the number of predictors. The F-statistic (32.44, $p < 2.22e-16$) confirms that the independent variables jointly provide a statistically significant explanation for changes in employment.

In summary, the results provide evidence that intangible asset growth is positively associated with firm-level employment, while CapEx does not show a significant effect. Also, recent years are associated with significant increases in employment, potentially reflecting broader macroeconomic or technological changes in the financial sector.

4.2.1 Extended Fixed effects Regression: Controlling for Firm Size

To further strengthen the analysis and ensure that the relationship between AI-related investments and employment is not simply a reflection of firm size, an extended fixed effects model was estimated with the inclusion of total assets (log-transformed) as an explicit control variable for firm size and financial capacity. This approach addresses the possibility that larger firms may invest more in digital transformation and employ more staff due to scale effects, thereby isolating the specific contribution of AI-related expenditures to workforce dynamics.

While total assets and market value are both correlated with firm size, they capture distinct aspects of the firm's position. Total assets represent the internal resource base and operational scale, whereas market value reflects external perceptions regarding future growth, innovation, and intangibles, which are factors often influenced by technological adoption. When including both variables, we allow for a more comprehensive control for firm heterogeneity, and we improve the credibility of the estimated effects.

The extended model (**Annex Table B2**), estimated using the same unbalanced panel structure and period as the baseline, shows an improved explanatory power, with the R-squared increasing to 0.354 and the adjusted R-squared to 0.265. Model residuals remain symmetrically distributed around zero, with a narrow interquartile range and a median close to zero, which indicates that there is a robust model fit across firms and time.

Key findings described in **Annex Table B2** reveal that total assets (logTotalAssets) are strongly and positively associated with employment (coefficient = 0.255, $p < 0.001$), affirming that firm size is a major driver of workforce scale in the financial sector. Importantly, the intangible assets (logIntangibles) remain a significant predictor for employment (0.048, $p < 0.001$) even after accounting

for size, which can indicate that investments in digital infrastructure and AI-related capabilities continue to independently shape labour demand. Market value ($\log\text{MarketValue}$) also retains a positive and statistically significant association (0.013, $p < 0.01$), capturing aspects of firm valuation not fully explained by size alone.

On the other hand, the effect of CapEx ($\log\text{CapEx}$) is still not statistically significant in this extended specification (-0.002 , $p = 0.45$). This means that, once firm size and other factors are controlled for, physical capital investments are not systematically linked to employment changes in the finance sector panel.

Among the year fixed effects, only 2022 and 2023 display significant positive coefficients relative to the 2015 baseline, suggesting that recent years have experienced unique, sector-wide increases in employment, potentially reflecting the recent accelerating technological transformation and/or any macroeconomic shifts.

Overall, the extended model provides robust evidence that the positive association between AI adoption and employment is not merely an impact of firm size. Rather, digital, and intangible investments exert an independent influence on workforce dynamics in the finance sector, beyond the general effects of firm scale and financial capacity.

4.2.2 Regional Differences in the Impact of AI investment on Employment

To examine whether the relationship between AI-related investment and employment varies by region, a fixed effects regression model was estimated with interaction terms for both intangible assets and CapEx by regional affiliation. The model also uses the same control variables as the extended fixed effects regression to ensure that the estimated relationships are not confounded by firm size or broader market trends.

The results described in **Annex Table B3** indicate that, for North American firms, intangible assets have a positive and highly significant association with employment ($\beta = 0.089$, $p < 0.001$), while CapEx is positively but not significantly related to employment ($\beta = 0.007$, $p = 0.26$). This suggests that, in these regions, increases in intangible assets are a primary driver of employment growth associated with digital transformation.

Crucially, the interaction terms demonstrate substantial regional heterogeneity. The coefficient for $\log\text{Intangibles:RegionEurope}$ is significantly negative ($\beta = -0.053$, $p < 0.001$), meaning that the employment effect of intangible asset investment is markedly weaker among European firms. For European firms, the marginal effect of intangible assets is the sum of the main and interaction coefficients ($0.089 - 0.053 = 0.036$), which remains positive and significant but is less than half the effect observed in North American firms.

The interaction for RegionEurope:logCapEx is negative and statistically significant ($\beta = -0.013$, $p = 0.046$), indicating that the (non-significant) positive effect of CapEx on employment observed in North American firms is even weaker, or potentially negative, in Europe. Thus, European firms do not appear to experience the same employment gains from AI adoption as their non-European counterparts.

The model further confirms that both market value ($\beta = 0.015$, $p = 0.001$) and total assets ($\beta = 0.244$, $p < 0.001$) are strong positive predictors of employment, reflecting the central role of firm size and financial strength in shaping workforce outcomes. Among the year fixed effects, only 2022 and 2023 again display significant positive coefficients, which suggest a gain in sectoral employment in the most recent years. The model accounts for a meaningful share of the variance ($R^2 = 0.365$), which supports the strength and credibility of the results.

These results reveal clear regional disparities in the labour market effect of AI adoption. While both intangible assets and CapEx are associated with employment growth in non-European financial firms, these effects are significantly attenuated within Europe. This points to possible differences in (i) regulatory environments, (ii) labour market rigidity, (iii) digital infrastructure, or (iv) innovation diffusion across regions.

4.2.3 Firm-Level Correlation Between AI Adoption and Employment

To complement the panel regression analysis, a firm-level scatter plot is produced to visualise the relationship between AI-related investment proxy, which was built as the average of the log-transformed values of CapEx and intangible assets, thereby capturing both the tangible and intangible components of AI adoption. For each firm, the x-axis reflects the average level of AI-related investment over the 2015-2023 period, while the y-axis shows the corresponding average number of employees. To provide a descriptive, firm-level perspective on the link between AI adoption and employment, a Pearson correlation analysis was conducted using data from all firms in the sample.

$$X_i = \frac{1}{T_i} \sum_{t=1}^{T_i} \left(\frac{\log(CapEx_{it} + 1) + \log(Intangibles_{it} + 1)}{2} \right)$$

X_i is the firm average AI adoption proxy, defined as the mean across years of the average of log-transformed capital expenditures and intangible assets.

$$Y_i = \frac{1}{T_i} \sum_{t=1}^{T_i} Employees_{it}$$

In the formula we also have Y_i which is the firm's average number of employees, calculated as the mean number of employees per year.

The Pearson correlation coefficient between these two variables across all N firms is given by:

$$r = \frac{\sum_{i=1}^N (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^N (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^N (Y_i - \bar{Y})^2}}$$

Where \bar{X} and \bar{Y} are the mean values of the AI adoption and average employment, respectively, across all firms.

Annex Figure C1.1 reveals a moderate positive association between AI-related investment and firm employment, as indicated by the Pearson correlation coefficient ($r = 0.323$). The fitted trend line and its confidence interval demonstrate that firms with higher average AI investment also tend to employ more staff on average. While the data points are dispersed due to sector heterogeneity, the overall direction of the relationship is consistently positive.

Although correlation does not imply causation, these results do provide robust descriptive evidence that greater investment in AI-related assets is generally linked to larger firm workforces. This finding supports the previously described regression-based results while highlighting the empirical connection between AI adoption and employment at the firm level in the finance sector.

Annex Figure C1.2 displays the annual Pearson correlation coefficients between firms' AI adoption and their employment levels for each year from 2015 to 2023. The correlation remains consistently positive and moderate, ranging from 0.31 to 0.35, with minimal year-to-year variation. This indicates that, in every year, firms with greater AI adoption tend to have more employees on average, and this association does not appear to be driven by isolated events or short-term fluctuations.

The stability of these correlations over time suggests that the positive relationship between AI adoption and firm size is a persistent structural feature in the financial sector during this period. While the correlation is moderate rather than strong, there is still robust complementary evidence that increased AI adoption is generally linked to larger workforces across firms.

4.2.4 Sub-Sector Comparison of AI-adoption and Employment Correlation

The firm-level correlation analysis presented in **5.2.3** reveals substantial variation across financial sub-sectors in the association between AI adoption and employment. For this analysis, a composite indicator of AI adoption was constructed for each firm by taking the mean of the log-transformed AI adoption proxies for each observation year, then averaging across all available years for each company. This model is also a Pearson correlation coefficient, and it is used as a measure of association to demonstrate

the magnitude and direction of the relationship between firms' AI adoption and their number of employees, which vary considerably by sub-sector (**Annex Table C2**).

In asset management ($r = 0.59$, $N = 39$), a moderately strong and statistically meaningful correlation is observed, which indicates that firms in this segment with higher AI adoption tend to employ more personnel on average. Insurance companies show a moderate positive correlation ($r = 0.35$, $N = 45$), suggesting a similar but relatively weaker pattern. In contrast, the banking sub-sector displays a very weak positive correlation ($r = 0.10$, $N = 65$), implying little to no systematic association between AI adoption and workforce size among banks.

Mathematically, the Pearson correlation coefficient (r) quantifies the linear relationship between two variables, ranging from -1 (perfect negative correlation) to +1 (perfect positive correlation). The observed coefficients suggest that, while the relationship between AI adoption and employment is positive across most sectors, its strength is substantially greater in asset management and insurance compared to banking. This variation may reflect differences in the extent to which AI technologies are integrated into core business processes in the multiple types of financial institutions addressed by the present Dissertation.

It should be noted that the accounting sub-sector, with a sample size of only six firms, is excluded from substantive interpretation, as such a limited number of observations precludes a reliable inference. Overall, these findings strengthen the importance of disaggregating the finance sector when assessing the labour market impact of AI adoption, as sector-specific dynamics can influence both the direction and magnitude of observed effects. Lastly, the previously described dataset limitations may also have an impact on the computation of this correlation statistics.

4.2.5 Trend in Labour Productivity

The analysis of sales per employee (SPE) provides key insights into the evolution of productivity within the finance sector, especially in this sector where direct measures of output per worker are difficult to obtain. In the context of the finance sector, SPE quantifies the average revenue generated by each employee within a firm over a given year. This metric enables comparisons of productivity both across firms and over time to capture how efficiently companies utilise their workforce to generate sales.

$$\text{Sales per employee} = \frac{\text{Revenue}}{\text{Average Number of Employees}_{(\text{Beginning and ending of the yr})}}$$

The mean SPE increased substantially in recent years, particularly after 2020, reaching over \$2,000 by 2023 (**Annex Figure C3**). The median SPE, which is consistently lower than the mean, shows a gradual increase from approximately \$600 in 2015 to around \$800 by 2023. The persistent gap between the mean and median SPE indicates a positively skewed distribution, where a subset of highly

productive firms drives the overall average upward, while the typical firm (represented by the median) remains less productive but is also improving over time.

The rationale for employing SPE as a productivity indicator is twofold. First, in knowledge-intensive industries like finance, traditional output measures, such as physical goods produced, are less relevant, but instead revenue reflects the value of services delivered. Secondly, SPE directly links workforce utilisation to firm performance. Higher values typically indicate that each employee is contributing more to overall business outcomes, which may result from improved processes, effective use of technology, or organisational restructuring.

In summary, the upward trend in SPE for both the mean and median shows an ongoing productivity improvement in the finance sector. The acceleration in mean SPE may reflect the capacity of leading firms to leverage automation or AI to scale up operations without a proportional increase in workforce size. However, the widening gap between the mean and the median points to increasing heterogeneity among firms, where leading financial institutions benefit disproportionately from technological advancement.

4.2.6 Firm Size and the Employment Impact of AI Adoption

The results of the fixed effects regression analysis present in **Annex Table B4** reveal several notable patterns. The dependent variable is the log number of employees, modelled as a function of log-transformed CapEx, intangible assets, and market value, very similar to the first panel regression. The difference in this specification is that we are interacting this time with a large firm indicator, alongside a set of year fixed effects to capture time-specific influences.

Among the components of the AI adoption proxy, intangible assets ($\log\text{Intangibles}$) have a strong and statistically significant association with employment (coefficient = 0.073, $p < 0.001$), indicating that a 1% increase in intangible assets corresponds to a 0.073% increase in employment, all else being equal. The interaction term for intangible assets and larger firms ($\text{large_firm}:\log\text{Intangibles}$) is also highly significant (0.064, $p < 0.001$), demonstrating that the employment effect of intangible asset investments is especially pronounced among large companies. For large firms, the total marginal effect of intangible assets on employment is the sum of the main and interaction terms ($0.073+0.064 = 0.137$), implying a substantial employment impact when these firms invest in digital and AI-related capabilities.

On the other hand, the CapEx ($\log\text{CapEx}$) component of the AI adoption proxy is not statistically significant (-0.004 , $p = 0.311$), nor is its interaction with firm size ($\log\text{CapEx}:\text{large_firm}$, 0.005 , $p = 0.280$). This result suggests that, while CapEx is included as part of the broader AI adoption proxy as per existing academic literature, it is primarily the intangible asset investments that are driving

the observed employment effects, especially for larger firms that may be better positioned to integrate and capitalise on these new technologies.

Year dummy variables show that industry-wide factors in recent years, potentially including accelerating digitalisation and post-pandemic labour market changes, have resulted in significant positive employment effects, as seen in 2020 (0.036, $p = 0.045$), 2021 (0.049, $p = 0.007$), 2022 (0.073, $p < 0.001$), and 2023 (0.100, $p < 0.001$).

In conclusion, the model explains approximately 25.7% of the within-firm variation in employment ($R\text{-squared} = 0.257$). Overall, these results highlight that AI adoption plays a significant and increasingly important role in shaping employment outcomes in the finance sector. The employment impact of these investments is particularly strong among large firms with substantial intangible asset growth, emphasising the critical role of digital and AI capabilities in the sector's evolving workforce dynamics.

5. Discussion

5.1 Restating the Aim and Key Findings

The primary objective of this Dissertation is to empirically assess the economic impact of AI-driven automation on job displacement within the finance sector. In this document, panel data analysis using 152 publicly listed financial firms across North America and Europe is conducted, in order to go beyond theory and see what the numbers show about how AI is impacting jobs in the finance sector. The goal is to get concrete real-world evidence on whether AI adoption is mostly leading to job loss, job creation, or simply changing what kinds of roles are needed across different sub-sectors and regions. Intangible assets and capital expenditures are used as a proxy for AI adoption to capture the broad spectrum of technological and digital investments that drive innovation and automation in the industry, as per existing academic literature.

The analysis revealed several notable findings. Firms that invested more heavily in intangible assets and CapEx tended to see stable or even increasing levels of employment, particularly when it comes to digital transformation. Although the effect was strongest for intangible assets, the combination of these two investment types is used throughout the analysis to reflect the reality that AI adoption in finance is not limited to one specific kind of expenditure. Using both intangible assets and CapEx as proxies together reflects more the full range of investments, both in digital capabilities and supporting infrastructure.

The findings also point to important regional and sectoral differences. North American firms, and especially those in asset management and insurance, experienced the strongest positive relationship between AI adoption and employment. In contrast, European banks and smaller firms showed weaker effects, marking the importance of context, firm size, and the specific nature of financial services work.

Taken together, these findings provide empirical support in support of the view that AI adoption in finance is less about outright job displacement and more about transformation and upskilling, at least within the studied context and time window. Rather than driving widespread job losses, AI appears to be associated with evolving skill demands and differentiated workforce outcomes across regions, sub-sectors, and firm sizes.

5.2 Interpretation of Main Results

The data indicates that firms with higher investment in intangible assets, tended to maintain or expand their workforce size. This relationship was especially visible among North American firms and was

most pronounced in asset management and insurance. In contrast, CapEx did not show a significant association with employment, which suggests that digital and intangible investments, rather than physical infrastructure spending, are the main drivers of workforce effects in this period. These findings are consistent with the growing body of literature stressing the “transformation” and “augmentation” effects of AI rather than just displacement (Choi & Leigh, 2024). AI adoption in finance is not simply a driver of displacement but interacts with firm strategy, sector, and region to shape workforce outcomes.

5.2.1 Sectorial differences

Breaking down the results by sub-sector, the correlation between AI adoption and employment was strongest in asset management ($r = 0.59$) and insurance ($r = 0.35$), while the association in banking was much weaker ($r = 0.10$). This suggests that sectors where AI is used to complement human expertise are those where workforce expansion is more likely. In asset management, AI is primarily used to enhance portfolio optimisation and expand personalised client services, collaborating with human professionals rather than substituting them (Bartram et al., 2020). In insurance, AI-driven automation is transforming claims processing and fraud detection (Cao et al., 2021). In fact, research suggests that the most effective strategies are to combine both automation and human oversight, instead of relying only on one or the other (Braunwarth et al., 2010)

In contrast, the limited employment effects observed in banking suggest that AI adoption in this sector primarily operates through *displacement effects* by automating highly routinised and standardised tasks such as transaction processing, compliance, and customer service (Doumpos et al., 2023; Filippi et al., 2023). This pattern reflects the interaction of different labour market effects that unfold as automation progresses. The displacement effect leads to reduced demand for labour in tasks that are readily automated, while the productivity effect raises labour demand in non-automated tasks, and the *reinstatement effect* creates entirely new tasks and occupations as technologies mature (Tyson & Zysman, 2022, pp. 258-259). Banking’s task structure is characterised by a high share of routine processes, which makes it particularly exposed to early-stage displacement. On the other hand, asset management and insurance continue to experience productivity gains as AI increases its ability to perform decision-making processes, with *reinstatement effects* likely to emerge over time as new roles develop in response to evolving technological capabilities.

5.2.2 Theoretical Interpretation through the GPT Framework

The results of these analyses strongly support the classification of artificial intelligence as a General-Purpose Technology (GPT), which refers to technologies that enable fundamental changes across

sectors but only generate economic returns when supported with complementary organisational investments (Brynjolfsson et al., 2019). The organisational investment, which was measured through CapEx, showed no statistically significant effect on employment, while intangible assets had a strong and consistent positive relationship with workforce growth across firms. This separation highlights that transformative technologies require supporting structures, such as human capital, process redesign, data systems, and managerial adaptation, to translate their potential into realised productivity or an increase in labour.

These results illustrate that AI technologies that have risen the last couple of years in finance do not function as plug-and-play automation tools. Instead, they are placed within **complex organisational ecosystems** that determine how effectively the technology impacts employment and productivity. Firms that limit their AI adoption to infrastructure purchases may see minimal impact on workforce outcomes, whereas those that pursue a more integrated approach. This means companies that build internal capabilities, investing in employee reskilling and reorganising operational processes within the company, tend to experience a bigger difference in workforce expansion. This finding is particularly notable in the finance sector, where AI is deployed not just for automation but also for supporting decision-making, risk assessment, and personalised client services. AI's role in labour dynamics cannot be fully understood without considering the quality and reach of complementary investments made alongside its adoption. The GPT framework helps explain this outcome and explains why AI can be associated with job transformation and augmentation, rather than just job loss, especially in firms that engage in strategic technology implementations.

5.2.3 Labour Market Interpretation

The observed employment effects of AI-related investment in this analysis can be further explained through the lens of Skill-Biased Technological Change (SBTC), which is the framework in labour economics that helps identify which categories of workers benefit or lose out from technological progress. As mentioned earlier in the literature review, SBTC suggests that technological innovation increases the productivity of high-skilled labour more than that of low-skilled labour, thereby shifting demand toward more educated workers (Autor et al., 2003)

Originally developed to explain rising wage inequality in advanced economies, the theory has since been applied to automation contexts. It describes how digital technologies tend to complement cognitive, non-routine tasks, while they can also substitute for manual or routine-based work (Autor & Dorn, 2013). In the context of this Dissertation, the positive and significant relationship between intangible assets and employment growth suggests that firms are not using AI to reduce headcount across the board but are instead transforming job requirements toward the incorporation of higher-

skilled roles within the sampled firms. That is, instead of eliminating roles, AI seems to drive demand for workers with expertise in skills that are adaptable for AI technologies. This workforce shift reflects the SBTC model in action, where firms investing in AI tend to increase hiring in roles that are complemented by AI, rather than a full-on job displacement.

This framework also explains why the employment effects are stronger in certain sub-sectors, such as asset management, compared to traditional banking. Sub-sectors such as banking seem to rely less on complex, information-intensive tasks and are therefore less likely to benefit from AI's complementarity with skilled, educated labour compared to sub-sectors such as asset management.

The shift in workforce composition is closely linked to the growing importance of human capital in the finance sector. When firms invest in AI and related technologies, the demand for advanced digital and analytical skills increases. Recent labour market evidence shows that postings requiring AI skills command significant wage premiums, with studies reporting that such roles offer an 11% higher wage within the same firm and a 5% higher wage within the same job title (Alekseeva et al., 2021). This shows the strategic value of AI expertise for firms that go through a digital transformation. Firms that successfully attract and develop high-skilled talents are better positioned to benefit from AI adoption, and workers with outdated skillsets are at risk of being left behind in the labour market. These changes make it even more important for these financial institutions to help their employees learn new skills and for policymakers to support education and training programs to be able to keep up with the demands of the AI-driven job market.

5.2.4 Regional differences

The regression results with interaction terms revealed that North American firms benefit much more from AI adoption than their European counterparts. The marginal effect of intangible asset investment on employment was more than twice as large for North American firms as for their European counterparts. For European firms, investments in AI may not translate into employment gains or may even be associated with workforce reduction. Several factors could explain this. North America's more flexible labour markets, larger average firm size, and greater risk tolerance for innovation may make it easier for firms to both scale up AI initiatives and adapt workforce structures quickly (Filippi et al., 2023). Recent research further shows that AI skills are spreading fastest in North America, with higher expectations for future job growth in digital roles (World Economic Forum, 2023). The AI wage premium is also highest in North America, with notable gaps when compared to European economies (Alekseeva et al., 2021). Labour market institutions and regulations, such as employment protection legislation and collective bargaining, can shape the employment effects of automation and digitalisation. Countries with rigid labour markets may experience slower or more gradual displacement

processes, whereas flexible labour markets may facilitate both job destruction and creation through easier reallocation (Filippi et al., 2023; OECD, 2023). Europe's stricter labour protections, slower digital infrastructure rollout, and possibly more conservative corporate cultures may limit the pace at which new tech investments convert into new jobs or skill transformation.

5.2.5 Firm size: The “AI winner’s circle” effect

Another interesting pattern in the data is that larger firms experienced the strongest positive employment effects from AI adoption growth. In large firms, the total marginal effect was almost double that of smaller firms. This points to a “winner’s circle” dynamic where big firms with more resources and established infrastructure are better equipped to absorb the costs and risks of technological advancements by hiring new types of workers and restructuring effectively according to the technological trends (Brynjolfsson et al., 2019). “If only a subset of firms are able to successfully adopt and deploy new technologies like AI, this could increase inequality across firms and potentially also across workers, especially if the benefits accrue disproportionately to ‘superstar’ firms.” (Brynjolfsson et al., 2019: p.37).

This finding has important policy and strategic implications. If smaller firms receive targeted support or guidance for digital transformation by AI and automation, we may see an “AI divide” within the finance sector. This dynamic can lead to a “winner-take-most” effect, where leading firms pull further ahead in productivity and workforce transformation, while smaller firms risk falling behind or missing out on the gains from digitalisation. Large firms may also benefit from ecosystem effects, as their digital platforms and data networks can set industry standards and attract talent, partners, and capital to further reinforce their technological lead (OECD, 2023). The results observed in this Dissertation provide empirical support for this argument: in the finance sector, the employment gains from AI-related investment spring disproportionately to large firms, strengthen their competitive advantage, and potentially widen the gap with smaller competitors.

5.2.6 Productivity Trends and Reframing the “job displacement” Narrative

The analysis of sales per employee (SPE) reveals a notable trend since 2020, where firms in the finance sector have become significantly more productive, with both mean and median SPE rising. This productivity growth aligns closely with the period of accelerating AI and related automation investments. This trend is particularly noticeable among firms reporting strong increases in intangible assets (Doumpos et al., 2023; Brynjolfsson et al., 2019). Although it is not the goal of this Dissertation to directly estimate the impact of AI adoption on SPE through regression analysis, the parallel trends do suggest some sort of link between AI-related investment and increasing productivity. The integration

of AI and automation helps workers to shift away from repetitive tasks and focus on higher-value activities (Filippi et al., 2023). Importantly, these productivity gains that have been shown to have been achieved without large-scale employment cuts.

This empirical pattern challenges the common perception of AI as an inevitable driver of mass job losses. Instead, these results go along with the academic narrative advanced in the recent academic literature that *AI adoption is primarily associated with the transformation and creation of new roles, particularly in sectors with a high capacity for innovation and collaboration between humans and AI* (Choi & Leigh, 2024; Filippi et al., 2023). That is, the financial sector encourages collaboration between new technology and humans, allowing the said sector to experience productivity gains and new job opportunities, while routine and low-value manual jobs can be reduced (Tyson & Zysman, 2022).

Additionally, the findings in the analysis support the “productivity paradox” where considerable investments in AI-related intangible assets do not immediately translate to improvements in productivity across all financial sub-sectors (Brynjolfsson et al., 2019). Asset management and insurance, for example, show a notable positive correlation between AI adoption, employment, and productivity. This is consistent with Bartram et al. (2020), who find that AI adoption in asset management has expanded the range of tasks and skill sets required, thereby influencing workforce growth and increased productivity. This tells us that complementary adjustments and upskilling are key to realising the full benefits of AI. In contrast, banking had a significantly weaker association, which can suggest a lagged or less visible productivity effect. This postulates that substantial investments in new technologies like AI do not always instantly produce measurable productivity improvements.

Altogether, these results reframe the “job displacement narrative,” where the empirical evidence from this research shows that AI adoption in finance primarily contributes to the emergence of new roles or transformation of existing ones (Choi & Leigh, 2024; Tyson & Zysman, 2022). The economic impact of AI is less about a widespread job loss crisis and more about dynamic adaptation and evolving skill requirements. There will be a remaining risk of displacement for certain job categories, but as the empirical evidence points, for now, to the fact that overall, the finance sector is more defined by job transformation than by job losses.

5.3 Policy Implications

The findings of the Dissertation carry several important policy implications that are highly relevant to, and corporate strategies, labour market institutions and educational systems aiming to address the challenges and opportunities emerging from AI adoption in the financial sector.

First, the persistent demand for AI-related skills, particularly in asset management, insurance, and client-facing financial services, emphasises the urgent need for policy interventions focused on

workforce development and reskilling. Educational institutions, governments, and private sector actors must collaborate to create and expand technical, analytical, and digital literacy training programs that prepare both displaced workers and new labour market entrants for the demands of knowledge-intensive AI-focused roles.

Active labour market policies will play a critical role in smoothing workforce transitions, particularly for regions and sub-sectors more exposed to routine task automation, which is clearly the case where transactional banking services are concerned. Well-designed interventions, including wage subsidies, mobility incentives, and vocational retraining, can enable reallocation of labour into emerging occupations and reduce the social and economic costs of displacement.

The empirical evidence herein presented also highlights a potential risk of growing asymmetry between large and small firms in terms of their ability to benefit from AI adoption, which could toughen existing disparities within the finance sector. In turn, this potential widening gap might have a significant impact on financial market structures, especially where industry concentration levels are concerned, which might have a subsequent impact on the prices set by these firms. Larger financial firms - those possessing greater financial resources, established data infrastructures, and access to specialised AI-skilled labour - are more capable of translating AI investments into both employment growth and productivity growth. These firms are thus better positioned to restructure operations, reallocate resources, and create new roles that leverage the synergy between human expertise and AI. In contrast, smaller firms often face greater financial constraints, limited access to specialised talent, and organisational challenges that hinder the effective implementation of AI in their systems. As highlighted in the ethical frameworks discussed by Kazim & Koshiyama (2021) and Tóth & Blut (2024), these disparities raise important questions of fairness, distributive justice, and corporate responsibility. Without targeted policy measures and institutional support to facilitate AI diffusion across firms' sizes, such as financial incentives, technical assistance, and digital workforce development programs, there is a risk that AI adoption may contribute to increasing concentration of technological capabilities and market power within a small group of dominant firms, with significant impacts on market structures and pricing.

In addition, regulatory flexibility and robust digital infrastructure are likely to be decisive to enable conditions for AI-driven employment growth. The stronger positive effects observed among North American firms suggest that supportive institutional environments, combined with more flexible labour markets and advanced digital ecosystems, improve firms' ability to adopt and scale AI technologies while expanding their workforces. European policymakers may need to carefully balance their already strong worker protections with regulatory adaptability to ensure that innovation diffusion does not stall labour market dynamism and broader economic benefits.

Lastly, the present Dissertation's findings show the growing importance of *Corporate Digital Responsibility* (CDR) frameworks. As AI adoption continues to transform workforce structures, financial institutions bear an ethical responsibility to proactively engage in transparent workforce planning, invest in reskilling and career transition programs, and ensure that digital transformation does not worsen social inequalities. Setting CDR principles into corporate governance will be critical for ensuring that AI deployment serves both firm-level competitiveness and broader societal durability in the face of technological disruption.

5.4 Research Limitations and Alternative Interpretations

While this research has offered important empirical insights into the relationship between AI adoption and employment in the finance sector, there are still some limitations that must be considered when interpreting the results herein presented.

One important consideration is the potential direction of causality. Firms with stronger financial performance, established organisational capabilities, and competitive market positions may be better equipped to simultaneously invest in both technological capabilities and an increase in workforce, which makes it difficult to specifically isolate the specific effect of technological investment on employment outcomes (Brynjolfsson et al., 2019). In asset management, for instance, firms with more advanced digital infrastructures may already have advantages that allow them to capitalise on new analytical tools, which makes it difficult to connect employment effects to technology adoption alone (Bartram et al., 2020).

Although fixed effects models control for time-invariant firm characteristics, unobserved factors may still influence the relationship. Managerial competence, internal organisational structures, and access to specialised skills can affect both investment decisions and workforce growth that may complexify the adequate interpretation of the results (Filippi et al., 2023). Successful integration of new technologies into work systems requires organisations to redesign business processes, restructure workflows, and develop new skill sets (Cascio & Montealegre, 2016).

While year fixed effects in the model capture common shocks in specific years, including 2020-2021, the extraordinary labour market disruption caused by COVID-19 pandemic may not be fully reflected through these dummies alone (Albanesi & Kim, 2021). In addition, the absence of broader macroeconomic controls such as GDP growth means that part of the estimated effects could be driven by wider business cycle dynamics as well as firm-level AI investment. These considerations do not undermine the findings but suggest cautious interpretation and highlight avenues for future research.

The overall reach of these findings is further influenced by structural differences between North America and Europe. Institutional conditions in North America provide financial firms with stronger

capacity to scale and implement modern technologies, supported by a flexible labour market, good access to innovation financing, and advanced digital ecosystems (OECD, 2023). Differences in AI-related skill supply further contribute to this divergence, as higher wage premiums for AI expertise in North America indicate stronger demand for specialised talents and greater organisational willingness to invest in these capabilities (Alekseeva et al., 2021). The observed employment outcomes likely reflect not only the differences in technology adoption but also the widening disparities in firm resources, organisational flexibility, and market structures, where larger firms are more capable of leveraging technological opportunities (Brynjolfsson et al., 2019).

The period analysed may reflect the early stages of organisational transformation, with workforce impacts potentially developing over a longer timeframe as new technologies mature and integrate into core business processes (Tyson & Zysman, 2022). As technologies develop, more substantial displacement effects may emerge beyond the current observation window as time lags. It's also important to consider with time lags that sector-specific differences influence the observed outcomes.

Overall, while these limitations justify caution in interpreting direct causal claims, they do not weaken the broader patterns observed. The findings show important empirical evidence on how AI-driven technological change interacts with sectoral structures, organisational capacities, and institutional environments to shape the employment outcomes in the finance sector.

5.5 Validity of the Research Hypothesis

The central hypothesis of this Dissertation stated that higher levels of AI adoption, proxied by CapEx and intangible assets, would be associated with reductions in employment in the finance sector, particularly in routine roles. By explicitly assessing a hypothesis that reflects a common concern in the literature and public debate, this study contributes to clarifying whether AI primarily substitutes or complements labour. The results presented in the empirical analysis do not confirm the expectations of job reductions. CapEx showed no significant relationship with employment, while intangible assets were consistently and positively associated with workforce growth. This pattern held across the panel regressions, the correlation analysis, and the extended specifications with controls for firm size and region.

This outcome indicates that the hypothesis cannot be validated. Rather than confirming a labour-substituting role for AI, the findings show that during the observed period AI adoption was linked to transformation and evolving skill demands. Although sector, region, firm size differences shape the magnitude of the effect, the overall pattern is that AI adoption has complemented labour rather than replaced.

6. Conclusion

6.1 Research Question

The purpose of this Dissertation is to explore the economic consequences of AI adoption on employment within the financial sector. The central research question that guides the whole research is:

- *“How does AI adoption influence employment outcomes and job displacement across sub-sectors, firm sizes, and regions within the finance sector?”*

The motivation for addressing this question stems from the growing integration of artificial intelligence technologies such as machine learning, natural language processing, and robotic process automation into financial operations. AI offers clear opportunities for improving efficiency and productivity but also raises concerns for many about workforce displacement, shifts in skill demand, and bigger inequalities between firms, regions, and occupational groups.

6.2 Methodology and Data

This research uses a quantitative research design using firm-level panel data to empirically evaluate the relationship between AI adoption and employment outcomes in the finance sector. The dataset was collected from Eikon Datastream and includes 152 publicly listed financial firms across North America and Europe, covering four major sub-sectors, which are banking, asset management, insurance, and accounting services. The data spans the period from 2015 to 2023.

Due to the limited availability of direct measures of AI adoption and AI investment, this research uses intangible assets and capital expenditures (CapEx) as financial proxies for AI adoption, which are established approaches according to the surveyed academic literature. Employment level was measured through the total number of employees reported by each firm annually.

The analysis conducts fixed effects panel regression models to account for unobserved firm-specific characteristics and year-specific macroeconomic factors. Interaction terms are added in order to examine sectoral, regional, and firm-size heterogeneity in employment effects. In addition, Pearson correlation analyses are also conducted in order to capture descriptive associations between AI-related investments and workforce size across sub-sectors and over time. Sales-per-employee (SPE) trends are also analysed to get more insight into labour productivity developments during the period of rising AI adoption.

6.3 Empirical Findings and Contributions

This Dissertation provides new and interesting empirical evidence on how AI adoption impacts employment in the finance sector. The main analysis uses firm-level panel data and fixed effects regression to demonstrate that higher investment in intangible assets, such as data infrastructure, software, and employee skills, is linked to increasing or stable employment levels at the firm level. This positive effect is especially strong for asset management and insurance, where AI technologies mainly complement rather than replace human expertise. For example, AI-driven portfolio optimisation (asset management) and claims processing (insurance) are associated with workforce growth or stability. These findings support the GPT framework, showing that economic returns from AI depend on complementary investments in human capital and internal organisational changes.

A key contribution of this research is its breakdown of both sub-sectors within finance and regional differences, which was done to provide a greater perspective on how AI adoption impacts employment. The positive employment effect of AI adoption is most noticeable in asset management and insurance but weak in banking, where automation is a bigger threat for displacement of routine roles. North American firms and larger firms see stronger employment gains from AI compared to their European or smaller counterparts. This is likely due to differences in labour market flexibility, legislation for employees, digital adaptation, and organisational resources.

By using intangible assets and CapEx as proxies for AI investment, this Dissertation offers a practical approach for empirical analysis in a field where direct AI adoption data is yet extremely scarce. The empirical findings herein described also have policy relevance, indicating that targeted workforce development and flexible institutional environments help companies maximise the benefits of AI adoption. Unlike many researches that generalise about job loss, these findings challenge the traditional narrative of widespread job displacement and show that AI adoption in finance primarily pushes in favour of workforce transformation and new skill demands. Ultimately, the Dissertation adds valuable new evidence and insights into the ongoing debates about automation, skills, and the future of work in finance under different perspectives. The main goal is to help financial institutions in making sound and fundamental decisions about their workforce strategies and to reassure stakeholders that AI adoption is more likely to drive transformation and add new opportunities for the workforce, rather than the common narrative of mass job displacement.

6.4 Advantages and Limitations

One of the main advantages of this Dissertation is related to its use of firm-level panel data, which cover multiple sub-sectors in different regions in order to allow for more detailed and comparative analysis. The application of fixed effects regression helps control for unobserved heterogeneity and increases the

reliability of the results. Another key strength is the innovative use of intangible assets and CapEx as proxies for AI adoptions (previously documented in the academic literature) in order to create a different practical solution to the common challenge of measuring technological investment at the firm level within the finance sector.

However, some limitations should be acknowledged. The reliance on financial proxies for AI adoption may not capture all dimensions of technological change, and the data availability for certain sub-sectors, such as accounting, was rather limited. Furthermore, while the fixed effects approach controls for many disorganised factors, it cannot fully eliminate the possibility of unobserved variables that are influenced by both AI investment and employment outcomes. Despite these limitations, the Dissertation provides a robust and timely insight into the economic impact of AI on employment in the finance sector.

6.5 Suggestion for Future Research

Future research could build on this research by applying a more direct approach to measure AI adoption for the results to be more straightforward. For example, natural language processing could be used to systematically analyse company reports and disclosures for detailed references to AI initiatives. As the range of possibilities with using AI is increasing, it also creates opportunities for using it for research in the immediate future. Leveraging data from different technology suppliers, firm-reported AI initiatives, or direct employee skill surveys can also offer real-time insight into actual adoption and workforce impact by AI. Additionally, combining these data-driven approaches with targeted surveys and/or, if possible, internal firm records on AI projects would further strengthen the accuracy of future analyses. Expanding research to new regions where finance and technology are strongly tied or linking AI adoption to job quality and the wage dynamics would also help with understanding how these technological changes affect the finance sector.

6.6 Concluding Thoughts

The finance sector will continue to evolve alongside the rapid advances in artificial intelligence, and understanding the true impact of these evolving technologies is essential for both economic progress and social well-being. By shedding a different light on where AI adoption creates opportunities instead of a widespread job displacement, this research supports a more balanced and constructive dialogue about the future of work. Throughout history, the appearance of disruptive technologies has often been accompanied by uncertainty, fear, and panic, particularly among those that sit comfortably with established ways of working. Yet, it is through embracing change and constantly adapting to new realities that true progress and growth are achieved. In the end, it is our willingness to learn, adapt, and

reimagine our roles that will determine whether the age of AI becomes an era of shared prosperity and meaningful work.

References

- Acemoglu, D., & Restrepo, P. (2018). *Artificial intelligence, automation and work* (NBER Working Paper No. 24196). National Bureau of Economic Research. <https://doi.org/10.3386/w24196>
- Albanesi, S., & Kim, J. (2021). The effects of the COVID-19 recession on the U.S. labor market: Occupation, family, and gender. *Journal of Economic Perspectives*, 35(3), 3–24. <https://doi.org/10.1257/jep.35.3.3>
- Alekseeva, L., Azar, J., Giné, M., Samila, S., & Taska, B. (2021). The demand for AI skills in the labor market. *Labour Economics*, 71, 102002. <https://doi.org/10.1016/j.labeco.2021.102002>
- Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the U.S. labor market. *American Economic Review*, 103(5), 1553–1597. <https://doi.org/10.1257/aer.103.5.1553>
- Autor, D., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4), 1279–1333. <https://doi.org/10.1162/003355303322552801>
- Bartram, S. M., Branke, J., & Motahari, M. (2020). *Artificial intelligence in asset management*. CFA Research Institute Foundation.
- Becker, G. S. (1993). *Human capital: A theoretical and empirical analysis, with special reference to education* (3rd ed.). University of Chicago Press.
- Braunwarth, K. S., Kaiser, M., & Müller, A.-L. (2010). Economic evaluation and optimization of the degree of automation in insurance processes. *Business & Information Systems Engineering*, 2(1), 29–39. <https://doi.org/10.1007/s12599-009-0088-6>
- Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 23–57). University of Chicago Press.
- Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*, 13(1), 333–372.
- Cao, L. (2021). AI in finance: Challenges, techniques, and opportunities. *ACM Computing Surveys (CSUR)*, 55(1), 1–38. <https://doi.org/10.1145/3502289>

- Cascio, W. F., & Montealegre, R. (2016). How technology is changing work and organizations. *Annual Review of Organizational Psychology and Organizational Behavior*, 3(1), 349–375. <https://doi.org/10.1146/annurev-orgpsych-041015-062352>
- Castro Silva, H., & Lima, F. (2017). Technology, employment and skills: A look into job duration. *Research Policy*, 46(8), 1519–1530. <https://doi.org/10.1016/j.respol.2017.07.007>
- Choi, T., & Leigh, N. G. (2024). Artificial intelligence's creation and displacement of labor demand. *Technological Forecasting and Social Change*, 209, 123824. <https://doi.org/10.1016/j.techfore.2024.123824>
- Corrado, C., Haskel, J., Jona-Lasinio, C., & Iommi, M. (2016). *Intangible investment in the EU and US before and since the Great Recession and its contribution to productivity growth* (EIB Working Paper No. 2016/08). European Investment Bank. <https://www.eib.org/en/publications/economics-working-paper-2016-08>
- Corrado, C., Hulten, C., & Sichel, D. (2005). Measuring capital and technology: An expanded framework. In C. Corrado, J. Haltiwanger, & D. Sichel (Eds.), *Measuring capital in the new economy* (pp. 11–46). University of Chicago Press. <https://doi.org/10.7208/chicago/9780226116174.003.0002>
- Corrado, C., Hulten, C., & Sichel, D. (2009). Intangible capital and U.S. economic growth. *Review of Income and Wealth*, 55(3), 661–685. <https://doi.org/10.1111/j.1475-4991.2009.00343.x>
- DeStefano, T., Kneller, R., & Timmis, J. (2020). Broadband infrastructure, ICT use and firm performance: Evidence for UK businesses. *Journal of Economic Behavior & Organization*, 176, 113–133. <https://doi.org/10.1016/j.jebo.2018.08.020>
- Dhieb, N., Ghazzai, H., Besbes, H., & Massoud, Y. (2020). A secure AI-driven architecture for automated insurance systems: Fraud detection and risk measurement. *IEEE Access*, 8, 58546–58558.
- Doumpos, M., Zopounidis, C., Gounopoulos, D., Platanakis, E., & Zhang, W. (2023). Operational research and artificial intelligence methods in banking. *European Journal of Operational Research*, 306(1), 1–16. <https://doi.org/10.1016/j.ejor.2022.04.027>
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>

- Filippi, E., Bannò, M., & Trento, S. (2023). Automation technologies and their impact on employment: A review, synthesis and future research agenda. *Technological Forecasting and Social Change*, 191, 122448. <https://doi.org/10.1016/j.techfore.2023.122448>
- Google Trends. (2024). *AI search trends over the past 5 years*. <https://trends.google.com/trends/explore?date=today%205-y&q=AI&hl=no>
- Guarascio, D., Sacchi, S., van Ours, J. C., & Fana, M. (2023). Just reallocated? Robots, displacement, and job quality. *Industrial Relations: A Journal of Economy and Society*, 62(2), 175–198.
- Haskel, J., & Westlake, S. (2018). *Capitalism without capital: The rise of the intangible economy*. Princeton University Press.
- IBM. (2023). *Types of artificial intelligence (AI)*. <https://www.ibm.com/think/topics/artificial-intelligence-types>
- Johnson, G. E. (1997). Changes in earnings inequality: The role of demand shifts. *Journal of Economic Perspectives*, 11(2), 41–54. <https://doi.org/10.1257/jep.11.2.41>
- Johnson, M., Jain, R., Brennan-Tonetta, P., Swartz, E., Silver, D., Paolini, J., Mamonov, S., & Hill, C. (2021). Impact of big data and artificial intelligence on industry: Developing a workforce roadmap for a data driven economy. *Global Journal of Flexible Systems Management*, 22(3), 197–217. <https://doi.org/10.1007/s40171-021-00272-y>
- Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255–260. <https://doi.org/10.1126/science.aaa8415>
- Kande, M., & Sonmez, M. (2020, October 26). Don't fear AI. It will lead to long-term job growth. *World Economic Forum*. <https://www.weforum.org/stories/2020/10/dont-fear-ai-it-will-lead-to-long-term-job-growth/>
- Kazim, E., & Koshiyama, A. S. (2021). A high-level overview of AI ethics. *Patterns*, 2(9), 100314. <https://doi.org/10.1016/j.patter.2021.100314>
- Keys, B. J. (2010). The credit market consequences of job displacement. *Finance and Economics Discussion Series, 2010-24*. Board of Governors of the Federal Reserve System.
- Mamede, H. S., Gonçalves Martins, C. M., & Mira Da Silva, M. (2023). A lean approach to robotic process automation in banking. *Heliyon*, 9(7), e18041. <https://doi.org/10.1016/j.heliyon.2023.e18041>
- McKinsey & Company. (2017). *Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages*. <https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages>

- McKinsey & Company. (2024). *Beyond the balance sheet: North American asset management 2024*. <https://www.mckinsey.com/industries/financial-services/our-insights/beyond-the-balance-sheet-north-american-asset-management-2024>
- Mittelstadt, B. (2019). Principles alone cannot guarantee ethical AI. *Nature Machine Intelligence*, 1(11), 501–507. <https://doi.org/10.1038/s42256-019-0114-4>
- OECD. (2023). *The impact of AI on the labour market: What do we know so far?* OECD Employment Outlook 2023. OECD Publishing. https://www.oecd.org/en/publications/oecd-employment-outlook-2023_08785bba-en.html
- Ruhm, C. J. (1991). Are workers permanently scarred by job displacements? *The American Economic Review*, 81(1), 319–324.
- Sanford, A., & Moosa, I. (2015). Operational risk modelling and organizational learning in structured finance operations: A Bayesian network approach. *Journal of the Operational Research Society*, 66(1), 86–115. <https://doi.org/10.1057/jors.2013.49>
- Son, H. (2017, February 28). JPMorgan marshals an army of developers to automate high finance. *Bloomberg*. <https://www.bloomberg.com/news/articles/2017-02-28/jpmorgan-marshals-an-army-of-developers-to-automate-high-finance>
- Sostero, M. (2020). Automation and robots in services: Review of data and taxonomy. *JRC Working Papers Series on Labour, Education and Technology*, No. 2020/14. European Commission, Joint Research Centre (JRC). <https://www.econstor.eu/handle/10419/231346>
- Stevens, A. H. (1997). Persistent effects of job displacement: The importance of multiple job losses. *Journal of Labor Economics*, 15(1), 165–188.
- Taecharungroj, V. (2023). “What can ChatGPT do?” Analyzing early reactions to the innovative AI chatbot on Twitter. *Big Data and Cognitive Computing*, 7(1), 35. <https://doi.org/10.3390/bdcc7010035>
- Tatsiramos, K. (2010). Job displacement and the transitions to re-employment and early retirement for non-employed older workers. *European Economic Review*, 54(4), 517–535.
- Tóth, Z., & Blut, M. (2024). Ethical compass: The need for corporate digital responsibility in the use of artificial intelligence in financial services. *Organizational Dynamics*, 53(2), 101041. <https://doi.org/10.1016/j.orgdyn.2024.101041>
- Tyson, L. D., & Zysman, J. (2022). Automation, AI & work. *Daedalus*, 151(2), 256–271. https://doi.org/10.1162/daed_a_01914
- World Economic Forum. (2023). *The future of jobs report 2023*. World Economic Forum. <https://www.weforum.org/publications/the-future-of-jobs-report-2023>

Appendices

Appendix A: Specification Test

Table A1. Hausman Test Comparing Fixed Effects and Random Effects Models

--- Hausman test (FE vs RE) ---

Hausman Test

```
data: fml
chisq = 69.728, df = 11, p-value =
1.376e-10
alternative hypothesis: one model is inconsistent
```

Appendix B: Regression outputs.

Table B1. One-way Fixed Effects Model (plm in R)

Oneway (individual) effect within Model

Call:

```
plm(formula = logEmployees ~ logCapEx + logIntangibles + logMarketValue +
     factor(Year), data = pdata, model = "within")
```

Unbalanced Panel: n = 152, T = 1-9, N = 1346

Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.676152	-0.065517	0.001468	0.060632	0.666966

Coefficients:

	Estimate	Std. Error	t-value	Pr(> t)	
logCapEx	-0.00031238	0.00320258	-0.0975	0.922314	
logIntangibles	0.08501727	0.00708501	11.9996	< 2.2e-16	***
logMarketValue	0.02015336	0.00494860	4.0725	4.960e-05	***
factor(Year)2016	0.00284854	0.01771945	0.1608	0.872312	
factor(Year)2017	0.01018675	0.01777991	0.5729	0.566797	
factor(Year)2018	0.01948841	0.01789670	1.0889	0.276403	
factor(Year)2019	0.03622575	0.01789559	2.0243	0.043165	*
factor(Year)2020	0.04322285	0.01805836	2.3935	0.016843	*
factor(Year)2021	0.05681862	0.01816093	3.1286	0.001799	**
factor(Year)2022	0.08133958	0.01829411	4.4462	9.561e-06	***
factor(Year)2023	0.10961337	0.01818807	6.0267	2.233e-09	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 35.546

Residual Sum of Squares: 27.309

R-Squared: 0.23172

Adj. R-Squared: 0.12652

F-statistic: 32.4374 on 11 and 1183 DF, p-value: < 2.22e-16

Table B2. Extended Fixed Effects Regression Results

```
> summary(extended_fixed_effects)
Oneway (individual) effect within Model

Call:
plm(formula = logEmployees ~ logCapEx + logIntangibles + logMarketValue +
     logTotalAssets + factor(Year), data = pdata, model = "within")

Unbalanced Panel: n = 152, T = 1-9, N = 1346

Residuals:
      Min.      1st Qu.      Median      3rd Qu.      Max.
-0.6695718 -0.0604224  0.0027196  0.0596612  0.7738795

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
logCapEx      -0.00222390  0.00294073  -0.7562  0.449655
logIntangibles  0.04726994  0.00697234   6.7796 1.898e-11 ***
logMarketValue  0.01268821  0.00456705   2.7782  0.005552 **
logTotalAssets  0.25489081  0.01704152  14.9570 < 2.2e-16 ***
factor(Year)2016 -0.00023624  0.01625658  -0.0145  0.988408
factor(Year)2017 -0.00159395  0.01632974  -0.0976  0.922258
factor(Year)2018  0.01285021  0.01642388   0.7824  0.434130
factor(Year)2019  0.01826215  0.01646073   1.1094  0.267467
factor(Year)2020 -0.00080953  0.01682572  -0.0481  0.961634
factor(Year)2021 -0.00986568  0.01724650  -0.5720  0.567404
factor(Year)2022  0.03423607  0.01707537   2.0050  0.045191 *
factor(Year)2023  0.05259531  0.01711512   3.0730  0.002167 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    35.546
Residual Sum of Squares: 22.963
R-Squared:              0.35399
Adj. R-Squared:         0.26491
F-statistic: 53.9748 on 12 and 1182 DF, p-value: < 2.22e-16
```

Table B3. Regional Differences in AI Investment Effects on Employment

Oneway (individual) effect Within Model

Call:
 plm(formula = logEmployees ~ logIntangibles * Region + logCapEx *
 Region + logMarketValue + logTotalAssets + factor(Year),
 data = pdata, model = "within")

Unbalanced Panel: n = 152, T = 1-9, N = 1346

Residuals:

	Min.	1st Qu.	Median	3rd Qu.	Max.
	-0.6823379	-0.0588338	0.0025414	0.0579268	0.7537896

Coefficients:

	Estimate	Std. Error	t-value	Pr(> t)	
logIntangibles	0.0899341	0.0140724	6.3908	2.37e-10	***
logCapEx	0.0063942	0.0056395	1.1338	0.2571045	
logMarketValue	0.0145371	0.0045535	3.1925	0.0014478	**
logTotalAssets	0.2447413	0.0170857	14.3244	< 2.2e-16	***
factor(Year)2016	-0.0018631	0.0161472	-0.1154	0.9081605	
factor(Year)2017	-0.0052115	0.0162396	-0.3209	0.7483333	
factor(Year)2018	0.0092960	0.0163335	0.5691	0.5693709	
factor(Year)2019	0.0141020	0.0163907	0.8604	0.3897619	
factor(Year)2020	-0.0064533	0.0167709	-0.3848	0.7004594	
factor(Year)2021	-0.0149333	0.0171685	-0.8698	0.3845835	
factor(Year)2022	0.0279519	0.0170190	1.6424	0.1007751	
factor(Year)2023	0.0478976	0.0170926	2.8022	0.0051578	**
logIntangibles:RegionEurope	-0.0533372	0.0149570	-3.5660	0.0003769	***
RegionEurope:logCapEx	-0.0130698	0.0065618	-1.9918	0.0466232	*

 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 35.546
 Residual Sum of Squares: 22.588
 R-Squared: 0.36454
 Adj. R-Squared: 0.27568
 F-statistic: 48.3515 on 14 and 1180 DF, p-value: < 2.22e-16

Table B4. Firm Size Interaction Model

```

Oneway (individual) effect within Model

Call:
plm(formula = logEmployees ~ logCapEx * large_firm + logIntangibles *
     large_firm + logMarketValue + factor(Year), data = pdata,
     model = "within")

Unbalanced Panel: n = 152, T = 1-9, N = 1346

Residuals:
      Min.      1st Qu.      Median      3rd Qu.      Max.
-0.68916497 -0.06388874  0.00044004  0.05981732  0.66395570

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
logCapEx      -0.0043570  0.0042984 -1.0136  0.310970
large_firm     -0.8862638  0.1953280 -4.5373 6.280e-06 ***
logIntangibles  0.0729076  0.0073363  9.9379 < 2.2e-16 ***
logMarketValue  0.0222205  0.0049341  4.5035 7.348e-06 ***
factor(Year)2016 -0.0017260  0.0174760 -0.0988  0.921343
factor(Year)2017  0.0053040  0.0175337  0.3025  0.762324
factor(Year)2018  0.0137229  0.0176687  0.7767  0.437506
factor(Year)2019  0.0319080  0.0176508  1.8077  0.070902 .
factor(Year)2020  0.0359237  0.0178690  2.0104  0.044618 *
factor(Year)2021  0.0486248  0.0179723  2.7055  0.006918 **
factor(Year)2022  0.0732783  0.0180962  4.0494 5.471e-05 ***
factor(Year)2023  0.1001297  0.0179986  5.5632 3.275e-08 ***
logCapEx:large_firm  0.0050287  0.0046552  1.0802  0.280268
large_firm:logIntangibles 0.0644097  0.0130864  4.9219 9.787e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    35.546
Residual Sum of Squares: 26.422
R-Squared:               0.25667
Adj. R-Squared:          0.15273
F-statistic: 29.1043 on 14 and 1180 DF, p-value: < 2.22e-16

```

Appendix C: Correlation & Descriptive Results

Figure C1.1. Firm-Level Correlation Between AI adoption and Employment

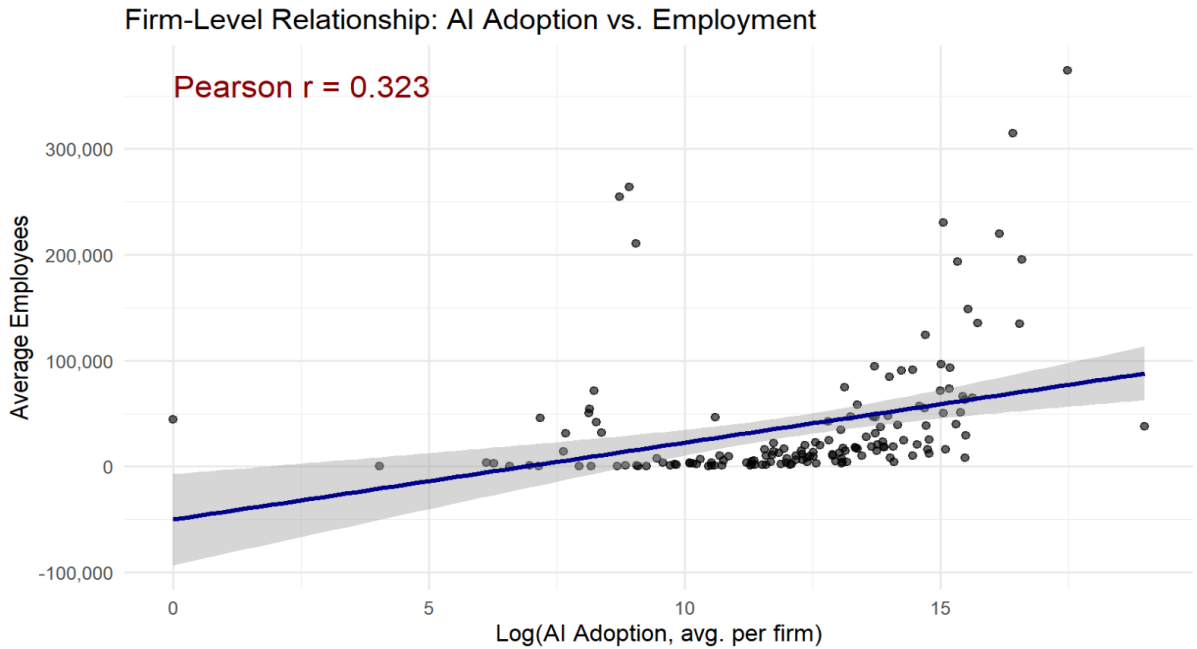


Figure C1.2. Yearly Correlation: AI Adoption and Employment

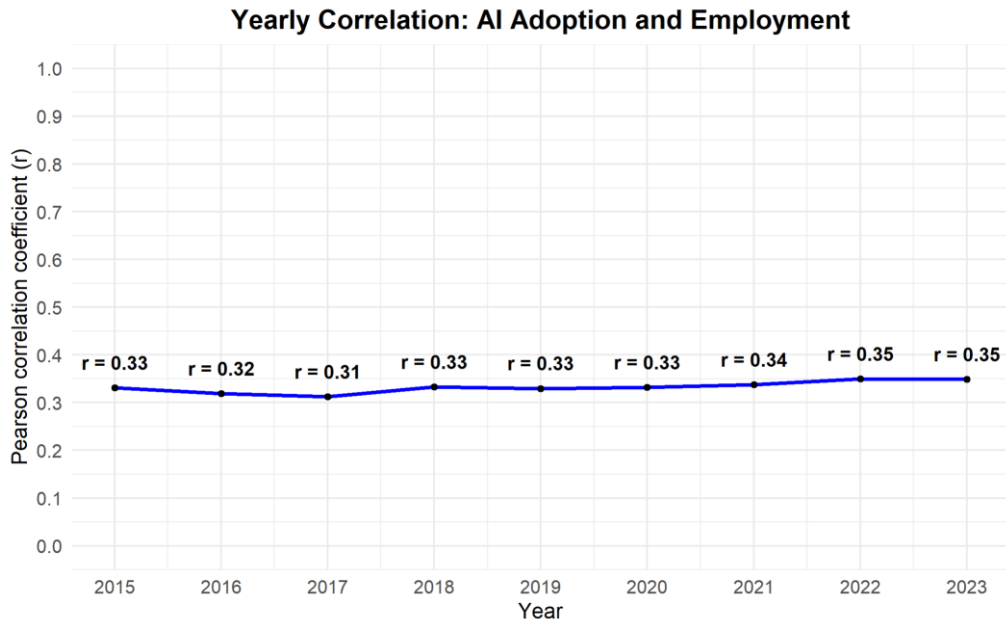


Table C2. Sub-Sector Correlation Coefficients

```
# A tibble: 4 × 3
  Type      correlation n_companies
<chr>      <dbl>      <int>
1 Accounting 0.723         6
2 Asset Management 0.594        38
3 Bank 0.0972        65
4 Insurance 0.349        45
```

Figure C3. Sales per Employee Trend (2015-2023)

