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Qualifying scientific work
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DISSERTATION

DEVELOPMENT OF THE FINANCIAL TRADING UNDER GLOBALIZATION

07 «Management and Administration»
072 «Finance, Banking and Insurance»
Applied for the degree of Doctor of Philosophy

The dissertation contains the results of own research. The use of ideas, results and texts of other authors has links to the sources
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ABSTRACT

Hou P. Development of the financial trading under globalization. – Qualifying scientific work (manuscript rights reserved).

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The dissertation focuses on enhancing theoretical and practical aspects and providing recommendations for the further development of financial trading under globalization in order to increase the efficiency, stability, and inclusivity of developed and emerging financial markets. It offers a systematized view of modern financial trading and is based on an overall approach, which allows for suggesting actionable solutions for problematic issues and achieving set tasks.

Grounded in a critical analysis of existing formulations of the "financial trading" concept, a more comprehensive definition was proposed. Specifically, financial trading is defined as an immediate or specifically pre-set process performed by financial trading participants, based on the features of one or more financial assets and market information, with the purpose of obtaining direct or indirect financial benefits. This definition holistically incorporates all components of the concept, namely, essence, content, and result.

Financial trading participants were generalised into two groups: systemic participants (brokers, market makers) and investment participants (individual traders, institutional investors, high-frequency traders, sovereign wealth funds). This approach makes it possible to identify critical variations in trading behaviour, profit strategies, trade sizes, risk horizons, and decision-making logic. Such grouping not only advances the theoretical understanding of participant heterogeneity but also supports targeted regulatory interventions and risk profiling.

The classification of financial trading was improved by combining hierarchical and faceted methods. The proposed approach provides a multidimensional structure of

financial trading by integrating hierarchical logic with flexible faceted classification, using such features as object, technology, place, execution, purpose, and market structure. It enables more precise analysis of financial trading and allows regulators to account for the diversity of its types.

The financial trading risks (including market, credit, operational, liquidity, and systemic risks) were characterized, which led to the generalisation of quantitative models into a toolkit for risk assessment in globalized, technologically advanced financial markets.

The types of financial trading strategies were defined. A fundamental shift from traditional rule-based strategies to data-driven and algorithmic approaches, including machine learning algorithms, deep reinforcement learning, and the emerging application of Large Language Models in predictive analytics, was identified. This analysis made it possible to create the Four-Quadrant of financial trading strategies, which categorizes financial trading strategies based on the machine technology level (i.e., the level of machine learning autonomy) and the trading strategy level. The four types include autonomous intelligent financial trading (high tech, high strategy), intelligent-assisted financial trading (low tech, high strategy), traditional modern financial trading (low tech, low strategy), and mechanical financial trading (high tech, low strategy). This approach provides a comprehensive framework for analysing the intersection of technology and financial trading strategy, aiding in the understanding of implications for financial market stability and regulation.

The five-level hierarchy of the information basis for financial trading efficiency was proposed. It includes: 1) foundational data (e.g., prices, volumes), 2) aggregated data (e.g., returns, volatility, correlations), 3) macroeconomic indicators (e.g., GDP, inflation), 4) financial systems data (e.g., regulatory frameworks, market interactions), and 5) economic context data (e.g., geopolitical factors, technological progress). This hierarchy helps organize complex data inputs, embodying an entropy-complexity-stability trade-off; prevents information overload; facilitates layered analytical depth; and provides a more structured understanding of the information environment within which efficient financial trading decisions are made.

The periodization of the development of financial trading and its regulatory environment was refined by identifying the six stages of financial trading functioning through focusing on the activities of international and national regulators; legal provisions (securities laws, anti-money laundering regulations, market abuse regulations); and Tech-specific regulations for algorithmic and high-frequency trading, Blockchain, and AI technologies, etc. In contrast to previous studies, which focused on pre-2010 events, this periodization emphasizes the post-2010 regulatory landscape, which is characterized by the impact of responsible investing, the implementation of new technologies, and the development of decentralized finance to ensure market stability, investor protection, and fair practices in a globalized context.

Founded on the generalisation of global financial trading tendencies, the “lag cycle” explanation of financial trading cyclicality in emerging and developed financial markets was proposed. Emerging markets’ financial cycles typically lag behind those of developed markets by one phase (accumulation, growth, distribution, correction). This approach highlights the deep interconnectedness and synchronization of global financial markets, providing a basis for understanding cyclical interdependence and risk transmission.

A dynamic model for assessing financial trading efficiency was developed. This comprehensive mathematical model integrates price dynamics (stochastic differential equations); a price-related efficiency index based on deviations from fundamental financial asset prices; liquidity factor and transaction costs; and information flow rates with exponential decay. These components were combined into a single metric of financial trading efficiency ($\varepsilon(t)$). The model provides a quantitative, dynamic measure of financial trading efficiency; integrates real-world frictions (liquidity, costs) and information dynamics; and is superior to traditional models for practical application in financial trading.

The financial trading risk management framework under globalization was developed. It considers market, credit, operational, liquidity, and systemic risks and includes AI enhancements for real-time monitoring and predictive insights. It features a structured 5-step process for real-world implementation, allowing for dynamic adaptation to information asymmetries, market shocks, and algorithmic bias. Unlike conventional static models, this framework provides a comprehensive, systematic, and adaptive approach to managing the full spectrum of financial trading risks in modern globalized markets. Its universality and adaptability make it suitable for both regulators and market participants to enhance forecasting, compare strategy efficiency, and strengthen systemic resilience.

Finally, the recommendations for a stable financial trading environment under globalization were generalised, based on five key conditions: 1) market efficiency and information availability, 2) cross-border capital flows and risk sharing, 3) regulatory framework and institutional support, 4) technological infrastructure and trading platforms, and 5) foreign exchange and currency market liquidity. These proposals integrate institutional, technological, and regulatory elements into a coherent system. Such an integrated approach ensures that market growth is not achieved at the cost of systemic vulnerability. It offers policymakers and institutions a universal and adaptable roadmap for fostering resilient, transparent, and sustainable financial trading globally, thereby reducing the probability of crises and strengthening investor confidence.

The dynamic model for enhancing financial trading profitability was developed. This model integrates macroeconomic variables (e.g., interest rates, trade balances, policy shifts) with trading contextual factors (e.g., liquidity depth, market access, AI utilization). It extends classical profitability models toward adaptive and future-oriented decision-making systems. The model enables scenario-based analysis and real-time strategic forecasting, offering value to institutional investors, regulatory bodies, and strategic analysts. Its flexibility allows it to adapt to varying market conditions and anticipate profit shifts in response to geopolitical, economic, or technological disruptions.

Key words: risk, risk assessment, risk management, cryptocurrency, stock market, S&P 100, foreign exchange market, exchange rate, liquidity, transaction costs, investment decision, investment efficiency, investment strategy, sustainable development, ESG.

АНОТАЦІЯ

Хоу П. Розвиток фінансового трейдингу в умовах глобалізації. – Кваліфікаційна наукова праця на правах рукопису.

Дисертація на здобуття наукового ступеня доктора філософії за спеціальністю 072 – фінанси, банківська справа та страхування. – Київський національний університет імені Тараса Шевченка Міністерства освіти і науки України. – Київський національний університет імені Тараса Шевченка Міністерства освіти і науки України. Київ, 2025.

Дисертація присвячена удосконаленню теоретичних і практичних аспектів та наданню рекомендацій щодо подальшого розвитку фінансового трейдингу в умовах глобалізації задля підвищення ефективності, стабільності та інклюзивності розвинених фінансових ринків і фінансових ринків, що розвиваються. В дисертаційній роботі на основі комлексного підходу представлено систематизований погляд на сучасний фінансовий трейдинг, що дозволяє запропонувати дієві рішення проблемних питань та досягти поставлених завдань.

На основі критичного аналізу існуючих дефініцій поняття «фінансовий трейдинг» запропоновано більш повне визначення фінансового трейдингу як безпосереднього чи спеціально заданого процесу, що реалізується його учасниками на основі характеристик одного або кількох фінансових активів і ринкової інформації з метою одержання прямих або непрямих фінансових вигод. Це визначення цілісно поєднує всі компоненти дефініції, зокрема сутність, зміст та результат.

Здійснено узагальнення учасників фінансового трейдингу на дві групи: системні учасники (брокери, маркет-мейкери) та інвестиційні учасники (індивідуальні трейдери, інституційні інвестори, високочастотні трейдери, суверенні фонди). Такий підхід дозволяє визначити критичні відмінності в торговельній поведінці, стратегіях отримання прибутку, обсягах торгів,

горизонтах ризику та логіці прийняття рішень. Таке групування не лише покращує теоретичне розуміння гетерогенності учасників, але й підтримує цілеспрямоване регуляторне втручання та профілювання ризиків.

Удосконалено класифікацію фінансового трейдингу на основі поєднання ієрархічного та фасетного методів. Запропонований підхід відображає багатовимірну структуру фінансового трейдингу шляхом поєднання ієрархічної логіки з гнучкою фасетною класифікацією на основі використання таких класифікаційних ознак, як об’єкт, технологія, місце здійснення фінансового трейдингу, мета, структура ринку тощо. Це уможливить здійснення більш точного аналізу фінансового трейдингу та дозволить регуляторам враховувати різноманітність його видів.

Охарактеризовано ризики фінансового трейдингу (ринкові, кредитні, операційні ризики, ризики ліквідності, системні ризики). Це дозволило узагальнити кількісні моделі у набір інструментів для оцінки ризиків на глобалізованих, технологічно розвинених фінансових ринках.

Визначено типи стратегій фінансового трейдингу. Виявлено фундаментальний перехід від традиційних стратегій фінансового трейдингу, заснованих на правилах, до підходів, керованих даними та алгоритмічними підходами, включаючи алгоритми машинного навчання, глибокого навчання з підкріпленням та застосування великих мовних моделей у прогнозній аналітиці. Це дозволило створити чотири квадранти стратегій фінансового трейдингу, що уможливлює групування стратегій фінансового трейдингу на основі рівня машинних технологій (тобто рівня автономності машинного навчання) та рівня торгової стратегії на чотири типи: автономний інтелектуальний фінансовий трейдинг (високий рівень машинних технологій, високий рівень торгової стратегії), фінансовий трейдинг з інтелектуальною підтримкою (низький рівень машинних технологій, високий рівень торгової стратегії), традиційний сучасний фінансовий трейдинг (низький рівень машинних технологій, низький рівень торгової стратегії), механічний фінансовий трейдинг (високий рівень машинних технологій, низький рівень торгової стратегії). Це забезпечує комплексну основу для аналізу перетину технологій та стратегій фінансового трейдингу, допомагаючи зрозуміти наслідки для стабільності та регулювання фінансового ринку.

Запропоновано п'ятирівневу ієрархію інформаційної основи ефективного фінансового трейдингу, а саме: рівень 1) базові дані (наприклад, ціни, обсяги); рівень 2) агреговані дані (наприклад, прибутковість, волатильність, кореляції); рівень 3) макроекономічні показники (наприклад, ВВП, інфляція); рівень 4) дані фінансових систем (наприклад, регуляторні рамки, ринкова взаємодія); рівень 5) дані економічного контексту (наприклад, геополітичні фактори, технологічний прогрес). Це допомагає впорядкувати складні вхідні дані, уможливлюючи компроміс між ентропією-складністю-стабільністю та запобігаючи інформаційному перевантаженню; а також сприяє багаторівневій аналітичній глибині для більш структурованого розуміння інформаційного середовища, в якому приймаються рішення щодо ефективного фінансового трейдингу.

Удосконалено періодизацію розвитку фінансового трейдингу та його регуляторного середовища шляхом ідентифікації шести етапів функціонування фінансового трейдингу, зосереджуючись на діяльності міжнародних і національних регуляторів; законодавчих положеннях про цінні папери, правилах боротьби з відмиванням грошей, правилах щодо зловживань на ринку; технологічних нормативних актах для алгоритмічного / високочастотного трейдингу, блокчейні, технологіях штучного інтелекту тощо. На відміну від попередніх досліджень, які зосереджувалися на подіях до 2010 року, така періодизація наголошує на регуляторному ландшафті після 2010 року, оскільки він має такі особливості, як вплив на фінансовий трейдинг відповідального інвестування, впровадження нових технологій, розвиток децентралізованого фінансування задля забезпечення стабільності ринку, захисту інвесторів та чесної практики в глобалізованому контексті.

На основі узагальнення тенденцій фінансового трейдингу в світі в умовах глобалізації було запропоновано пояснення циклічності фінансового трейдингу на фінансових ринках, що розвиваються, та розвинених фінансових ринках через наявність «лаг-циклу». Це означає, що цикли фінансові ринків, що розвиваються, зазвичай відстають від циклів розвинених фінансових ринків на одну фазу (накопичення, зростання, розподіл, корекція). Такий підхід підкреслює глибокий взаємозв'язок та синхронізацію фінансових ринків у світі, забезпечуючи підхід для розуміння циклічної взаємозалежності та передачі ризиків.

Побудовано динамічну модель оцінки ефективності фінансового трейдингу. Це є комплексна математична модель, яка інтегрує динаміку цін (стохастичне диференціальне рівняння); індекс цінової ефективності, що базується на відхиленні від фундаментальної ціни фінансового активу; коефіцієнт ліквідності та транзакційні витрати; швидкість потоку інформації з експоненціальним спадом, що були об'єднані в єдину метрику ефективності фінансового трейдингу ($\varepsilon(t)$). Така модель забезпечує кількісну, динамічну міру ефективності фінансового трейдингу; інтегрує реальні тертя (ліквідність, витрати) та динаміку інформації; перевершує традиційні моделі в контексті практичного застосування у фінансовому трейдингу.

Набув подальшого розвитку фреймворк ризик-менеджменту фінансового трейдингу в умовах глобалізації. Він враховує ринкові, кредитні, операційні, системні ризики та ризики ліквідності, включає застосування штучного інтелекту для моніторингу в режимі реального часу, прогнозного аналізу та має структурований 5-етапний процес для впровадження в реальних умовах, що дозволяє динамічно адаптуватися до інформаційної асиметрії, ринкових потрясінь та алгоритмічних упереджень. На відміну від традиційних статичних моделей, ця система забезпечує комплексний, систематичний та адаптивний підхід до управління повним спектром ризиків фінансового трейдингу на сучасних глобалізованих фінансових ринках. Універсальність та адаптивність роблять фреймворк прийнятним як для регуляторів, так і для учасників фінансового ринку для покращення прогнозування, порівняння ефективності стратегій та зміцнення системної стійкості.

Узагальнено пропозиції щодо формування стабільного середовища фінансового трейдингу, що базуються на п'яти ключових умовах. Пропозиції поєднують інституційні, технологічні та регуляторні компоненти в цілісну систему та включають такі ключові умови стабільності: 1) ефективність ринку та доступність інформації, 2) транскордонні потоки капіталу та розподіл ризиків, 3) регуляторна база та інституційна підтримка, 4) технологічна інфраструктура та торговельні платформи, 5) ліквідність валютного ринку. Таке поєднання забезпечує інтегративний та збалансований підхід, який гарантує, що зростання ринку не досягається ціною системної вразливості. Він забезпечує універсальну та адаптовану дорожню карту для полісімейкерів і установ задля сприяння стійкому, прозорому та сталому фінансовому трейдингу в усьому світі, тим самим знижуючи ймовірність криз і зміцнюючи довіру інвесторів.

Побудовано динамічну модель для підвищення прибутковості фінансового трейдингу. Ця модель інтегрує макроекономічні змінні (наприклад, процентні ставки, торговельні баланси, політичні зміни) з факторами трейдинг контексту (наприклад, глибина ліквідності, доступ до ринку, використання штучного інтелекту). Дана модель розширює класичні моделі прибутковості до адаптивних та орієнтованих на майбутнє систем прийняття рішень. Модель також дозволяє проводити сценарний аналіз та стратегічне прогнозування в режимі реального часу, пропонуючи цінність інституційним інвесторам, регуляторним органам та стратегічним аналітикам. Гнучкість моделі дозволяє їй адаптуватися до змінних ринкових умов та передбачати зміни прибутку у відповідь на геополітичні, економічні чи технологічні збої.

Ключові слова: ризик, оцінка ризику, ризик-менеджмент, криптовалюта, фондовий ринок, S&P 100, валютний ринок, валютний курс, ліквідність, трансакційні витрати, інвестиційне рішення, інвестиційна ефективність, інвестиційна стратегія, сталий розвиток, ESG.

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CONTENT

INTRODUCTION

Relevance of the topic. The development trend of globalization over the past few decades shows that financial trading has been fully and richly developed in multiple dimensions. Financial trading, which once consisted of basic transactional functions, has now become a multifaceted mechanism deeply embedded in the technological, institutional, and economic matrices of the global financial system. In developed economies, financial trading has long functioned not only as a means of capital allocation but as a core mechanism of liquidity provision, systemic stability, and innovation. In contrast, emerging markets often face inefficiencies in regulatory coordination, conceptual ambiguity, and limited technological integration in financial trading practices. Current trends in the development of global financial markets indicate that their full functioning and continued modernization under globalization are facing difficulty without the comprehensive conceptualization and systemic modelling analysis of financial trading. At the same time, financial trading under globalization represents a unique hybrid of traditional financial mechanisms and cutting-edge technologies, such as algorithmic trading, artificial intelligence, and machine learning models. These innovations make it possible to get higher market precision and efficiency, but simultaneously introduce new layers of systemic risk and regulatory complexity. All of the above factors confirm the timeliness and necessity of exploring this research topic.

The subject matter has widely been studied in financial economics and econometrics. The foundational work was carried out by Bollerslev T., Engle R. F., Glasserman P., and Lo A. W., who examined adaptive market hypotheses, volatility clustering, and risk modelling, providing the basis for high-frequency financial analysis. Further critical insights were provided by Fama E. F., Kindleberger C. P., Malkiel B. G., Markowitz H. M., and Stiglitz J. E., whose work remains deeply influential. The hierarchical theory developed by Allen T. F. and Starr T. B. also offered a methodological foundation for structuring financial trading data in this study. Technological advances in financial trading have been analyzed by Barber B. M., Brogaard J., Cooper M. J., Easley D., Gulen H., Hendershott T., O’Hara M., Odean T., Rau P. R., and Riordan R., focusing on investor behavior, algorithmic trading, and liquidity provision. Further contributions came from Chaboud A. P., Chiquoine B., Hjalmarsson E., Jones C. M., Kirilenko A., Menkveld A. J., and Vega C., who studied trading microstructure, market efficiency, and the role of intermediaries. The systemic effects of trading and information transmission were explored by Chen Z., Hong H., Knez P. J., Petajisto A., Ready M. J., and Stein J. C. Broader perspectives on systemic risk and financial stability were developed by Acharya V. V., Cooley T. F., Harvey C. R., Merton R. C., Richardson M., and Walter I. Analyses by Bernanke B. S., Eichengreen B., Reinhart C. M., Rogoff K. S., and Savastano M. have expanded the understanding of financial crises, systemic risk, and regulatory impacts. Amihud Y., Jegadeesh N., Kyle A. S., Roll R., and Titman S. provided important insights into trading strategies and market efficiency.

In addition, among the contributors to the broader discourse on financial trading and investment dynamics are the following Ukrainian scholars and economists: Alekseyenko L., Bilenko D., Bulkot O., Hreshko R. I., Ihnatiuk V., Ivanyuta N., Kaminskyi A., Kharabara V. M., Kozlovskyi S., Liubkina O., Lobova O., Prykaziuk N., Shevchenko L., Sholoiko A., Tomchuk O., and Volosovych S. Their research spans a wide range of topics including cryptocurrency investment efficiency, transaction costs in stock trading, ESG (Environmental, Social and Governance) and sustainable investment, and digital security in networked economies. Their contributions serve as critical reference points for comparative analysis and theoretical grounding within the dissertation, particularly in understanding the evolving intersections of technology in financial trading, regulation, and financial market behaviour.

Paying tribute to the achievements in the field of financial trading and its technological and regulatory transformation, it should be emphasized that several issues still require more profound analysis. Till this moment, the definition of “financial trading” is fragmented among practitioners and scholars. Such a definition that encompasses the essence, content, and result does not exist. This study systematically synthesizes existing conceptualizations in order to formulate a comprehensive definition that reflects both theoretical foundations and practical realities, and also reevaluates improvements in the classification, participant roles and risk factors in financial trading; revisits assessing the implications of artificial intelligence (AI) based trading on systemic risk; examines the harmonization of legal and institutional frameworks in a globalized environment, and the role of modelling complexity in financial trading. Furthermore, the risk management framework and dynamic models discussed in the empirical sections of this work have yet to be integrated into unified strategic frameworks for international market governance. The high significance of these issues, their insufficient scientific and applied elaboration, and the fragmentation of conceptual approaches to financial trading determined the choice of the dissertation topic, its goal, and main objectives.

Connection of the work with scientific programs, plans, topics. The dissertation was carried out within the framework of the theme of the Department of insurance, banking and risk-management of the faculty of economics of Taras Shevchenko National University of Kyiv "Strategic vectors of the financial services market development of Ukraine" (№22КФ040-06) in 2023. As part of this theme, the author contributed proposals for a comprehensive rethinking of the theoretical and methodological foundations of financial trading, with particular emphasis on its essence and classification.

Purpose and tasks of the dissertation. The aim of the dissertation is to enhance theoretical and practical aspects and provide recommendations for the further development of financial trading under globalization in order to increase the efficiency, stability, and inclusivity of developed and emerging financial markets.

For achieving this goal, the following tasks were completed:

- to clarify the essence, classification and risks of financial trading;
- to characterize the financial trading strategies;
- to determine the information basis of the efficient financial trading;
- to generalize the institutional and legal provisions governing financial trading;
- to examine the tendencies of global financial trading;
- to assess the financial trading efficiency;
- to design a financial trading risk management framework;

- to provide proposals for the formation of a stable financial trading environment;
- to develop recommendations for enhancing financial trading profitability.

The object of the study is the processes of the financial trading development under globalization.

The subject of the study is the theoretical, methodological and practical aspects of financial trading development under globalization.

Research Methods. The complexity of the research objectives set forth in the dissertation necessitated the application of a wide range of methodological approaches, carefully selected to reflect the multidimensional nature of financial trading and its evolution under the conditions of globalization. To formulate a comprehensive definition of financial trading, the methodological framework developed by Starostina A. and Kravchenko V. was employed. For enhancing the classification of financial trading, a combination of faceted and hierarchical methods was utilised. The characteristics of financial trading strategies were examined using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) reporting guidelines in conjunction with the four-quadrant approach. To determine the information basis of effective financial trading, data hierarchy techniques and the generalisation method were employed. The historical and logical methods facilitated the generalisation of institutional and legal provisions governing financial trading. To analyse global financial trading trends, both analytical and statistical methods were applied. Comparative analysis enabled an in-depth examination of the efficiency performance of financial trading across developed and emerging financial markets. A set of advanced methods was adopted to assess financial trading efficiency, design the risk management framework, formulate proposals for establishing a stable financial trading environment, and develop recommendations for enhancing financial trading profitability. Specifically, modelling methods were used to empirically assess efficiency and volatility parameters; forecasting and scenario modelling were employed to construct models. Graphical methods were applied to visualise the dynamic model of financial trading. Finally, the inductive and deductive methods were utilised to formulate the key conclusions of the dissertation.

The information base of the dissertation includes statistical data and analytical reports from international financial institutions such as the International Monetary Fund (IMF), the World Bank, and the Bank for International Settlements (BIS); central banks and regulatory agencies of major economies including the Federal Reserve, the European Central Bank (ECB), the People's Bank of China and so on; academic databases Scopus; and global market platforms such as the New York Stock Exchange (NYSE), the National Association of Securities Dealers Automated Quotations (NASDAQ), the London Stock Exchange (LSE) and the Shanghai Stock Exchange (Shangzheng). In addition, normative legal acts, strategic regulatory documents, and white papers related to global financial trading were analysed. Monographs, peer-reviewed scientific publications, empirical research studies, and conference materials were used to ensure a comprehensive review of theoretical and applied aspects of financial trading. The dissertation also incorporates original data collections and algorithmic simulations conducted using Scopus-based literature datasets and econometric software tools. Other Internet resources were used.

The scientific novelty of the results obtained. The scientific novelty of the results obtained lies in the enhancing of theoretical and practical aspects and providing recommendations for the further development of financial trading under globalization in order to increase the efficiency, stability, and inclusivity of developed and emerging financial markets. The most important results that constitute the scientific novelty of the dissertation research and are presented for defence are as follows:

The subsequent provisions were enhanced:

- theoretical basis of financial trading, namely the definition of financial trading was enhanced providing essence, content and result of the concept, particularly financial trading is an immediate or specifically pre-set process performed by financial trading participants, based on the characteristics of one or more financial assets and relevant market information, with the purpose of achieving direct or indirect financial benefits. Unlike previous approaches that offered fragmented or overly generalized definitions, this definition integrates the transactional nature, actor dynamics, and value output of trading. Financial trading participants were generalised into two groups: systemic participants (brokers, market makers) and investment participants (individual traders, institutional investors, high-frequency traders, sovereign wealth funds). The classification of financial trading was developed by combining the hierarchical and faceted methods. This approach allows regulators to account for the diversity of financial trading types and provides a basis for analysis. Additionally, financial trading risks were characterised, namely market, credit, liquidity, operational, and systemic risks, each analysed through quantitative models. These contributions collectively establish a theoretical foundation for analysing financial trading under globalization and provide a basis for future regulatory, risk management, technological, and strategic advancements in financial markets;

- dividing financial trading strategies into four types by introducing the Four-Quadrant of financial trading strategies, a conceptual framework that classifies financial trading strategies along two axes: machine technology level and the trading strategy level. This yields four distinct quadrants: autonomous intelligent trading, intelligent, assisted trading, traditional-modern trading, and mechanical trading. That accounts for the interplay between automation level and strategic complexity;

- generalising institutional and legal provisions of financial trading by identifying and characterizing the six historical periods of financial trading. In contrast to previous studies that focus on pre-2010 events, this research emphasizes the post-2010 regulatory landscape, especially in relation to high-frequency trading (HFT), artificial intelligence (AI) trading, and decentralized finance (DeFi), sustainability and ESG concerns, identifying regulatory innovations aimed at integrating financial market stability with long-term societal goals;

- approach for assessing financial trading efficiency by developing a dynamic model, focusing on the dual impact of technological innovation and macroeconomic variability. A core contribution is the development of the $\varepsilon(t)$ single metric of financial trading efficiency, a novel multidimensional tool that quantifies financial trading performance in real time by integrating trading volume, bid-ask spread dynamics, and adaptive response to market shocks. Unlike traditional financial trading efficiency assessments, the dynamic model offers greater detail and predictive ability.

The provisions outlined below acquired further development:

- determining the information basis for efficient financial trading. The five-level hierarchy information basis (Level 1: Foundational Data, Level 2: Aggregated Data, Level 3: Macroeconomic Indicators, Level 4: Financial Systems Data, Level 5: Economic Context Data) was developed to provide the background for financial trading efficiency, integrating traditional financial indicators with alternative data sources (e.g., social media, satellite data). By applying entropy as a novel complexity metric, this hierarchy information basis links data quality with systemic efficiency, filling gaps in conventional data-centric approaches;

- designing a financial trading risk management framework, tailored to the conditions of globalized financial markets. In contrast to conventional static models, the framework integrates traditional risk typologies: market, credit, liquidity, operational, and systemic risks, with entropy-based uncertainty metrics, enabling dynamic risk evaluation in real time. It emphasizes adaptability as a core principle, allowing the system to recalibrate according to shifts in data patterns, algorithmic behaviour, and macroeconomic volatility;

- explaining the financial trading cyclicality under globalization in the developed and emerging financial markets through "lag cycle" existence (accumulation, growth, distribution, correction) to describe interregional market interdependencies and risk transmission. This approach highlights interconnectedness and synchronization of global financial markets, providing a basis for understanding cyclical interdependence;

- generalising recommendations for a stable financial trading environment under globalization by identifying five key conditions: market efficiency and access to information, cross-border capital flows and risk sharing, regulatory framework and institutional support, technological infrastructure and trading platforms, and foreign exchange and currency market liquidity. This approach provides a comprehensive view of the stable financial trading environment;

- constructing a dynamic model for enhancing financial trading profitability, which connects trading contextual factors with macroeconomic variables (e.g., interest rates, trade policies). This enables real-time forecasting of financial trading profitability under varying global conditions.

The practical significance of the research results. The main provisions and results of the dissertation on the development of the financial trading under globalization, were implemented in the educational process at the Department of insurance, banking and risk management of the faculty of economics of Taras Shevchenko National University of Kyiv within teaching the disciplines “Financial services market” and “Financial information and strategic decision making” (Implementation letter №013/178 on 11.04.2025).

Proposals for the implementation of a comprehensive risk management framework were used in the activity of LLC “Financial Company “Finexpress”” (Implementation letter №14/04-2025-6 on 14.04.2025).

Personal contribution of the applicant. The scientific provisions, conclusions and recommendations submitted for defence are obtained by the author independently. The dissertation is independent scientific research that reflects the author’s vision of the financial trading development under globalization. The author’s contribution in scientific articles and publications is given in the list of published works of the applicant.

Approbation of the results of the dissertation. The main provisions of the dissertation work were submitted for consideration and reported at 4 international scientific and practical conferences and 1 international forum, in particular: the international and practical conference Shevchenkivska Vesna 2023 “Problems and prospects of Ukraine’s post-war economic recovery” (Kyiv, March 29-31, 2023), the international and practical conference “World trends and prospects of development of the financial system of Ukraine” (Kyiv, May 25-26, 2023), the international forum 3.0 Economics. Finance. Business. Management “From recovery to growth” (Kyiv, May 21-24, 2024), the international and practical conference December readings “Financial business: stability, inclusiveness and social responsibility” (Kyiv, December 5-6, 2024), the 1st Modern Finance Conference (Warsaw, September 15-17, 2024).

Publications. The main results of the dissertation were published in 9 scientific works with a total volume of 4,21 printed pages (the author's personal contribution is 2,53 printed pages), including: 4 articles in Ukrainian professional journals and one of them is indexed in Scopus (1,68 printed pages); 5 publications based on materials of international scientific and practical conferences and international forum (0,85 printed pages).

Structure and scope of the dissertation. The dissertation research consists of an introduction, three chapters, nine subchapters, conclusions to the chapters, general conclusions to the dissertation, a list of references and annexes. The total volume of the dissertation research is 297 pages. The main volume of the dissertation research is 216 pages. The dissertation contains 55 formulas, 21 figures and 27 tables, has 7 annexes. The list of references has 294 items.

CHAPTER I
THEORETICAL FOUNDATIONS OF FINANCIAL TRADING

1.1. Essence, classification and risks of financial trading

The concept of financial trading appeared with the emergence of financial markets. Nowadays, with the development of the financial industry and the expansion of the financial market under globalization and the digital economy, this concept is becoming more and more important. At the same time, the concept of financial trading has gradually turned out to be more complex with the emergence of new financial assets and the improvement of financial trading methods. Along with that, it is quite difficult to find a clear and grounded definition of the financial trading. Due to this fact many misunderstandings and inadequate regulations can appear. To further meet the research demand of academics and financial practitioners in the field of financial trading it is necessary to conceptualize the financial trading [1] through scientifically and comprehensively defining the concept of "financial trading". For achieving this, the next tasks were done: to analyse completeness of existence definitions of financial trading; to develop the definition of financial trading; to characterize the main financial trading participants (individual traders, institutional investors, high-frequency traders, market makers, brokers, and sovereign wealth funds); to create a comprehensive classification of financial trading [1]; to characterize the main financial trading risks.

According to previous research on financial trading, financial trading is an inherently complex and risky domain [2, p. 2]. Regarding the concept of financial trading, most financial practitioners and theoreticians define it as an act of buying or selling a financial instrument (equities, bonds, and so on) [3; 4; 5; 6; 7]. Traditional financial trading methodologies are typically classified as either technical analysis, which focuses on price patterns and market data, or fundamental analysis, which evaluates the intrinsic value based on economic and financial factors. Technical financial trading usually represents a class of investment strategies for financial markets based on the analysis of trends and recurrent patterns in price time series [8]. However, this financial trading method based on technical analysis has also been questioned scientifically. According to the efficient market hypothesis (EMH), the hypothesis imposes substantial limitations on financial trading and makes it impossible to surpass efficient markets via arbitrage or trading strategy [9]. Then, the adaptive market hypothesis (AMH) was introduced in 2004 by Andrew Lo. It combines principles of the well-known and often controversial EMH with behavioural finance. AMH believes that people are mainly rational but sometimes can overreact during periods of heightened market volatility [10]. This explains how stocks do not always trade at fair value during financial bubbles, crashes, and crises [1].

With the development of the financial industry and computer science during the recent decades, trading systems based on machine learning have been actively studied in all fields including the financial field [11]. In the cutting-edge financial trading technology practice, “Quantamental” hedge funds utilize commercial satellite imagery for observing the area density of human activity as a source of intelligence for their financial trading algorithms in order to generate access returns (alpha) [12]. In recent years, Large Language Models (LLMs) have significantly impacted the financial sector, offering innovative solutions to complex problems. The innovative emergence LLMs such as “GPT-4” has initiated a paradigm shift within the domain of financial trading [13]. These technical and theoretical advances also promoted our further study of the developing of the “financial trading” definition and the grouping of the financial trading participants and financial trading classification [1].

The formulating of the “financial trading” definition is carried out applying the methodological framework developed by Starostina A. and Kravchenko V., the algorithm of which consists of seven consecutive stages: 1) making of a definition list of the “financial trading” term (definitions from practitioners and theoreticians are taken into account); 2) decomposition of the definitions of the “financial trading” concept into three components: the essence, the phenomenon content and its result; 3) generalisation of views on the definition of the “financial trading” concept; 4) classification of generalized approaches to defining the “financial trading” concept; 5) critical analysis of the identified approaches to defining the “financial trading” concept; 6) development of the author’s definition of the “financial trading” concept; 7) analysis of the possibility of practical use of the author’s definition of the “financial trading” concept [1; 14, p. 7].

At the first and the second stages gathered “financial trading” definitions are divided into three components: the essence, the content, and result (table 1.1) [1].

Table 1.1

Definitions components for the concept of “financial trading”

№	Author / source	Definitions components		
		Essence	Content	Result
1	2	3	4	5
1	Sikuni, 2021 [3]		buying and selling of financial assets	
2	Infinox, 2022 [4]		buying and selling of assets in financial markets	in the hopes of a positive outcome
3	Lawinsider, 2020 [15]		trading for own account or for customers’ account, whether on an investment exchange, in an over-the-counter market or otherwise, in financial product	
4	BajajFinserv, 2022 [5]	a method	that involves buying and selling stocks and other financial instruments like futures and options, ETFs, etc. for a short period	
5	Teall, 2018 [16, p.1]	a security transaction	that creates or alters a portfolio position based on an investment decision	
6	Investopedia, 2023 [17]		purchasing and selling securities, commodities, or derivatives	
7	Wikipedia, 2023 [18]	an exchange	of a security for “cash”, typically a short-dated promise to pay in the currency of the country where the ‘exchange’ is located.	
8	Buczynski, Cuzzolin & Sahakian, 2021 [6]	act	of buying or selling a financial instrument (equities, bonds, commodities, etc.)	
9	DNBC markets, 2022 [7]		buying and selling of financial instruments	
10	Tradingmasters, 2023 [19]		exploiting the variation in the prices of securities quoted in the financial markets	to obtain a high profit

Source: based on [1; 3; 4; 5; 6; 7; 15; 16, p.1; 17; 18; 19]

At the third stage, the generalisation of views on the definition of the “financial trading” concept based on the presence of the necessary components is made. All three components are not revealed in any definitions. Only four out of ten definitions contain the essence and content components and only two out of ten definitions include the content and result components [1].

Then the next stage involves the classification of generalized approaches to defining the “financial trading” concept (table 1.2) [1].

Table 1.2

Theoretical approaches to defining the “financial trading” concept

№	Author or source	Essence				Content (+/-)	Result (+/-)
		Method	Security transaction	Exchange	Act		
1	Sikuni, 2021	-	-	-	-	+	-
2	Infinox, 2022	-	-	-	-	+	+
3	Lawinsider, 2020	-	-	-	-	+	-
4	BajajFinserv, 2022	+	-	-	-	+	-
5	Teall, 2018	-	+	-	-	+	-
6	Investopedia, 2023	-	-	-	-	+	-
7	Wikipedia, 2023	-	-	+	-	+	-
8	Buczynski, Cuzzolin & Sahakian, 2021	-	-	-	+	+	-
9	DNBC markets, 2022	-	-	-	-	+	-
10	Tradingmasters, 2023	-	-	-	-	+	+

Source: [1]

Based on the materials in table 1.1 different understandings of financial trading can be distinguished: 1) financial trading is buying or selling financial assets; 2) financial trading is buying or selling financial assets with the aim to obtain a high profit (positive outcome) [1]. The main difference between these two definitions lies in the result of financial trading, which also can be a point that is prone to academic criticism. In wider and more practical financial applications, financial trading can not only obtain direct profits through price differences but also be used in investment portfolio strategies and hedge funds to avoid financial risks or to obtain indirect financial benefits [1].

Analysing the information collected about the financial trading definitions, there is an academic consensus that the essence of the “financial trading” concept is the transaction, which is also usually described as buying and selling. Besides, to introduce a more scientific and practical financial trading definition, it is necessary to define the objects of the transaction as financial assets. But other objects as financial instruments should also be noticed here and distinguished from financial assets. "Financial instruments are assets that can be traded, or they can also be seen as packages of capital that may be traded. These assets can be in the form of cash, a contractual right to deliver or receive cash, or another type of financial instrument, or evidence of one's ownership in some entity" [20]. In a rigorous scientific definition, "a financial instrument creates a financial asset for one party and a liability for the other party" [21]. "Financial assets derive their value from a contractual claim on an underlying asset" (tangible (real or financial) and intangible) [1; 22]. Financial assets, rather than financial instruments, are therefore chosen for the definition here because they directly embody the economic value exchanged in transactions, whereas financial instruments represent a broader legal framework that may not always involve the transfer of underlying value.

Accordingly, at the fifth stage, it is necessary to carry out a critical analysis of the identified approaches (table 1.3) [1].

Table 1.3

Estimation of theoretical approaches to defining the "financial trading" concept

№	Author or source	Estimation criteria (maximum 5 points for each criterion)				
		Presence of all definition components	Popularity of definition	Theoretical background	Use in practice	Total points (maximum 20 points)
1	Sikuni, 2021	2	5	2	3	12
2	Infinox, 2022	4	4	4	5	17
3	Lawinsider, 2020	2	2	2	3	9
4	BajajFinserv, 2022	4	5	4	3	16
5	Teall, 2018	4	2	4	5	15
6	Investopedia, 2023	2	5	2	3	12
7	Wikipedia, 2023	4	2	4	3	13
8	Buczynski, Cuzzolin & Sahakian, 2021	4	5	4	3	16
9	DNBC markets, 2022	2	5	2	3	12
10	Tradingmasters, 2023	4	4	4	5	17

Source: [1]

The data given in the table 1.3. is the basis for the formulation of our own scientific definition of financial trading. In our opinion, the scientific definition of financial trading is as follows: "financial trading is an immediate or specifically pre-set process performed by financial trading participants based on the features of one or more financial assets and market information with the purpose of direct or indirect financial benefit".

In our definition, financial trading participants are different from financial trading organizers or regulators and are the real executors and the main parties of financial trading. Moreover, financial trading follows a financial trading nature because the transactions are based on the features of one or more financial assets and market information considered by financial trading participants. This approach is necessary for distinguishing the financial trading from gambling with non-financial purposes [1].

It is necessary to find out whether our proposed definition of the "financial trading" concept is the basis for its practical use. In our opinion, the above mentioned definition is highly likely to become widespread in practical use, as it generally reflects the focus of financial trading on the performance of its main task, namely: providing direct or indirect financial benefits. This definition can be widely used in various fields of financial trading in the future [1].

Regarding financial trading participants, generally, it is possible to divide them into two groups: investment participants and systemic participants. Systemic participants include brokers and market makers, they do not directly profit from financial transactions, but act for the purpose of earning commissions. Investment participants include individual traders, institutional investors, high-frequency traders and sovereign wealth funds. All types of financial trading participants often have obvious differences in trading frequency, trade size, investment duration and risk management [1; 23; 24] (table 1.4).

The findings show that the characteristics of various types of financial trading participants differ significantly in their trading behaviours and outcomes. Individual traders have relatively low professional experience and are more likely to engage in speculation and high-risk trading behaviour. In contrast, institutional investors and sovereign wealth funds tend to have higher professional experience and access to better market information and resources and prefer long-term investment strategies [24].

Table 1.4

Main characteristics of the financial trading participants

№	Participant and unique important characteristics	Main source of profit	Trade size	Investment duration	Trade frequency	Risk management
I. Systemic participants						
1	Market makers provide liquidity to financial markets, and often play a critical role in reducing bid-ask spreads and improving market liquidity	Commissions	Small	Short term	High	No
2	Brokers as intermediaries between buyers and sellers, can influence the behaviour of individual investors by recommending trades and providing market information	Commissions	Small	Short and long term	Low	No
II. Investment participants						
3	Individual investors or traders, also called retail investors who trade financial instruments with their own capital, are prone to behavioural biases and engage in excessive risk-taking behaviour	Trading actions	Small	Short and long term	Low	Low
4	Institutional investors which invest on behalf of their clients are usually less prone to herding behaviour and have better risk management practices	Trading actions	Large	Short and long term	High and low	High
5	HFT traders usually use algorithms to execute high-speed trades in milliseconds and can also contribute to market efficiency by improving price discovery	Trading actions	Small	Short term	High	Low
6	Sovereign wealth funds are usually state-owned investment funds that manage and invest a country's wealth. Most of them have unique investment objectives and can have a significant impact on financial markets due to their large size and long-term investment horizons	Trading actions	Large	Long term	Low	High

Source: compiled based on [1; 23; 24; 25; 26; 27; 28; 29; 30]

The classification of financial trading is based on the combination of two classification methods: 1) hierarchical classification method takes into account the division of financial trading into separate groups with their subsequent division into types with more detailed characteristics; 2) faceted classification method is based on only individual and freely chosen characteristics of financial trading [1].

For developing a comprehensive classification of financial trading by applying a combination of classification methods it is necessary to start with consideration of main classification features of faceted classification: the object of financial trading, trading technology, transaction place, transaction execution, financial trading purpose and market structure (table 1.5) [31].

Table 1.5

Key classification features of faceted classification of the financial trading

№	Classification feature	Characteristic
1	2	3
1	Object of financial trading	This means that financial trading can be classified according to the objects traded. In the traditional financial concept, financial instruments traded in financial markets “may be divided according to an asset class, which depends on whether they are debt-based or equity-based. Foreign exchange instruments comprise a third, unique type of financial instrument” [33]. With the development of computer technology and the rising of the Internet finance in the 21st century, cryptocurrency and digital goods have gradually become the object of financial transactions and are becoming more and more important
2	Trading technology	Refers to the strategy and technology used in the financial transaction process. In the former study, traditional trading strategies employed can be classified as fundamental, technical, and quantitative strategies. In our new classification, according to the financial industry and the history of financial transaction technology, financial transaction technology can be roughly divided into three levels: traditional financial trading, modern financial trading and next-generation financial trading. Traditional financial trading technology includes fundamental analysis and technical analysis. Modern financial trading technology includes algorithmic trading and Machine learning-based trading. The next-generation financial trading technology includes advanced artificial intelligence technology and infinite information algorithm
3	Place of transaction	This item indicates the place where the financial transaction takes place, usually divided into physical financial trading (offline) and online financial trading
4	Transaction execution	This item indicates the execution method of financial trading, usually divided into immediate trading and pre-set trading
5	Financial trading purpose	Indicates the purpose of financial trading, usually divided into investment and non-investment
6	Market structure	This item indicates whether financial trading is conducted through exchanges. The market structure can be classified as over-the-counter (OTC) and exchange-traded markets

Source: compiled based on [31; 32; 33; 34, p. 42-47]

The faceted classification method deeply categorizes financial trading according to multiple dimensions. Whereas this financial trading classification method is relatively rigid and simple, it lacks practicality in some complex financial transaction scenarios. For further development of the comprehensiveness and interactivity of financial trading classification, a combination of the faceted classification method and the hierarchical classification method is used (table 1.6) [1; 31].

This classification is comprehensively developed according to the various characteristics of financial trading with financial transaction technology as the core. This financial trading classification approach divides the application scenarios of different financial transaction technologies in details and makes a preliminary prediction for the possible application situation of next-generation financial transaction technologies in the future [1; 31].

Table 1.6

Comprehensive classification of financial trading

Feature	Types of financial trading						
Financial trading techno-logy generation	Traditional financial trading				Modern financial trading	Next generation financial trading	
Trading techno-logy implementation	Trading based on fundamental analysis method		Trading based on technical analysis method		Algorithmic trading and ML-based trading	Trading based on advanced AI technology	Trading based on infinite information
Place of transaction	Physical financial trading	Online financial trading	Physical financial trading	Online financial trading	Online financial trading	Online financial trading	Online financial trading
Market structure*	Financial trading in exchange-traded markets	Financial trading in OTC markets	Financial trading in exchange-traded markets	Financial trading in OTC markets	Financial trading in OTC markets	Financial trading in OTC markets	Financial trading in OTC markets
transaction execution	Immediate and pre-set trading	Immediate and pre-set trading	Pre-set trading	Pre-set trading	Pre-set trading	Immediate and pre-set trading	Pre-set trading

Ending of the table 1.6

Objects of financial trading	1.Commodity market trading**	1.Commodity market trading**	1.Commodity market trading**	1.Commodity market trading**	1.Commodity market trading**	1.Commodity market trading**	1.Commodity market trading**
	2.Bond market trading	2.Bond market trading	2.Bond market trading	2.Bond market trading	2.Bond market trading	2.Bond market trading	2.Bond market trading
	3.Stock market trading	3.Stock market trading	3.Stock market trading	3.Stock market trading	3.Stock market trading	3.Stock market trading	3.Stock market trading
	4.Fund market trading	4.Fund market trading	4.Fund market trading	4.Fund market trading	4.Fund market trading	4.Fund market trading	4.Fund market trading
	5.Deriva-tives market trading	5.Derivatives market trading	5.Derivatives market trading	5.Derivatives market trading	5.Derivatives market trading	5.Derivatives market trading	5.Derivatives market trading
	6.Forex market trading	6.Forex market trading	6.Forex market trading	6.Forex market trading	6.Forex market trading	6.Forex market trading	6.Forex market trading
		7. Cryptocurrency market trading		7. Cryptocurrency market trading	7. Cryptocurrency market trading	7. Cryptocurrency market trading	7. Cryptocurrency market trading
		8.Special digital goods market trading		8.Special digital goods market trading	8.Special digital goods market trading	8.Special digital goods market trading	8.Special digital goods market trading
Purpose	Investment trading for investment participants; non-investment trading for systemic participants						

* Nowadays, large exchange-traded markets trade the majority of physical financial trading objects. Traditional exchange-traded markets usually don't trade commodities and derivative objects.

** In the context of underlying assets

Source: created by author based on [1; 31]

Moreover, during the study of scientific conceptualization of "financial trading", it is necessary to indicate the relationship and distinction between financial trading, investment, speculation, and gambling for further description of financial trading risks arising (table 1.7) [1].

Table 1.7

Conceptual similarities and differences among gambling, speculation, investment and financial trading

Comparative characteristic	Gambling	Speculation	Investment	Financial trading
Activities & Instruments	Fairly distinctive from speculation, investment and financial trading	Fairly distinctive from gambling, less distinctive from investment and financial trading	Fairly distinctive from gambling, less distinctive from speculation and financial trading	Fairly distinctive from gambling, less distinctive from speculation and investment
Time frame	Usually short	Variable	Long	Variable
Level of risk	Usually high	Usually high	Low	Low
Expected returns	Usually negative with low variability	Mixed and highly variable	Usually positive and somewhat variable	Mixed and highly variable
Role of chance	High	High	High	Variable
Asset purchase	No	Sometimes	Yes	Yes
Stake	Yes	Yes	No	No
Definitive event/outcome	Yes	Usually	Usually not	Usually
Economic utility	Low	Mixed	High	High

Source: added by author based on [1; 35, p. 5]

Most financial activities such as financial trading are usually closely related to two concepts: speculation and investment. In addition, financial trading may sometimes in some cases be criticized as gambling. In a 2016 sociological study that analysed the relationship and distinction among gambling, speculation, and investment it was clearly shown that: "Gambling differs from investment in many different attributes and should be seen as conceptually distinct. On the other hand, speculation is conceptually intermediate between gambling and investment. Speculation and gambling have conceptual overlap and a strong empirical relationship" [1; 35, p.5].

The risks, as the most crucial difference among these activities, can usually be mainly categorised into market risk, liquidity risk, credit risk, operational risk and systemic risk in the context of financial trading. The first category, market risk, usually refers to the potential for losses due to fluctuations in the value of financial assets or markets. In a globalized financial environment, market risk has become more complex due to the interconnectedness of markets, the rapid flow of information, and the impact of international events on financial instruments. In order to scientifically and effectively understand and manage market risks, these classical financial models are usually used: the Value-at-Risk (VaR) model and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model.

The VaR model is one of the most widely used tools to quantify market risk. It estimates the maximum potential loss in the value of an asset or portfolio over a defined time horizon with a given confidence level. The model is based on the concept of a normal distribution for asset returns, and it provides a threshold below which the loss is expected to fall with a certain probability (usually 95% or 99%). The use of VaR in financial risk management is discussed extensively, which emphasizes its widespread adoption due to its simplicity and ability to provide a single number summarizing potential risk [36]. However, it is also noted that VaR has limitations such as its inability to capture extreme market events (tail risks), which can be problematic in times of market stress, a common occurrence in globalized markets. Another research explores how VaR is adjusted to account for tail risk by utilizing models such as Extreme Value Theory (EVT), which focuses on modelling the extremes of the distribution rather than the central tendency [37]. The basic formula for VaR is given as:

$$VaR_\alpha = \mu_P - \sigma_P \cdot Z_\alpha, \tag{1.1}$$

where:

- μ_P is the expected return of the portfolio,

- σ_P is the standard deviation (volatility) of the portfolio returns,

- Z_α is the quantile corresponding to the confidence level α, such as 1.645 for a 95% confidence level.

GARCH models are an extension of the basic VaR model and allow for time-varying volatility. In the context of globalization, market volatility is not constant but fluctuates due to various factors such as macroeconomic events, geopolitical risk, and market sentiment. GARCH models provided a foundation for understanding the volatility persistence observed in financial markets, particularly during periods of heightened uncertainty [38]. Further extensions of GARCH models, such as Multivariate GARCH models, show how these models allow for the estimation of correlations between multiple asset returns. These models are particularly useful in a globalized context, where markets in different regions often experience correlated volatility [39]. The GARCH (1,1) model, a commonly used specification, is expressed as:

$$\sigma_t^2 = \omega + \alpha \cdot \epsilon_{t-1}^2 + \beta \cdot \sigma_{t-1}^2, \tag{1.2}$$

where:

- σ_t^2 is the conditional variance (volatility) at time t,

- ω are parameters estimated from historical data,

- ϵ_{t-1}^2 is the squared residual (error term) from the previous period.

This model captures volatility clustering, which refers to the tendency of high-volatility periods to be followed by more high-volatility periods.

The second category of risks, credit risk, arises from the possibility that a counterparty might default on its financial obligations, leading to a potential loss. In the context of financial trading, especially in a globalized environment, credit risk is amplified due to interconnected financial markets, cross-border lending, currency fluctuations, and the complexity of credit derivatives. In order to scientifically and effectively understand and manage credit risks, these classical financial models are usually used the Credit VaR model and the Copula Model.

The Credit VaR model, often used in conjunction with copula models, can help quantify and manage credit risk, incorporating a range of factors that reflect the complexities of global markets. The use of Credit VaR in managing credit risk demonstrated how Credit VaR can be used to estimate potential losses in a portfolio due to credit events. In this study, the limitations of Credit VaR in capturing systemic risk, especially during market crises, are also discussed [36]. Another research extends the standard VaR model by incorporating copulas to model the joint distribution of defaults. It is shown that copulas allow for more accurate modelling of dependencies between credit risks and demonstrate their utility in credit portfolio management [40]. The application of copulas in credit risk modelling, especially in a globalized context, where the Gaussian copula is employed to model the dependencies between defaults in a portfolio of assets. The paper also critiques the Gaussian copula for its inability to model tail risk effectively, which became apparent during the global financial crisis of 2008.

The Credit Value-at-Risk (Credit VaR) model is an extension of the traditional VaR model that specifically focuses on credit risk. It quantifies the potential loss in a portfolio due to default events over a specified period, under certain assumptions about the distribution of credit defaults and market movements.

In the Credit VaR framework, the loss is driven by the default of one or more counterparties. The basic formulation of Credit VaR can be represented as:

$$Credit\ VaR_{\alpha} = \mu_P - \sigma_P \cdot Z_{\alpha}, \tag{1.3}$$

where:

- μ_P is the expected portfolio return,

- σ_P is the portfolio's credit risk volatility,

- Z_{α} is the quantile corresponding to the desired confidence level α.

However, unlike the standard VaR model, Credit VaR requires additional factors to capture credit-specific features like default probability, credit spreads, and recovery rates.

Then, the copula approach is a mathematical function that allows for the modelling of dependencies between random variables, such as the joint default probabilities of multiple counterparties. In credit risk management, copulas are used to model the dependency structure of defaults, which is crucial when calculating joint default probabilities or assessing systemic risk.

The most commonly used copula in credit risk modelling is the Gaussian Copula, which allows for the modelling of correlations between defaults across different counterparties. The Gaussian copula is defined as:

$$C(u_1, u_2, \dots, u_N) = \Phi_{\Theta}^{-1}(u_1, u_2, \dots, u_N), \tag{1.4}$$

where:

- $C(u_1, u_2, \dots, u_N)$ is the copula function representing the joint default probability,

- Φ_{Θ}^{-1} is the inverse of the Gaussian cumulative distribution function,

- $u_1, u_2, \dots, u_N$ are the marginal default distributions of the individual counterparties.

The copula approach is useful because it allows for modelling of non-linear dependencies between defaults, a feature often overlooked in traditional linear correlation models.

Then, the third category, operational risk, is the risk of loss resulting from inadequate or failed internal processes, systems, people, or external events. This risk is inherently non-financial and can result from various factors, including system failures, human errors, fraud, legal risks, and external threats such as natural disasters or cyber-attacks. In order to scientifically and effectively understand and manage operational risks, the classical financial tools such as the Monte Carlo Simulations and Risk Control Matrices (RCM) are usually used.

The management and quantification of operational risk thus require specialized tools like Monte Carlo simulations and RCM to accurately capture the likelihood and impact of potential operational failures. The use of Monte Carlo simulations in operational risk management is well-documented. Monte Carlo methods emphasize their utility in modelling complex and non-linear risk scenarios, including operational risks [41]. The application of Monte Carlo simulations to operational risk events such as system failures and fraud can help estimate potential operational losses and assess the impact of risk mitigation strategies [42]. The development of RCM as a tool for operational risk management highlights the importance of structured risk identification and control assessment [43]. RCMs are particularly useful for tracking the effectiveness of controls over time and ensuring that organizations address emerging risks. Scenario analysis in the RCM framework allows for dynamic adjustments to risk management strategies as new information or risks emerge [44].

Monte Carlo simulations are a class of computational algorithms that rely on repeated random sampling to obtain numerical results. They are particularly useful in assessing operational risk by modelling the uncertainty and variability inherent in complex systems. Monte Carlo simulations generate a range of possible outcomes for operational risk events, enabling firms to estimate the potential losses arising from different risk scenarios.

In the context of operational risk, Monte Carlo simulations involve defining a set of risk events and their probability distributions. By simulating these events many times, it is possible to create a probability distribution of the total operational loss. The steps involved in Monte Carlo simulations for operational risk are as follows:

1. Identify risk events: the first step is to define the types of operational risk events. These could include technological failures, fraud, process breakdowns, or external events like natural disasters.

2. Assign probability distributions: each identified risk event is assigned a probability distribution based on historical data or expert judgment. For example, the severity of a technological failure could follow a lognormal distribution, while the frequency of fraud could follow a Poisson distribution.

3. Simulate scenarios: a large number of simulations are run, each time sampling from the probability distributions for the risk events. These simulations generate a wide range of potential operational loss outcomes.

4. Analyse the results: the outputs of the simulations are analyzed to determine the risk of extreme operational losses. This could include calculating the VaR for operational risk, which quantifies the potential loss at a given confidence level.

Key parameters are:

- Severity of losses: the financial impact of an operational risk event. Different types of operational risks may result in different loss severities, and these need to be modelled appropriately.

- Frequency of occurrence: the likelihood of an operational risk event occurring. For example, some events like IT system failures may be more frequent than rare events like fraud.

- Correlation between risk events: in a globalized environment, operational risk events are not isolated; one event may trigger others. For example, a cyber-attack could result in both a direct financial loss and damage to reputation.

RCM are structured tools used to identify, assess, and mitigate operational risks. An RCM is a grid that maps operational risks against control measures, allowing organizations to assess the effectiveness of their risk management processes. The RCM typically involves the following components:

- Risk event: a specific operational risk that may lead to a loss (e.g., failure of an information technology (IT) system).

- Control measure: an action or process designed to mitigate the risk (e.g., regular system updates, employee training).

- Control effectiveness: an assessment of how effective the control measure is in reducing the risk. This is often rated on a scale (e.g., ineffective, partially effective, or highly effective).

The RCM can be used to:

- identify key operational risks: RCMs help organizations identify and document the most significant risks they face in terms of operational processes;

- evaluate control effectiveness: organizations assess the current controls in place for each risk event to ensure they are adequate;

- implement mitigation strategies: for risks where controls are ineffective, organizations can develop and implement new mitigation strategies.

RCM is particularly useful in the context of operational risk management because it not only helps identify potential losses but also allows for tracking and improving the risk management processes. Key parameters include:

- Impact rating: the potential financial loss associated with an operational risk event.
- Likelihood rating: the probability of the risk event occurring within a specified time period.
- Control rating: the effectiveness of existing controls in mitigating the identified risks.

RCMs also allow for scenario analysis, where different operational risk scenarios are simulated based on changing risk conditions or hypothetical events. This can be especially useful when considering the impact of new business processes, technologies, or regulatory changes.

The fourth category, liquidity risk, refers to the potential losses that arise from an inability to buy or sell assets without causing significant price changes, particularly during periods of market stress. In order to scientifically and effectively understand and manage liquidity risks, these classical financial models are usually used: the Liquidity-Adjusted VaR (L-VaR) and Market Depth Models.

L-VaR is an extension of the traditional VaR framework, developed to incorporate liquidity considerations into risk assessments. L-VaR adjusts the standard VaR calculation by accounting for the impact of liquidity on market transactions, which is particularly important during times of market stress when asset prices can become more volatile due to changes in market depth.

The basic formulation of L-VaR is as follows:

$$L - VaR_{\alpha} = VaR_{\alpha} + \Delta Liquidity\ Impact, \tag{1.5}$$

where:

- VaR_{α} is the traditional VaR measure,

- $\Delta Liquidity\ Impact$ represents the additional risk due to liquidity constraints, often quantified by factors such as bid-ask spreads or market depth.

Key parameters:

- Market depth: market depth refers to the ability of a market to absorb large buy or sell orders without significantly affecting the price. A shallow market depth increases liquidity risk because even small trades can cause significant price movements.

- Bid-ask spread: the difference between the bid price (the price at which a buyer is willing to purchase an asset) and the ask price (the price at which a seller is willing to sell). A wider spread indicates lower liquidity and higher transaction costs.

- Order size: the size of a transaction relative to the market depth. Larger orders in illiquid markets increase the cost of execution.

Market depth models are used to quantify the impact of market liquidity on asset prices. These models focus on the relationship between trading volume, order size, and price movement. Market depth models are particularly useful for estimating the impact of large trades in less liquid markets, such as emerging market assets or specific asset classes during market distress.

One common approach to market depth modelling is based on the price impact function, which estimates how much an asset's price will change given a specific trade size. A general form of the price impact function can be expressed as:

$$\Delta P = \lambda \cdot \frac{Q}{D}, \tag{1.6}$$

where:

- ΔP is the change in asset price due to a trade,

- λ is the price impact coefficient, which depends on the liquidity of the market,

- Q is the size of the order (trade volume),

- D is the market depth, representing the amount of trading volume available without impacting the price.

In this model, a larger order relative to market depth causes a more significant price impact, reflecting higher liquidity risk. During periods of low liquidity, such as during financial crises, even small changes in market depth can lead to large price fluctuations.

Finally, the last category, systemic risk, refers to the risk of collapse or significant instability in the entire financial system, often triggered by the failure of a large financial institution or interconnected entities. In order to scientifically and effectively understand and manage systemic risks, the classical financial models such as the L-VaR Model and Market Depth Model are usually used.

Network models are a powerful tool for representing the interconnections between financial institutions, markets, and other economic entities. These models treat financial institutions as nodes in a network, with the edges representing financial transactions, such as loans, securities holdings, or interbank lending. By modelling the financial system as a network, it is possible to simulate how shocks propagate through the system and identify potential vulnerabilities that could lead to systemic collapse. In a network model, the key parameters are:

- Interbank links: financial institutions are linked through lending relationships, derivatives, and other financial instruments. These links can be weighted to represent the size or strength of the relationship.
- Network structure: the structure of the network (e.g., centralized vs. decentralized) significantly influences the resilience of the financial system. A highly connected network may be more efficient but more susceptible to contagion during crises.
- Shock propagation: a network model can simulate the effects of a shock, such as the default of a large financial institution, on the entire system. The propagation of a shock depends on the connectivity of the network and the exposure of institutions to one another.

Contagion effects refer to the transmission of shocks or risks from one institution to others, resulting in a ripple effect throughout the financial system. The failure of one institution can lead to a chain of failures, especially in interconnected financial markets. This contagion can occur through various channels, including:

- Interbank lending: the failure of one bank can lead to liquidity shortages in others, triggering a domino effect.

- Asset price correlations: financial institutions holding similar assets may face joint losses during market downturns, which exacerbates the contagion.

- Investor panic: widespread loss of confidence can lead to panic selling, which further erodes asset values and increases the risk of default.

Mathematical models of contagion typically focus on the spillover effects and the degree of interconnectivity between financial institutions. A commonly used framework for modelling contagion is the contagion network model, which tracks how a default or a shock to one node can propagate through the network, affecting other nodes.

The propagation of systemic risk in a network can be modelled using the following framework:

$$\Delta x_i = \sum_{j \neq i} A_{ij} f(x_{ij}), \tag{1.7}$$

where:

- Δx_i represents the change in the state (e.g., asset price, solvency) of institution i,

- A_{ij} is the weight of the link between institutions i and j,

- $f(x_{ij})$ represents the impact function, which quantifies the effect of the state of institution j on institution i.

This equation models how the state of one institution can influence others in the network. The weight A_{ij} could depend on factors such as the size of the financial exposure between institutions or the degree of correlation between their assets. The impact function $f(x_{ij})$ captures how the change in the state of one institution (e.g., a default or liquidity shock) affects the others.

Thus, these are five key financial risks in financial trading and the quantitative models used to assess and manage them. Together, these models and approaches enable institutions to rigorously quantify and mitigate diverse risk exposures in an increasingly volatile and interlinked global financial environment. To better explain the interconnection between financial trading and the five categories of risks (market risk, credit risk, operational risk, liquidity risk, and systemic risk). The relationship can be summarized as follows:

1. Market risk is the direct risk source in financial trading. Every transaction is inherently exposed to asset price volatility. Both investors and trading algorithms operate within the domain of market risk, embedding risk management tools such as VaR and GARCH models into trading execution strategies.

2. Credit risk is intertwined with financial trading, particularly in leveraged trading, derivative transactions, and counterparty credit evaluations. High-frequency and structured financial products amplify the speed and scale of credit risk transmission.

3. Operational risk originates within the execution processes of financial trading, including algorithmic errors, execution anomalies, model misspecifications, system failures, and compliance breaches. The stability of any trading system directly determines its operational risk exposure.

4. Liquidity risk both influences and is influenced by financial trading. Trading activity shapes market liquidity, while in periods of market stress or large-scale transactions, traders may face the risk of being unable to execute orders at expected prices. Conversely, liquidity risk constrains the feasibility of trading strategies.

5. Systemic risk aggregates through the breadth and interconnectedness of financial trading activities. Large institutional trades and the high correlation among market participants form propagation channels for systemic risk. Any single trading failure can evolve into systemic events via market pricing mechanisms, leverage

structures, and credit linkages.

In summary it is necessary to generalize:

- financial trading is a process driven by direct or indirect financial objectives;

- financial trading participants were grouped into systemic (e.g., brokers, market makers) and investment groups (e.g., institutional investors, individual traders), in order to clarify roles, risk profiles, and profit mechanisms;

- the hierarchical-faceted classification of financial trading provides the scaffolding for subsequent analyses of technological evolution, data hierarchies, regulatory frameworks, and global market dynamics;

- explicitly delineating financial trading from speculation and gambling, the study contributes to the formulation of more targeted regulatory approaches and provides a necessary lens for assessing trading efficiency, systemic risk, and market stability of financial trading under globalization in subsequent analyses;

- financial trading is not only directly exposed to each risk dimension but also serves as a trigger, amplifier, and conduit for the five risks through trading networks, capital flows, and asset price feedback mechanisms.

1.2. Characteristics of financial trading strategies

The definition and structural analysis of financial trading provide the essential conceptual foundation; however, the practical execution and evolution of financial trading are driven by the continuous advancement of strategies. This subchapter moves from theory to practice, conducting a systematic examination of the characteristics that define and differentiate financial trading strategies in the modern era. Within the context of this study, financial trading strategies are defined as the comprehensive methodologies and rule-based systems, ranging from human-executed analysis to fully autonomous algorithms, which are designed to efficiently achieve profitability by identifying and capitalizing on market opportunities. These strategies represent the critical nexus where theoretical market understanding meets practical execution of financial trading under globalization, and their evolution is intrinsically linked to technological progress. By tracing the transition from traditional approaches such as fundamental and technical analysis to modern algorithmic, high-frequency, and AI-enhanced trading systems, this section outlines the progressive integration of machine intelligence and automation in financial decision-making. The evolution of these technologies not only transforms the speed and scale of transactions but also introduces new strategic paradigms and regulatory challenges, forming a critical framework for understanding the contemporary landscape of financial trading.

Financial trading as a research area that has received significant attention from researchers, and its approaches can usually be categorized into traditional methods and modern methods [1]. The traditional trading approaches contain fundamental analysis [45] and technical analysis [46, p.1-10], which are often implemented manually by humans. Fundamental analysis of finance, which arose with the emergence of the financial market, is a method of valuing assets such as stocks, using financial analysis and economic research to assess the value of enterprises or predict securities' value trends (such as stocks or bonds, etc.). Technical analysis refers to the study of past financial market information (mainly by using charts and indicators) to predict price trends and determine investment strategies. In pure theory, the technical analysis only considers the real price behaviour of the market or financial instruments, under the assumption that its price will reflect all relevant factors before investors know it through other channels, and tries to use a large number of statistical data to predict market trends. And modern trading approaches are executed automatically by computers and usually refer to algorithmic trading and its machine learning approaches [47]. Algorithmic trading can be performed by either rule-based methods or ML-based approaches [48]. In rule-based algorithmic trading, computers trade in financial markets through predetermined rules specified by humans. These rules can be defined based on traditional trading methods, mathematical models, or human-made strategies. On the other hand, in ML-based algorithmic trading, computers are trained on historical data to trade in markets [49]. It can also work independently without any direct human interventions [50].

ML models have received significant attention from researchers. According to different learning styles, ML models have three different types: Supervised learning, Unsupervised learning and Reinforcement learning [51]. These three types of algorithms nowadays have developed into a large number of application models such as: Support Vector Regression (SVR), Random Forest (RF), Long Short-Term Memory (LSTM), Fully connected neural networks (FNN), Convolutional neural networks (CNN), Recurrent neural network (RNN), Reinforcement learning (RL), Deep Reinforcement learning (DRL), etc. [50; 51].

A systematic review of publications on modern financial trading technology applications was done for financial trading strategies description. A scoping review is a type of knowledge synthesis that uses a systematic and iterative approach to identify and synthesize an existing or emerging body of literature on a given topic [52]. A scoping review is useful to map the literature on evolving or emerging topics and to identify gaps [53]. To ensure a rigorous and scientifically valid approach, the PRISMA 2020 standard for conducting the systematic literature review (SLR) is adopted here [54]. PRISMA is widely recognized for providing evidence-based guidelines to enhance the reporting and quality of systematic reviews. The review process comprises a 27-item checklist and a four-phase flow process that includes the following stages: identification, screening, eligibility and inclusion [50; 54].

Systematic reviews go beyond traditional literature reviews to encompass systematic, structured, and explicitly described steps of gathering and analysing relevant existing knowledge [55; 56; 57]. To scientifically design the systematic review, the following specific steps have been taken:

Step 1: identifying the research question. Defining the scientific range of the research question is a vital first step. A too-broad range will dramatically increase the number of papers for consideration, and a too-narrow range may compromise the breadth and depth of the review research.

Step 2: identifying relevant studies. Build the search strategy, keywords, Subject Headings, databases and further refine the strategy based on the papers found.

Step 3: selecting studies to be included in the review. Define the inclusion and exclusion criteria, and finally determine the target studies. The actual screening of papers should consist of reading not only the title of the paper, but the abstract as well. If an abstract is not available, a full-text review of the paper is required.

Step 4: charting the data. Develop the data extraction form based on the review articles database. The main categories of information will be listed, including author, source, year, citations, technology applied, benchmark technology and main results. These categories are vital for financial trading technology study and usually popularly applied in scientific scoping review research [58; 59].

Step 5: collating, summarizing, and reporting the results. Once the data have been extracted from all papers, numerical and thematic analyses have been conducted, the findings from the numerical analysis will be presented in a table to showcase the most salient aspects of the review [50].

To capture a comprehensive range of studies related to financial trading technology, an extensive search across reputable academic database Scopus has been conducted here [60]. Then relevant key words commonly associated with technological advancements in financial trading, such as ‘algorithm’, ‘model’, ‘prediction’, ‘forecasting’ have been utilized. These carefully chosen key words made it possible to focus exclusively on studies directly related to financial trading technology, avoiding unrelated topics. The initial searching codes set according to the topic relevance are as follows [60]:

TITLE-ABS (financial AND market AND trading AND (algorithm OR model OR prediction OR forecasting)) AND PUBYEAR > 2012 AND PUBYEAR < 2024 AND (LIMIT-TO (SRCTYPE , “p”) OR LIMIT-TO (SRCTYPE , “j”)) AND (LIMIT-TO (OA, “all”)) AND (LIMIT-TO (DOCTYPE, “ar”)) AND (LIMIT-TO (LANGUAGE , “English”)) AND (LIMIT-TO (PUBSTAGE , “final”)) [50].

At the same time, to ensure the effective inclusion and exclusion of relevant studies within the review, and further promote transparency and accuracy in the findings, there are established specific inclusion criteria (IC) to guide the selection of studies, which are detailed as follows:

IC1: availability online: This review considered only sources that were digitally available online, excluding works that were not published electronically.

IC2: language of publication: the inclusion was limited to studies published in English.

IC3: original empirical research: to ensure the reliability of findings, only studies based on original empirical research, including qualitative and quantitative approaches, were considered for inclusion.

IC4: peer-reviewed publications: the review focused solely on peer-reviewed publications – journal articles while excluding dissertations and preprint papers.

IC5: time frame: the search was confined to articles published between 2013 and 2023 to capture the period coinciding with the widespread adoption and growth of algorithmic trading and financial artificial intelligence.

IC6: quality criteria: in adherence to scientific rigor, quality criteria were applied to exclude studies published in predatory journals, ensuring the credibility and validity of the selected sources [50].

The exclusion criteria are basically the counter side of the inclusion criteria. To intuitively present all the criteria, all our inclusion and exclusion criteria are shown in table 1.8 [50].

Table 1.8

Inclusion and exclusion criteria

Inclusion criteria	**Exclusion criteria**
Publications during 2013-2023 (IC5)	Publications before 2013 (IC5)
Publications in English (IC2)	Publications not in English
Publications as Journal articles (IC4)	Non-peer-reviewed publications, e.g., preprint and dissertations
Publications in non-predatory journals (IC6)	Publications in predatory journals
Publications available online (IC1)	Publications unavailable online
Empirical research output except for preprints and dissertations (IC3)	Non-empirical research outputs, e.g., conceptual papers
‘Trading’ outputs, e.g., exemplified in their titles, keywords, abstracts (Not an IC)	Non - ‘Trading’ outputs

Source: [50]

The financial landscape has been continually reshaped by technological advancements, propelling trading strategies to new levels of sophistication. As algorithmic trading, artificial intelligence, and machine learning have gained prominence, it has become evident that a comprehensive framework is necessary to understand the dynamic interplay between technology and trading strategy [50].

To conduct in-depth research on the progress of financial trading technology, we raise two important non-performance characteristics in empirical research on financial trading, namely: machine technology and trading strategy. Machine technology represents the advanced level and complexity of machine technology in financial trading technology. Trading strategy represents the advanced level and complexity of trading strategies in financial trading technology [50].

To fulfill this methodology, during the review study process, we evaluated the level of machine technology and trading strategy for each empirical study of more than 100 articles in the database and manually assigned a score from 1 to 4 [50].

The score of machine technology level is calculated based on the following factors:

1. Technology type (for example DL, RL, DRL, and other models), advancement, and innovation.

2. Model automation and self-upgrading process.

3. Algorithm complexity (computing power required).

4. Others (advanced models and theories from other academic fields) [50].

Then, we rated the traditional econometrical models and algorithm trading technologies at 2 points (such as technical indicators, and Monte-Carlo simulation) and the advanced 2-point models and classic models of ML and DL (SVM, RF, CNN, DNN, RNN) at 3 points. The improved ML/DL models and new models (such as RL, DRL, and advanced models from other subjects) are rated 4 points.

The score of the trading strategy level is calculated based on the following factors:

1. Type, advancement and innovation of strategies.

2. Financial factors considered in the strategy.

3. Multi-environment adaptability of strategies.

4. Others (introduction of theories in non-financial fields) [50].

Next, we scored 2 points for trading strategies that use model prediction as the main means to make profits, and 3 points for automated trading strategies and portfolio strategies that are executed as a whole. We rated the more advanced ones, with higher adaptability to multiple situations, and considered more dimensional parameters as 4 points. In addition, it should be noted that both machine technology level and trading level have no direct relationship with trading performance in empirical research on financial trading, and only reflect the technological level of financial trading [50].

Then we counted all the scores of 130 academic articles on machine technology and trading strategy under the coordinate system of figure 1.1 and obtained four quadrants with different characteristics: Quadrant I: high machine technology level, high trading strategy level. Quadrant II: low machine technology level, high trading strategy level Quadrant III: Low machine technology level, Low trading strategy level and Quadrant IV: high machine technology level, low trading strategy level. Under this system, each quadrant represents a unique intersection of these two crucial dimensions. Each one represents a unique type of financial trading technology [50].

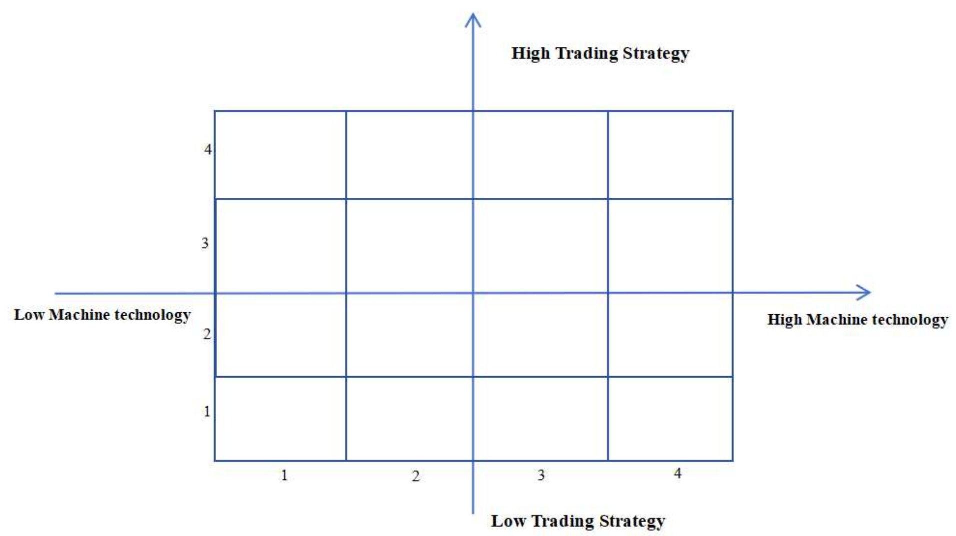

Fig. 1.1. The coordinate system and Four-Quadrant of financial trading strategies

Source: [50]

In subsequent research, we evaluated and summarized the financial trading technology in the selected articles, as well as the characteristics and main performance of the Four-Quadrant of financial trading strategies. The coordinate system and Four-Quadrant of financial trading strategies is a conceptual framework that seeks to provide a comprehensive understanding of the complex interplay between machine technology and trading strategies in the financial trading area [50].

By following the PRISMA 2020 standard, the initial search yielded 2,351 potentially relevant articles published between 2013 and 2023 (before August) and underwent further screening based on the relevance of their titles and abstracts. Subsequently, 522 articles were considered for eligibility after rigorous examination from the updated searching codes [60]:

TITLE-ABS (financial AND market AND trading AND (algorithm OR model OR prediction OR forecasting AND NOT effect AND NOT phenomenon AND NOT carbon AND NOT behavior)) AND PUBYEAR > 2012 AND PUBYEAR < 2024 AND (LIMIT-TO (SRCTYPE, “p”) OR LIMIT-TO (SRCTYPE, “j”)) AND (LIMIT-TO (OA, “all”)) AND (LIMIT-TO (DOCTYPE, “ar”)) AND (LIMIT-TO (LANGUAGE, “English”)) AND (LIMIT-TO (PUBSTAGE, “final”)) [50].

To ensure methodological integrity, the full texts of these 143 articles were thoroughly assessed for relevance, resulting in 130 articles that met the inclusion criteria and were ultimately selected for the final review. As a result by adhering to the PRISMA model, this systematic review guarantees a robust and unbiased analysis of advancements in financial trading. The 130 selected articles provide valuable insights into algorithmic trading, financial artificial intelligence, and other emerging technologies that have significantly impacted financial markets over the years [50].

Figure 1.2 shows the publication year distribution of the 130 selected articles. There is an obvious fluctuating increase trend in the publication number from 2013 to 2022. The reason is due to the widespread adoption and rapid growth of algorithmic trading technology and financial artificial intelligence from 2013 to 2022 whereas the publication amount has a sharp decrease in 2020. The situation may have been caused by the global shock of Covid-19 in the scientific research field. Figure 1 also shows the huge scientific research potential of financial trading science publishing, and this topic may remain long-term scientific popularity in the future [50].

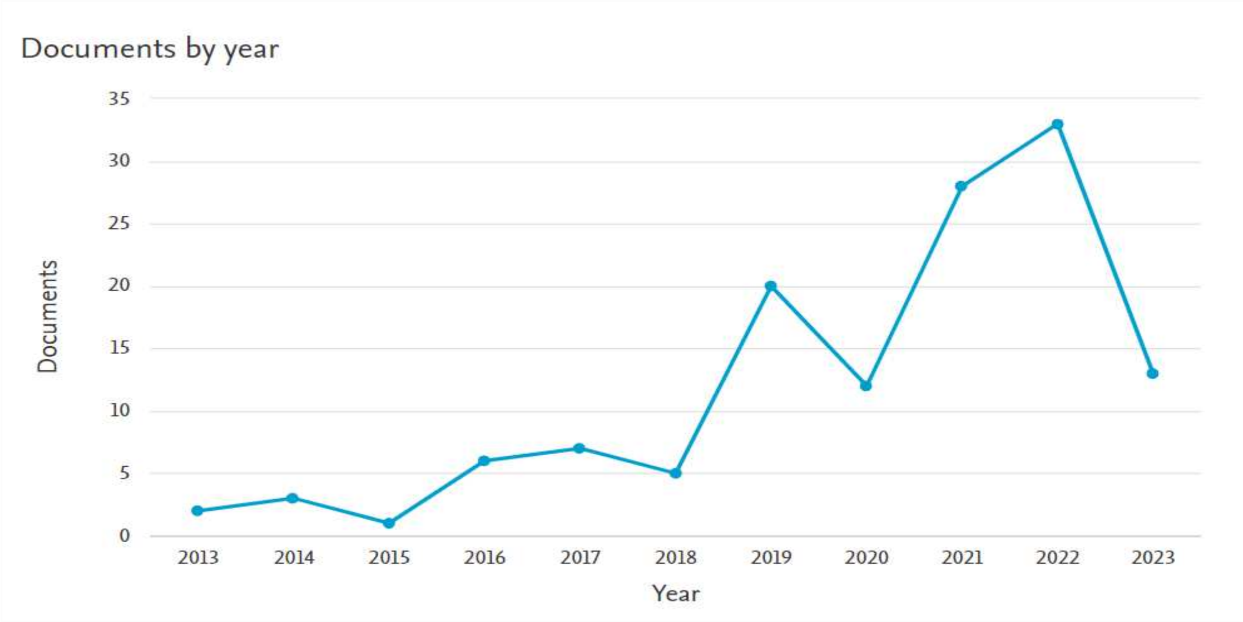

Fig. 1.2. Selected documents publication during 2013-2023

Source: [50].

Figure 1.3 shows the main publication country/territory of the 130 selected articles. China is in the first rank in this chart, which has total 55 publications between 2013 and 2023 (including Taiwan and Mainland China). This is closely related to the rapid development of the Chinese financial trading market in the past decade, a large number of Chinese scholars have poured into the field of financial trading technology research. The UK and the USA also have over 10 publications between 2013 and 2023 respectively [50].

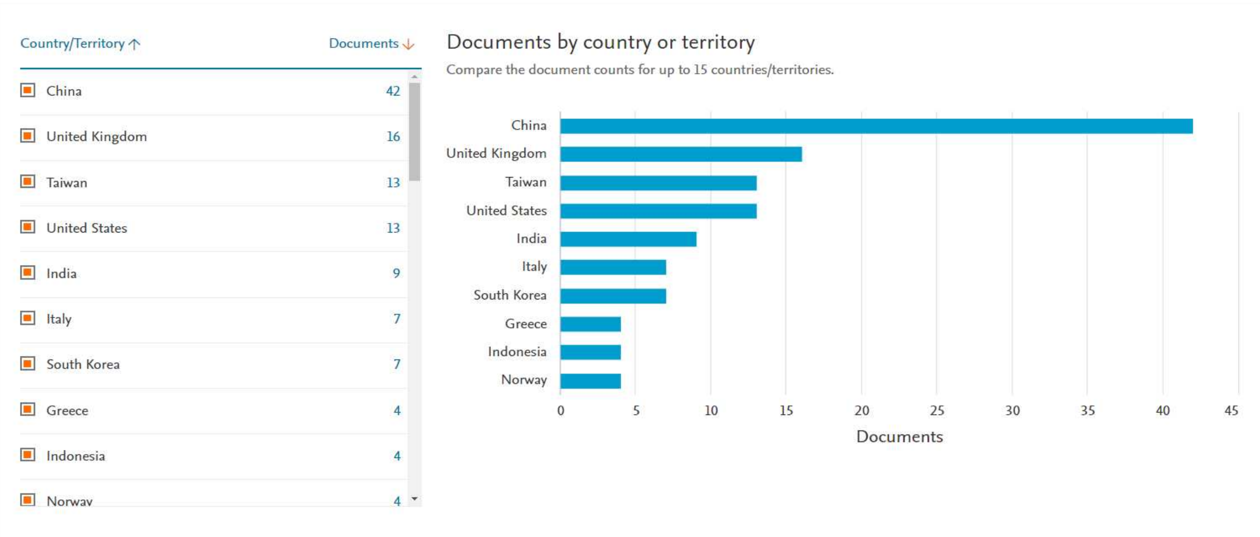

Fig. 1.3. Selected documents by country or territory during 2013-2023

Source: [50]

Furthermore, fig. 1.4 shows the main subject area of the 130 selected articles, which mostly corresponds to their scientific publisher and academic classification. It shows the high percentages of Computer Science, Engineering, Mathematics, Economics/Econometrics/Finance, Business/Management/Accounting, Material Science and Physics. This shows that financial trading technology is a highly interdisciplinary research topic. The simultaneous integration of multiple disciplines also provides a steady stream of research output for financial trading research.

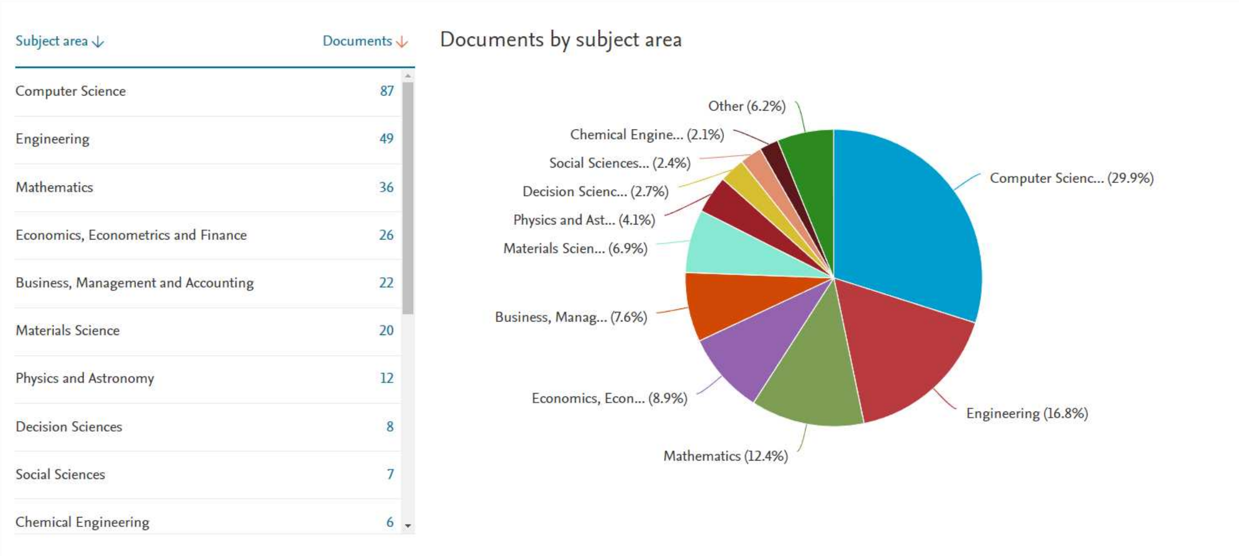

Fig. 1.4. Selected documents by subject area during 2013-2023

Source: [50].

In order to fully understand the characteristics of the selected 130 research articles (Annex A), the characteristics of the selected research show the main categories of information, which are author, source, year, citations, technology applied, benchmark technology and main results. The systematic review of advancements in financial trading yielded several prominent themes and key findings, contributing to a deeper understanding of this evolving field:

– Algorithmic trading innovations: the review highlighted significant advancements in algorithmic trading strategies and methodologies. Researchers explored various machine learning techniques, neural networks, deep learning models, and reinforcement learning algorithms, demonstrating their application in financial trading to enhance efficiency and accuracy.

– Predictive analytics and forecasting: many studies focused on the integration of predictive analytics and forecasting methods in financial trading. By leveraging sophisticated algorithms, traders were able to make data-driven predictions, analyse market trends, and anticipate price movements, thereby gaining a competitive edge in the financial markets.

– Market liquidity and efficiency: financial trading technology was found to have a substantial impact on market liquidity and efficiency. By reducing trading frictions and enhancing market transparency, technological developments have contributed to more liquid and efficient markets.

– Risk management and mitigation: the review revealed how financial trading technology has revolutionized risk management practices. Advanced risk assessment models and real-time monitoring systems have been employed to mitigate potential financial risks and ensure robust risk management protocols.

– Automated trading systems: the systematic review emphasized the prevalence and impact of automated trading systems. These systems execute trades based on predefined algorithms, minimizing human intervention and responding rapidly to market changes, thus increasing the speed and efficiency of trading.

– Big Data and market analysis: researchers explored the role of big data in financial trading and its effect on market analysis. The review demonstrated how vast amounts of data are processed and analysed to gain insights into market behaviour and identify profitable trading opportunities.

– Regulatory implications: some studies addressed the regulatory challenges associated with technological advancements in financial trading. The review examined the need for appropriate regulations to govern algorithmic trading and mitigate potential risks to market stability and investor protection [50].

The financial landscape has been continually reshaped by technological advancements, propelling trading strategies to new levels of sophistication. As algorithmic trading, artificial intelligence, and machine learning have gained prominence, it has become evident that a comprehensive framework is necessary to understand the dynamic interplay between technology and trading strategy [50].

During the systematic review study, we scored all the articles based on the scoring basis of machine technology and trading strategy. Figure 1.5 shows the number of papers for each score of machine technology and trading strategy. Because of the high level and advanced nature of the selected article database, neither machine technology nor trading strategy has a score of 1. Regarding the scores of machine technology, 33 articles scored 2 points, 46 articles scored 3 points, and 51 articles scored 4 points. On the other hand, the scores of trading strategy were 78 articles with a score of 2, 37 articles with a score of 3, and 15 articles with a score of 4. There are a lot of articles with a score of 2 for trading strategy and a score of 3-4 for machine technology, accounting for nearly half of all articles. At the same time, the different number of articles and numerical distribution in the matrix intuitively reflect the technical level and scientific research quality of financial transaction research to a certain extent [50].

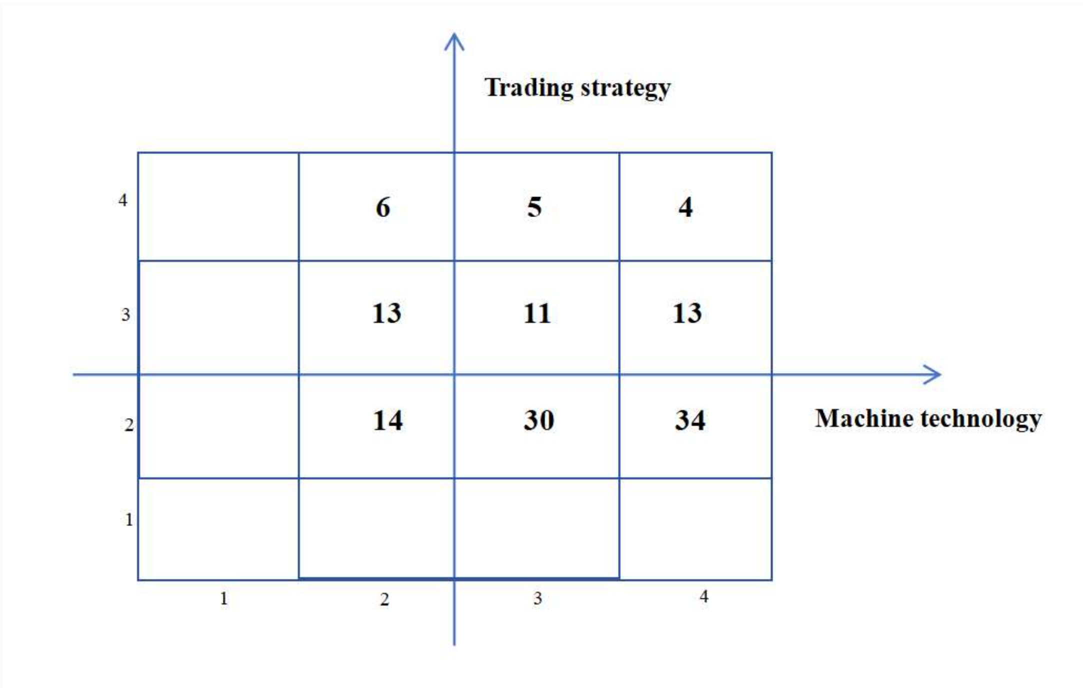

Fig. 1.5. Matrix of the number of papers for each score

Source: [50].

By analysing and summarizing the financial trading technology in the selected articles, here this study introduces the Four-Quadrant of financial trading strategies, a conceptual framework that seeks to provide a comprehensive understanding of the complex interplay between machine technology and trading strategies in the financial trading area [50]. By mapping machine technology on the abscissa axis and trading strategy on the ordinate axis, this theory delineates four distinct quadrants, each representing a unique intersection of these two crucial dimensions [50] (fig. 1.6).

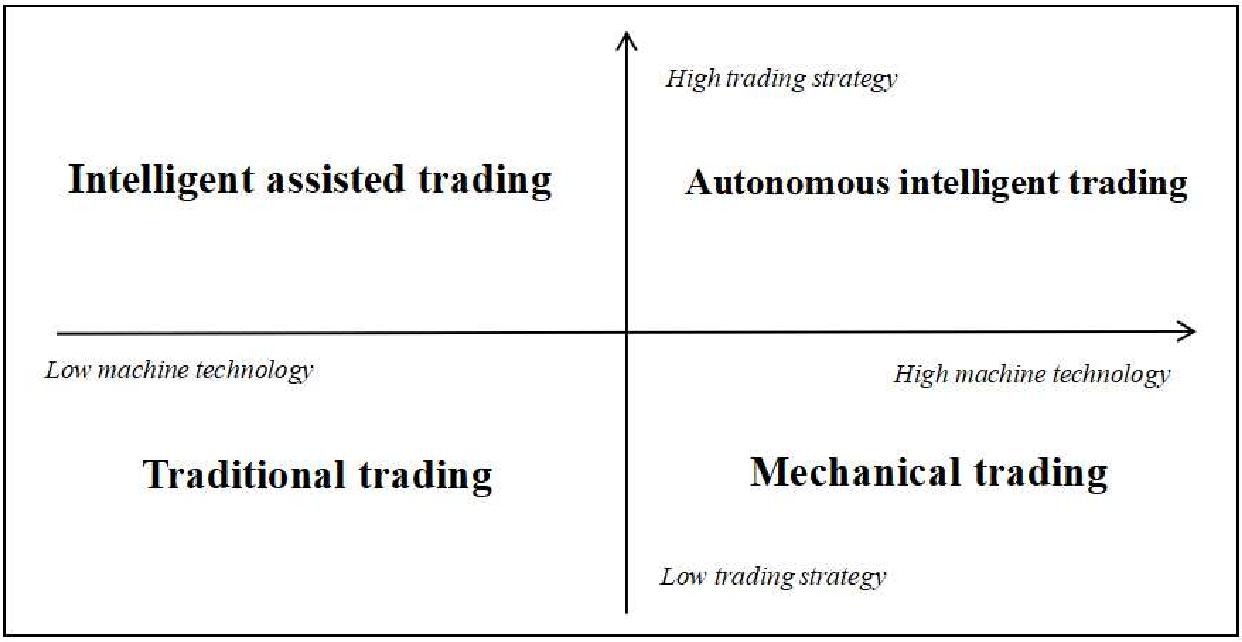

Fig. 1.6. Four-Quadrant of financial trading strategies

Source: [50].

Figure 1.6 shows the Four-Quadrant approach divides the technology-trading strategy space into four distinct quadrants [50]. The Four-Quadrant of financial trading strategies is as follows:

Quadrant I: Autonomous intelligent trading (high machine technology, high trading strategy). This quadrant represents the future development trend of financial trading technology. The autonomous intelligent trading system has powerful machine learning and deep learning capabilities, and can independently formulate complex trading strategies, adapt to market changes and continuously optimize strategies [50].

Autonomous intelligent trading, as the trading method with the highest level of technology and strategy in the Four-Quadrant approach, usually has its research and applications with the highest difficulties and complexity. As an example, a study in the article database (Annex A. No.67) has introduced a novel decision support system for automated stock trading based on deep reinforcement learning that observes both past and future trends of stock prices whether they are single or multi-step ahead as an observing state to make the optimal trading decisions of buying, selling, and holding the stocks [62].

Quadrant II: Intelligent assisted trading (low machine technology, high trading strategy). In this quadrant, artificial intelligence enhances human decision-making by providing analytical support and insights. Through the analysis of large amounts of historical data, AI can provide insights and recommendations, but trading strategies are still dominated by traders. The researchers of Intelligent assisted trading are usually financial research and application experts in the field, and often use advanced financial quantitative trading strategies in their research [50].

Quadrant III: Traditional modern trading (low machine technology, low trading strategy). In this quadrant, trading also takes use of the advantages of machine learning technology. Traders make decisions based on their experience and market insight, and the application of technology is relatively limited. Methods such as traditional stock and futures trading dominate this quadrant [50].

Traditional modern trading, on the one hand, includes fundamental analysis and technical analysis, but on the other hand, it also includes the application of primary machine learning tools, such as regression models, time series analysis, etc. Previously algorithmic trading has rapidly grown inspired by the help of these tools whereas nowadays this type of new research has declined, and at the technological level Traditional modern trading research is gradually being replaced by a large number of Mechanical trading research institutes [50].

Quadrant IV: Mechanical trading (high machine technology, low trading strategy). Mechanical trading uses pre-set rules and algorithms to automatically execute transactions, reducing the interference of human factors. This trading approach relies heavily on technical analysis and market signals; however, its strategies remain relatively simplistic, limiting its ability to effectively address the complexities of modern financial markets [50].

Mechanical trading usually relies on forecasting and executing simple financial trading schemes. In the article database, more than half of the research types are more biased toward Mechanical trading, and they rely on simple forecasting strategies to make financial trading through advanced ML/AI applications. As an interdisciplinary technology, financial transaction technology has received contributions from mathematics, physics, computer and engineering scholars on the one hand, and has attracted extensive attention from these non-finance scholars on the other hand [50].

A large number of financial transaction research based on non-finance theory emerged in 2013-2023. In addition to most of the research on various ML/AI forecasting models, there is also some transfer research based on theories of other scientific disciplines. As an example, a study in our article database (Annex A. No.28) builds a prediction model in trading in the financial Forex market. The prediction model is based on the deviations from the closed string/pattern form, which is from string theory in Physics [63]. Furthermore, nowadays, the Large Language Models have significantly impacted financial trading, offering innovative solutions to complex problems. LLMs, such as GPT-4, have emerged at the forefront of this revolution, combining the complexity of natural language understanding with the precision of machine learning to offer unparalleled insights and decision-making tools. With the potential to drive predictive analytics, enhance risk management, and refine algorithmic trading, LLMs present both an opportunity and a challenge for financial institutions [13].

Table 1.9. shows the main traits of every type of financial trading approach in the Four-Quadrant of financial trading strategies.

It is possible to summarise that the Four-Quadrant of financial trading strategies provides a comprehensive framework for analysing the intersection of machine technology and trading strategy. By categorizing interactions into four distinct quadrants, it can enhance the understanding of the complex financial trading technology applications. It highlights the diversity of interactions within this space and emphasizes the role of human expertise in harnessing the potential of technology. With the continuous evolution of technology and financial markets, trading technology will innovate in different quadrants, bringing new opportunities and challenges to the future of financial markets. Through further exploring of the financial trading technology development it will become more intelligent and diversified, and data-driven decision-making and powerful artificial intelligence systems may become the core of transactions. In addition, the practical utility lies in aiding traders, researchers, and policymakers in understanding the implications of different intersections for market stability, investor protection, and regulatory considerations [50].

Table 1.9

Description of financial trading strategies for different trading approaches

Trading approach	Machine technology level	Trading strategy level	Example of application	Description of financial trading strategy
Autonomous intelligent trading	High	High	AI-driven deep reinforcement of learning trading systems	Applies self-learning models to identify alpha signals and adapt in real time to market regimes
Intelligent assisted trading	Low	High	AI-assisted decision-making in quantitative finance	Relies on human-guided models enhanced by machine learning for predictive analytics and portfolio optimization
Traditional modern trading	Low	Low	Fundamental & technical analysis with minimal ML tools	Profit is driven by manual interpretation of market trends, news, and economic indicators
Mechanical trading	High	Low	Pre-programmed AI executing of simple trading strategies	Uses fixed-rule algorithms for arbitrage or signal-based execution with limited adaptability

Source: author's own generalisation

The findings from this study have significant implications for the future of research and practice in financial trading technology [50]:

– Continued technological advancements: future research should focus on exploring and evaluating the potential of emerging technologies, such as quantum computing and blockchain, in further transforming financial trading practices [50].

– Ethical considerations: as financial trading technology becomes more sophisticated, researchers and practitioners must address ethical considerations related to algorithmic decision-making, fairness, and transparency in financial markets [50].

– Interdisciplinary collaboration: collaboration between experts in finance, computer science, data analytics, and regulatory fields is essential to develop and implement robust and effective financial trading systems that meet both technical and regulatory requirements [50].

– Market regulation and oversight: policymakers and regulatory bodies should continuously review and update existing regulations to keep pace with the evolving landscape of financial trading technology and ensure market stability and investor protection [50].

– Risk management and cybersecurity: enhancing risk management protocols and cybersecurity measures is crucial to safeguard financial markets from potential cyber threats and protect against systemic risks [50].

– Real-world testing: future research should include real-world testing and validation of financial trading technologies to assess their practicality and reliability in live market conditions [50].

In conclusion, this section offers valuable insights into the strategies advancement in financial trading, encompassing algorithmic trading, machine learning, predictive analytics, and other emerging technologies. The identified themes and implications provide a foundation for further research and practical applications, contributing to the continued growth and development of financial markets in an increasingly technologically-driven landscape. Furthermore, this study proposes a Four-Quadrant of financial trading strategies as a comprehensive framework for analysing the intersection of machine technology and trading strategy. This approach enhances our understanding of complex financial trading technology applications and can aid traders, researchers, and policymakers in understanding the implications of different intersections for market stability, investor protection, and regulatory considerations [50].

1.3. Information basis for efficient financial trading

The previous study reveals that the evolution of modern financial trading is deeply intertwined with advances in computer and artificial intelligence strategies. Equally important is the role of data and information input, which underpins the effectiveness and adaptability of trading models. Building on the previously outlined developments in financial trading, this section undertakes a systematic analysis of financial trading data within a comprehensive hierarchical framework. This model organizes information from foundational metrics to aggregated financial indicators and broader macroeconomic variables, offering a systematic approach to understanding how data drives decision-making in trading systems. Such a hierarchy not only enhances the conceptual clarity of financial data utilization but also provides a critical foundation for exploring the efficiency and strategic sophistication of financial trading in a globalized context.

Financial trading data and information here, which is different from the common concept of the financial data and information used in the corporate finance field and financial statement analysis, represents generalized financial-related data and information input of the financial trading methods [64]. The data used during financial trading analysis and decision-making usually refers to raw, unprocessed facts and figures related to financial trading, events, or activities of an organization. The information used during financial trading analysis and decision-making usually refers to the processed and structured outcome of data analysis, usually given in complex forms such as charts, reports, and text. Advanced financial trading AI algorithm model can take text input into model analysis to evaluate the financial impact of the convergence of news events for predicting stock trends [65]. In advanced financial trading models, financial trading information input is usually converted into simpler data by specific algorithms. Therefore, both data input and information input during the financial trading process can be collectively seen as financial trading data.

Drawing inspiration from classic scientific hierarchy methodologies, this study proposes a multi-level structure that captures the intricate relationships between various financial elements. By applying this hierarchy theory we aim at enhancing the comprehension, analysis, and utilization of financial trading data/information input in modern financial trading decision-making processes.

The methodology underlying the proposed hierarchy approach of financial trading data and information draws inspiration from classic hierarchical organization principles, established by Allen and Starr (1982) in their work on ecological hierarchy theory [66]. Ecological hierarchy theory is a means of studying ecological systems in which the relationship between all of the components is of great complexity. Hierarchy theory focuses on levels of organization and issues of scale, with a specific focus on the role of the observer in the definition of the system [67]. Adapting these principles to the domain of finance can provide a robust and structured framework that captures the complexities and interdependencies present in financial trading data. The methodology involves categorizing financial trading data into distinct levels based on their granularity and complexity, forming a multi-tiered structure. The levels shown in fig 1.7 include:

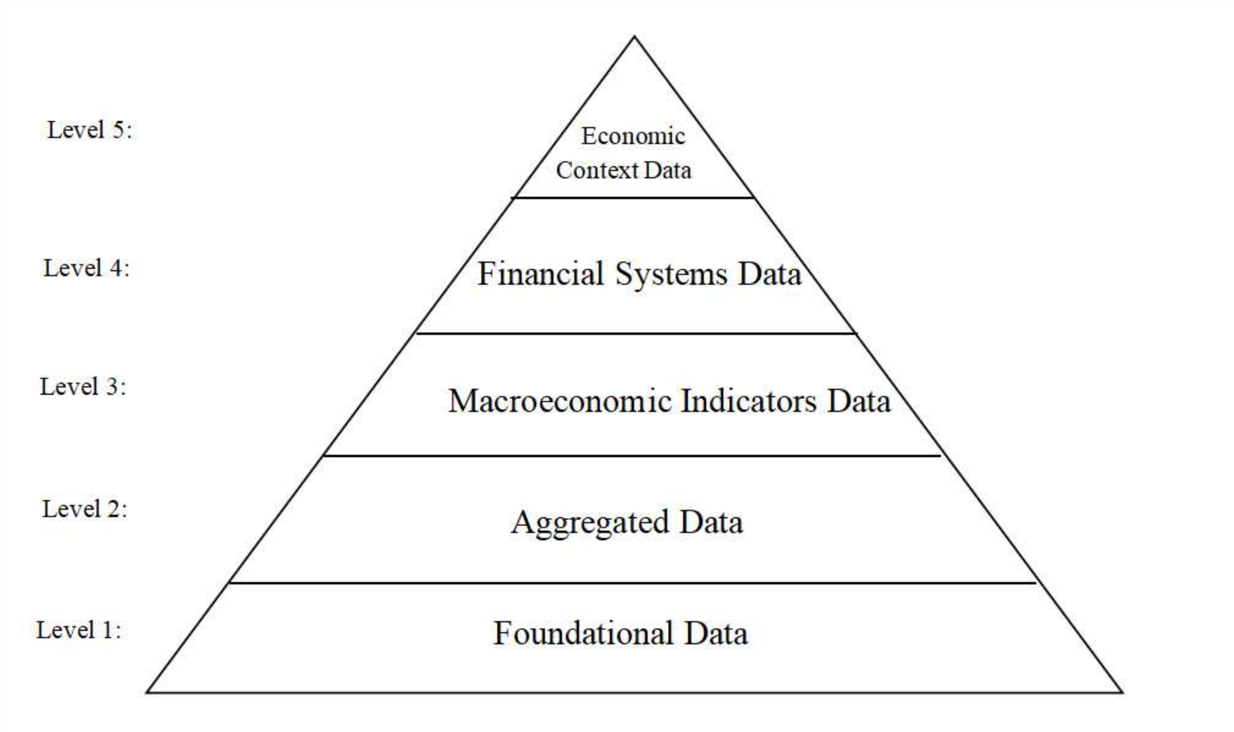

Fig. 1.7. Five-level hierarchy of financial trading information

Source: author's own generalisation

Level 1. Foundational data: it represents individual trading action, market prices, trading volumes, interest rates, and other basic data elements [68, p.10-30]. As the basis of our hierarchy theory, foundational data constitutes the fundamental building blocks of financial information. Foundational data are often heterogeneous, originating from various sources such as stock exchanges, financial news platforms, and economic databases.

Level 2. Aggregated data: it involves the transformation of raw financial data into more coherent and manageable forms. This level's data include the calculation of metrics like average returns, standard deviations, correlations, and other statistical summaries derived from foundational data. Aggregated data serve to increase the information-carrying capacity and provide a broader financial perspective.

Level 3. Macroeconomic indicators: macroeconomic indicators capture the overall health and performance of an economy, integrating aggregated financial data with real-world economic factors [69, p.1-20]. Examples of such indicators include the Gross Domestic Product (GDP), unemployment rates, inflation indices. These indicators offer insights into the larger economic context within which financial activities take place.

Level 4. Financial systems data: the fourth level encompasses the analysis of how different markets, financial institutions, and regulatory frameworks interact and influence, which can show the intricate interactions and relationships within financial systems. Financial Systems Data involve studying the flows of capital, the dynamics of credit markets, the roles of central banks, and financial regulations.

Level 5. Economic context data: this level involves the information about global economic landscape, including geopolitical factors, international trade dynamics, major economic trends, and socio-political influences. At the highest level of the hierarchy, it considers the broader economic context that shapes financial systems and activities.

Structuring financial trading data and information according to this hierarchy theory can gain a powerful tool to navigate the complexities of different types of massive financial trading data and information. This multi-level framework allows for a systematic financial trading analysis of financial elements, from granular data points to macroeconomic trends. The main types of data at every level and their role in modern financial trading analysis are: in the hierarchy approach of financial trading data, Level

1 encompasses Foundational data, representing the raw and unprocessed data points extracted directly from financial markets. These foundational data types play a crucial role in shaping financial analysis, as they provide the raw material from which insights, patterns, and trends are extracted. Each type of foundational data offers unique information that contributes to a comprehensive understanding of market dynamics. The main types of Foundational data are as follows (table 1.10).

Table 1.10

Main data types of Level 1. Foundational data

Data type	Description	Role in trading
Prices	Valuation indicators showing Open, High, Low, Close values (OHLCV)	Base for trend analysis, technical indicators, valuation
Trading volumes	Total traded amount for a financial instrument over a time frame	Reveals liquidity, market interest, and event impact
Interest rates	Cost of borrowing and returns on savings; central bank tool	Influences asset valuation and macroeconomic assessment
Order book data	Shows active buy/sell orders, indicating supply/demand	Used for price prediction, market depth estimation
Fundamental company data	Company earnings, revenue, expenses, balance sheet of listed companies	Used for fundamental analysis and valuation

Source: author's own generalisation

It is necessary to provide a detailed description of every data type for Foundational data:

1. Prices. Prices are fundamental indicators of the valuation of financial assets within a given market. These prices reflect the equilibrium between supply and demand and are the starting point for various analyses, including technical analysis, trend identification, and valuation models. Prices that are widely used as the main forms of data include OHLC: those which represent the first, the highest price, the lowest price and the last price during a specified interval separately [70].

2. Trading volumes. Trading volumes represent the total number of shares or contracts traded for a specific financial instrument within a given timeframe [70]. Volumes offer insights into market liquidity, reveal the intensity of trading activities, and provide valuable information about market trends and sentiment. High trading volumes can indicate significant market interest or price movement, while low volumes

might suggest reduced participation or uncertainty [71]. Unusual volume spikes can signal important events, such as earnings releases or news announcements, influencing asset prices. Analysing trading volume in conjunction with price movements helps identify potential trends or market manipulation.

3. Interest rates. Interest rates are a key component of financial markets, influencing borrowing costs, savings returns, and the valuation of fixed-income securities. Central banks use interest rates as a policy tool to control inflation and stimulate economic growth. Financial trading participants also analyse interest rate data to assess the impact on different asset classes, including bonds, equities, and currencies.

4. Order book data. Order book data reveal the current buy and sell orders for a particular asset, indicating the immediate supply and demand levels. Traders use order book data to gauge support and resistance levels, assess market depth, and make informed trading decisions. Order book analysis helps financial trading participants or models anticipate potential price movements based on order imbalances [72].

5. Fundamental company data. Fundamental company data encompasses financial metrics like earnings, revenue, expenses, and balance sheet information. These data points are crucial for fundamental analysis, enabling the valuation of stocks based on intrinsic factors. Financial trading participants can assess fundamental company data to determine a company's financial health, growth prospects, and potential investment value.

Foundational data are the building blocks of financial analysis, providing the essential raw material for financial trading decision-making. Without a solid foundation of raw data points, higher-level financial trading analyses, such as technical analysis, quantitative modelling, and risk assessment, would lack credibility and accuracy. There are a large number of financial trading research models based on advanced machine learning techniques that rely solely on OHLCV data to predict stock market prices and have shown high returns [73; 74; 75; 76; 77; 78]. Furthermore, the real-time nature of foundational data allows for timely decision-making in rapidly changing markets. The automatic financial trading algorithm based on high-frequency foundational data can even make trading decisions at the millisecond level [79, p. 6-7].

At Level 2 of the hierarchy approach, it progresses from raw Foundational data to Aggregated data, where individual data points are combined and summarized to provide a broader perspective on market activities. These aggregated data types play a pivotal role in enhancing the understanding of market trends and volatility risk. The main types of Aggregated data are as follows (table 1.11).

Table 1.11

Main data types of Level 2. Aggregated data

Data type	Description	Role in trading
Returns	Average historical price performance	Evaluate asset performance
Volatility	Measures dispersion of asset prices	Quantify market risk and uncertainty
Correlation coefficients	Measures relationship between asset movements	Diversify and construct portfolio
Moving averages	Smoothed trends of prices over time windows	Identify trends and technical signals
Market indices	Aggregated asset performance benchmarks	Provide benchmarking and sentiment analysis
Sector performance metrics	Aggregated performance of industry sectors	Identify sector strengths/weaknesses and guide sector rotation strategies

Source: author’s own generalisation

It is needed to provide a detailed description of every data type for Aggregated data:

1. Returns. Returns (Average returns) represent the arithmetic mean of historical price changes for a specific financial instrument over a defined period. Calculating returns provides a measure of the financial instrument’s historical performance. It helps financial trading participants/models assess whether a financial asset has generated positive or negative returns directly.

2. Volatility. Volatility measures, such as standard deviation or the Average True Range (ATR), quantify the dispersion of asset price movements around their mean. Volatility is a critical concept in risk management and portfolio construction. Higher volatility suggests greater price fluctuations, potentially indicating increased uncertainty and risk.

3. Correlation coefficients. Correlation coefficients quantify the degree of linear relationship between two financial assets. Positive correlations indicate that assets move in the same direction, while negative correlations imply opposite movements. Analysing correlations helps diversify portfolios and manage risk by identifying financial assets that are less likely to move in tandem during market turbulence [80].

4. Moving averages. Moving averages smooth out price fluctuations by calculating average prices over a specific time window. Simple Moving Averages (SMAs) and Exponential Moving Averages (EMAs) are commonly used to identify trends, potential support/resistance levels, and crossovers that signal changes in market sentiment [81].

5. Market indices. Market indices aggregate the performance of a group of related assets, providing a benchmark for evaluating market trends. Widely recognised indices, such as the S&P 500 and Dow Jones Industrial Average, serve as key indicators of prevailing market conditions and investor sentiment. Financial trading participants/models can use index performance to gauge economic health and identify sector-specific trends.

6. Sector performance metrics. Sector performance metrics aggregate data for companies within specific industry sectors. By analysing sector-level data, investors gain insights into the relative strengths and weaknesses of different industries.

Aggregated data, by summarizing historical trends, relationships and patterns, bridge the gap between individual data points and higher-level analyses, and offer a more comprehensive view of financial market dynamics. Their significance lies in their ability to:

- identify trends: average returns, moving averages, and indices reveal underlying trends that may be obscured by the noise of individual data points. Identifying trends helps human and AI Financial trading analysts make informed predictions and construct the most basic investment strategies;

- quantify risk: volatility measures and correlation coefficients contribute to risk assessment. Understanding asset volatility and correlations assist in constructing diversified portfolios that can better weather market fluctuations;

- benchmark performance: indices and sector performance metrics offer benchmarks for evaluating the performance of individual assets and portfolios. These benchmarks provide a reference for assessing investment success;

- be cornerstones of technical analysis and algorithmic trading: aggregated data types include a large number of technical indicators and factors that are popularly used in financial technical analysis and algorithmic trading, and have great significance to traditional and modern financial trading.

At Level 3 of the hierarchy approach, it delves into Macroeconomic indicators. These indicators offer a high-level perspective on economic conditions, helping analysts, policymakers, and investors understand the overall health and trajectory of an economy. Each type of macroscopic indicator carries distinct information that contributes to informed decision-making in financial markets. The main types of Macroeconomic Indicators are as follows (table 1.12).

Table 1.12

Main indicators of Level 3. Macroeconomic indicators.

Indicator	Description	Role in trading
Gross Domestic Product	Measures total economic output	Assess economic cycles and growth trends
Unemployment rates	Constitutes percent of unemployed labour force	Gauge labour market and consumption power
Inflation Indices	Tracks changes in prices of goods/services	Guide interest rates and purchasing power
Balance of trade	Exports vs. Imports balance	Forecast currency strength and trade policies
Consumer confidence index	Measures consumer's optimism/pessimism	Predict consumer spending and economic health

Source: author's own generalisation

Then it is necessary to consider examples of indicators for Level 3. Macroeconomic indicators:

1. GDP. GDP measures the total economic output of a country over a specific time period. It serves as a barometer of economic health, indicating the size and growth rate of an economy. Changes in GDP reflect shifts in consumer spending, business investment, government spending, and net exports. GDP data can help financial analysts

assess economic cycles and make predictions about future economic performance [82].

2. Unemployment rates. Unemployment rates quantify the percentage of the labour force that is unemployed and actively seeking employment. Low unemployment rates are indicative of a strong job market, while high rates suggest economic distress. Unemployment data are essential for assessing labour market conditions, consumer spending power, and potential shifts in inflation.

3. Inflation indices. Inflation indices, such as the Consumer Price Index (CPI) and Producer Price Index (PPI), measure changes in the general price level of goods and services. Inflation impacts purchasing power and affects interest rates set by central banks. Monitoring inflation indices aids in understanding changes in cost of living and guiding monetary policy decisions.

4. Balance of trade. It compares a country's exports to its imports. A positive balance of trade (surplus) indicates that a country exports more than it imports, contributing to economic growth. A negative balance (deficit) implies that imports exceed exports, potentially impacting currency exchange rates and trade policies.

5. Consumer confidence index. It reflects consumer sentiments about the overall state of the economy and their own financial prospects. High consumer confidence typically correlates with increased spending, while low confidence can lead to reduced consumption and economic slowdowns [83].

Macroeconomic indicators offer a broader context for financial analysis, allowing financial analysts to understand the larger economic environment in which financial markets operate. Their significance includes:

- predicting economic trends: GDP, unemployment rates, and inflation indices provide valuable information for forecasting economic trends. Financial analysts and policymakers use these indicators to anticipate changes in growth, employment, and price stability;

- assessing market conditions: balance of trade data and PMI readings offer insights into market conditions, both domestically and globally. These indicators help evaluate the competitiveness of industries and assess potential risks;

- guiding investment strategies: macroeconomic indicators guide investment decisions by providing insights into economic cycles. Financial trading participants/models can adjust strategies based on the stage of the business cycle, inflation expectations, and overall economic health. In the most cutting-edge financial trading technology practice, Quantamental hedge funds utilize satellite imagery as a source of Macroeconomic intelligence for their financial trading algorithms in order to generate access returns [84].

Level 4 of the hierarchy approach, Financial systems data, shows the complex interplay of markets, institutions, and regulations that collectively shape the global financial landscape. A thorough understanding of these systems is essential for analysing the systemic risks, interconnections, and factors influencing financial markets. Each type of financial system elements plays a distinct role in shaping financial market dynamics and economic stability. The main types of Financial systems data are as follows (table 1.13).

Table 1.13

Main components of Level 4. Financial systems data

Component	Description	Role in trading
Market interactions	Cross-asset relationships and spillovers	Understand contagion and cross-market trends
Financial institutions	Capital providers and risk conduits	Monitor credit risks and systemic health
Regulatory frameworks	Rules and oversight of financial activities	Comprehend compliance and market structure
Central banks	Monetary policy setters and market stabilizers	Forecast interest and liquidity conditions
Financial innovations and technology	Fintech, blockchain, and automation drivers	Incorporate tech-driven changes and tools

Source: author’s own generalisation

Then it is needed to consider examples of components for Level 4. Financial systems data:

1. Market interactions. Market interactions encompass the relationships between various financial markets, such as equities, fixed income, foreign exchange, and commodities. These interactions influence cross-market correlations, capital flows, and asset valuation. Studying market interactions enables financial analysts to assess the

potential contagion of risks across different asset classes.

2. Financial institutions. Financial institutions, including banks, investment firms, and insurance companies, form the backbone of the financial system. These entities facilitate the allocation of capital, provide liquidity, and offer financial products and services. Analysing the health and stability of financial institutions is crucial for identifying systemic risks and vulnerabilities [85, p.1].

3. Regulatory frameworks. Regulatory frameworks encompass laws, regulations, and oversight mechanisms that govern financial markets and institutions. These frameworks aim to ensure market integrity, protect investors, and maintain financial stability. Changes in regulations can impact market behaviour, risk-taking, and investor confidence.

4. Central banks. Central banks play a critical role in monetary policy and financial stability. They control the money supply, set interest rates, and act as lenders of last resort. Central bank decisions influence liquidity conditions, borrowing costs, and macroeconomic trends [86, p.1].

5. Financial innovations and technology. Advancements in financial technology (FinTech) and innovations, such as blockchain and digital currencies, are transforming the financial landscape. These innovations impact market liquidity, transparency, and operational efficiency.

Financial Systems Data provides a comprehensive view of the interconnectedness and influences that shape financial markets and at the same time play a vital role in shaping market behaviour, risk propagation, and economic stability. The significance of Financial systems data in the financial trading analysis includes:

- systemic risk assessment: understanding market interactions and financial institutions help identify sources of systemic risk. This knowledge is crucial for pre-emptively addressing vulnerabilities that could lead to financial crises;

- investment strategy: financial trading participants/models can assess the health of financial institutions and anticipate regulatory changes to inform investment strategies. In addition, market interactions also influence asset allocation decisions to manage risks and returns.

Level 5 of the hierarchy approach ascends to the realm of Economic context data – panoramic economic views encompassing the global economic landscape, geopolitical factors, and overarching trends that exert profound influences on financial systems and market activities. Understanding this context is paramount for making well-informed financial decisions, as it provides a comprehensive understanding of the shape of economies and financial markets under globalization. The main types of Economic context data are as follows (table 1.14).

Table 1.14

Main Factors of Level 5. Economic context data

Factor	Description	Role in trading
Geopolitical Factors	Political events influencing global markets	Anticipate market disruptions or tailwinds
International trade Dynamics	Flows of goods/services and related policies	Analyse trade-sensitive assets and currency moves
Socioeconomic trends	Shifts in demographics and consumer behaviour	Identify thematic and demographic investments
Environmental considerations	Climate impacts and sustainability efforts	Align with ESG and green finance strategies
Global financial flows	Cross-border capital and investment flows	Predict capital movement and currency impact
Technological progress	Innovations in AI, automation, energy and so on	Evaluate tech-driven growth, productivity shifts, and sector transformations

Source: author's own generalisation

It is essential to consider examples of factors for Level 5. Economic context data:

1. Geopolitical factors. Geopolitical factors encompass political relationships, international conflicts, and diplomatic events that influence global markets. Geopolitical tensions can impact market sentiment, trade dynamics, and investment flows. Analysts can monitor geopolitical developments to assess potential financial risks and opportunities.

2. International trade dynamics. International trade dynamics encompass the flow of goods, services, and capital across borders. Trade agreements, tariffs, and trade imbalances affect economic growth, exchange rates, and market access. Understanding trade dynamics helps forecast economic trends and international currency movements.

3. Socioeconomic trends. Socioeconomic trends capture shifts in demographic

patterns, consumer behaviour, and societal preferences. These trends influence industries, consumption patterns, and investment opportunities. Monitoring socioeconomic trends can aid in identifying emerging markets and adapting investment strategies.

4. Environmental considerations. Environmental factors, such as climate change policies and sustainable practices, have far-reaching implications for economies and markets. Environmental regulations and investor demands for sustainability impact industries, resource allocation, and business strategies.

5. Global financial flows. Global financial flows encompass cross-border capital movements, foreign direct investment, and international financial transactions. These flows influence currency values, interest rates, and economic stability. Analysing financial flows helps anticipate shifts in capital allocation and potential financial vulnerabilities.

6. Technological progress. Technological progress includes artificial intelligence, automation, and energy innovations. These advancements shape economic productivity, labour markets, and industry dynamics.

Level 5. Economic context data provides a holistic understanding of the forces beyond financial markets that impact economies and shape financial systems. The information about geopolitical factors, international trade dynamics, socioeconomic trends, environmental considerations, global financial flows, and technological progress collectively contribute to a comprehensive understanding of the global economy and financial markets. The economic context in financial trading here is broadly defined. It not only covers traditional financial and macroeconomic factors but also encompasses non-economic dimensions such as regulatory and legal frameworks, cultural and social dynamics, behavioural and psychological influences, and natural or environmental shocks, all of which interact to shape market conditions and trading outcomes. By acknowledging the broader economic context, financial trading participants can navigate the complexities of the financial world with greater foresight and adaptability.

Now it is possible to summarise the basics of the five-level hierarchy information basis for efficient financial trading (table 1.15).

Table 1.15

Basics of the five-level hierarchy information basis for efficient financial trading

Hierarchy level	**Data type**	**Description**	**Application in financial trading**
Level 1: Foundational data	Raw trading data	Market prices, volumes, interest rates, bid-ask spreads	Fundamental inputs for technical and quantitative analysis
Level 2: Aggregated data	Processed metrics	Average returns, standard deviations, correlations	Enhances statistical market analysis
Level 3: Macroeconomic indicators	Economic trends	GDP, inflation, employment rates	Connects financial trading with broader economic conditions
Level 4: Financial systems data	Market structure data	Regulatory frameworks, credit flows, systemic risk indicators	Helps assess financial stability and institutional interactions
Level 5: Economic context data	Global financial ecosystem	Geopolitical events, international trade, economic crises	Provides a strategic macroeconomic perspective for trading

Source: author's own generalisation

Table 1.15 shows the basics of the whole hierarchy of the 5-level financial trading information in summary. The methodology for adapting hierarchy theory to financial trading data and information presents a systematic approach to understanding the complexities of financial trading models' data input. By categorizing data into hierarchical levels and acknowledging the interdependencies between them, the methodology equips financial trading analysts and decision-makers with a structured framework to navigate the intricate dynamics of financial markets. In order to explore the relationship between different levels of data in the hierarchy approach of financial trading data/information and the complexity of the data hierarchy system for further study of efficient financial trading, this research proposes "an entropy explanation in financial trading data hierarchy".

Entropy, as a concept rooted in thermodynamics and information theory, is widely applied in diverse fields to quantify disorder, randomness, and complexity [87]. Then the concept was extended to the realm of finance, specifically within the framework of the Hierarchy approach to financial trading data. All factors of disorder, complexity, and unpredictability that lead to distortions or biases in specific financial trading data are collectively referred to as the entropy of financial trading data (EFTD).

EFTD arises as a means to quantify the randomness and uncertainty inherent in financial trading data, providing a measure of the level of disorder, complexity and unpredictability. In the context of the financial trading data hierarchy and its application to financial systems, the emergence of EFTD can be attributed to several key factors:

1. Information complexity. Entropy emerges as a measure of information complexity. In financial systems, a vast array of variables, including market prices, transaction volumes, interest rates, and economic indicators, interact in intricate ways. The aggregation and interplay of these variables lead to increased information complexity.

2. Variability and uncertainty. Financial markets are inherently dynamic and subject to constant fluctuations. The multitude of market participants, external factors, and unpredictable events contribute to high levels of variability and uncertainty.

3. Interconnectedness and relationships. Financial systems are characterized by complex relationships between different assets, markets, institutions, and economic factors. These interconnections create a web of dependencies that can lead to cascading effects and amplify the impact of localized events.

4. Data compression and summarization. As data progresses through the hierarchy levels, it undergoes aggregation and summarization. This process results in the compression of diverse individual data points into higher-level data representations.

5. Nonlinear relationships. Financial systems often exhibit nonlinear relationships, where changes in one variable can lead to disproportionate effects on others. These nonlinear interactions contribute to the emergence of complexity, as linear models and simple cause-and-effect relationships become inadequate for describing system behaviour.

6. Unpredictable Events (Black Swans Events). Financial markets are susceptible to unpredictable events commonly referred to as ‘black swan’ events. These events have a low probability but a high impact, leading to abrupt and significant market shifts [88].

7. Adaptive Behaviour and Feedback Loops. The adaptive behaviour of market

participants and feedback loops contribute to financial system complexity. Market reactions to information, sentiment shifts, and investor behaviour create dynamic feedback loops that amplify or dampen market movements [89].

With the help of the definition of the Entropy of financial trading data, researchers can further investigate the relationship between data hierarchy levels and entropy and explore how entropy can serve as an indicator of complexity and stability within financial transaction models. According to the definition and the Five-Level Hierarchy of Financial Data, three statements related to the entropy explanation of financial trading data can further be deduced:

Statement 1: Entropy increase with data hierarchy level. As financial trading data progresses through the hierarchy levels, its entropy consistently increases. This phenomenon stems from the aggregation and synthesis of information as data ascends the hierarchy. The aggregation process introduces new dimensions and variables, leading to higher entropy values. Mathematically, the EFTD increases with the data hierarchy level (L), represented as:

$$\text{EFTD}\ (L+1) > \text{EFTD}\ (L) \tag{1.8}$$

According to Statement 1, financial trading models with higher-level data input have higher entropy values. Common financial trading models, involving macroeconomic indicators and international economic situations, have higher entropy values than models that only take Foundational Data and Aggregated Data as input. Mathematically, the entropy of financial trading model (EM) increases with the model input of data hierarchy level (L), and can be represented as:

$$\text{EM}(L+1) > \text{EM}(L) \tag{1.9}$$

Statement 2: Model complexity correlates with entropy. Within financial trading models, complexity demonstrates a positive correlation with entropy values. As trading data encompass more diverse variables and interactions, the complexity of the system increases. The higher the entropy value is, the more intricate the relationships among market participants, trading strategies, and external factors are. Mathematically, financial trading model complexity (C) and EFTD exhibit a positive correlation:

$$C \propto \text{EFTD} \tag{1.10}$$

According to Statement 1 and 2, the financial trading models with higher-level data input have higher model complexity. Common financial trading models, involving macroeconomic indicators and international economic situations, have higher model complexity than models that only take Foundational Data and Aggregated Data as input. Mathematically, the complexity of financial trading model (C) increases with the model input of data hierarchy level (L), and it is represented as:

$$C(L+1) > C(L) \tag{1.11}$$

Statement 3: Entropy-Complexity Trade-off Affects Stability. There exists a trade-off between entropy (complexity) and system stability in financial trading models. As entropy increases, financial trading model complexity heightens, leading to a greater number of potential interactions and outcomes. This intricate web of interactions amplifies the likelihood of unforeseen events and cascading effects, thereby reducing financial trading model's system stability. Mathematically, the trade-off between EFTD and financial trading model stability (S) can be expressed as:

$$EFTD \uparrow \Rightarrow S \downarrow \tag{1.12}$$

According to statement 3, only financial trading models with low complexity can guarantee long-term high stability. This also reveals the particularity of financial trading technology, compared with other social sciences, that is, the long-term predictive ability and profitability of financial trading models will not necessarily improve as the model considers more comprehensive financial factors. On the other hand, the research of modern financial trading technology cannot be achieved only by increasing the complexity of the model. The research on next-generation financial trading technology needs to be explored and constructed at a higher scientific level. Table 1.16 below shows this Entropy-Complexity trade-off under different financial trading model types: basic technical analysis, statistical arbitrage, AI-based sentiment trading and global macroeconomic trading.

These proposed statements encapsulate the fundamental principles of the Entropy explanation within the context of the financial trading data hierarchy. They provide a formal framework for understanding how financial trading model's entropy, complexity, and stability interact in financial systems, shedding light on the intricate dynamics that underlie financial trading. In addition, further research and empirical validation will be essential to refine and strengthen these statements and their implications for financial trading analysis and decision-making.

Table 1.16

Entropy-complexity trade-off for different financial trading model types

Trading model type	EFTD Level	Complexity (C)	Stability (S)
Basic Technical Analysis	Low	Low	High
Statistical Arbitrage	Medium	Medium	Medium
AI-Based Sentiment Trading	High	High	Low
Global Macro Trading	Very High	Very High	Very Low

Source: author's own generalisation

The hierarchical design proposed in this study has several critical functions within financial trading analysis. Firstly, it organizes complex and heterogeneous data inputs into a structured, multi-level framework, enhancing clarity in analysis and preventing information overload. By systematically categorizing data from foundational market data to aggregated indicators, macroeconomic metrics, financial systems data, and finally to economic context data, it provides analysts and AI models with a clear roadmap for data processing and integration.

Secondly, the hierarchy design facilitates layered analytical depth, enabling trading models to extract insights progressively from micro-level price movements to macro-level geopolitical influences. This layered approach supports both high-frequency trading strategies relying on Level 1 and Level 2 data, as well as long-term global macro strategies informed by Levels 4 and 5.

Thirdly, the hierarchical approach embodies an entropy-complexity-stability trade-off framework, as introduced in the entropy explanation. By understanding how data complexity increases across hierarchical levels, analysts and model designers can strategically select the appropriate data scope to balance predictive power and model stability.

In practical financial trading operations and research, this hierarchical design can be applied as follows:

1. Model Input Selection: trading system designers can use the hierarchy to select input data based on strategy objectives. For example, a high-frequency trading model would focus primarily on Level 1 (Foundational data) and Level 2 (Aggregated data), enabling millisecond-level decision-making. In contrast, a global macro hedge fund would integrate Levels 3, 4, and 5 to inform long-term positioning and thematic investments.

2. Feature Engineering Pipeline: data scientists and quantitative researchers can implement the hierarchy as a feature engineering pipeline, processing raw data through each hierarchical level to generate multi-scale features. For instance, foundational OHLCV data can be aggregated to compute volatility and moving averages, then combined with macroeconomic indicators as additional model features.

3. Risk management framework: risk managers can apply the hierarchy to identify data-driven risk factors at each level. Market risk can be assessed from Level 1 volatility, while systemic and geopolitical risks are analysed from Level 4 and Level 5 data, informing integrated risk dashboards and scenario analysis models.

4. Trading strategy design: portfolio managers can design multi-layered trading strategies by integrating signals from different hierarchy levels. For example, a strategy might use technical signals (Levels 1-2) for entry timing, macroeconomic trends (Level 3) for asset allocation, and geopolitical analysis (Level 5) for hedging decisions.

5. Educational and training tool: finally, the hierarchy serves as an effective educational framework for training financial analysts, helping them understand the interconnectedness of data scales, from microstructural order book dynamics to global economic trends, and fostering holistic market analysis skills.

Overall, the hierarchy design functions as a conceptual and operational architecture, facilitating efficient data utilization, adaptive trading model development, and integrated risk management. Its practical applications span from high-frequency algorithmic strategies to global macroeconomic trading, supporting the construction of robust, multi-scale, and scientifically rigorous financial trading systems.

CONCLUSIONS TO CHAPTER I

The essence of financial trading has been elucidated, and a comprehensive definition has been formulated. This definition encompasses the phenomenon's essence, content, and outcomes. Specifically, financial trading is defined as an immediate or pre-set process carried out by financial market participants, based on the characteristics of one or more financial assets and relevant market information, with the objective of obtaining direct or indirect financial benefits. The significance of this definition lies in its applicability across various trading environments and its ability to draw a clearer conceptual boundary between financial trading, speculation, and gambling.

The participants of financial trading were divided into two groups: systemic and investment. Such structuring allows to highlighting their roles, profit mechanisms, and risk exposure, which increases the transparency of the market and supports more effective regulation and strategy development.

The classification of financial trading was enhanced, and it is based on a combination of faceted and hierarchical methods. Main features of the classification include the object of trading, trading technology, transaction place, execution, purpose, and market structure. The value of this result lies in the comprehensive framework that enables flexible categorization of both traditional and modern forms, as well as the prediction of future applications of next-generation technologies.

The risks of financial trading were characterized, covering market, credit, operational, liquidity, and systemic risks. For each type, classical and modern quantitative models were systematized, including VaR, GARCH, Credit VaR, copula models, Monte Carlo simulations, L-VaR, and network models. The contribution of this result consists in providing a scientifically grounded toolkit for risk assessment and management in globalized and technologically advanced markets.

Financial trading strategies were systematically analysed, and a four-quadrant approach was introduced to describe the interplay between machine technology level and strategy level. This novelty highlights the diversity of trading approaches, from traditional analysis to autonomous intelligent trading, and provides a framework for future development of financial trading.

The information basis of financial trading was structured through a hierarchical model, which systematizes data from foundational trading metrics to macroeconomic and contextual levels. The importance of this finding is reflected in the creation of a universal approach that supports efficient use of financial data in advanced trading systems.

To conclude, the obtained results ensure novelty through the elaborated definition, advanced classification, comprehensive risk assessment, types of financial trading strategies, and a hierarchical information approach. These findings form a strong conceptual and practical foundation for further studies and real-world applications in financial trading.

CHAPTER II
CURRENT TRENDS OF FINANCIAL TRADING UNDER GLOBALIZATION

2.1. Institutional and legal provision of financial trading

This section addresses the regulatory challenges emerging from the technological advancements and structured data systems previously discussed. Financial trading involves the buying and selling of financial instruments such as stocks, bonds, derivatives, and currencies. It plays a crucial role in the economy by enabling the allocation of capital, providing liquidity, and facilitating risk management.

Over the past few decades, financial trading has been profoundly impacted by globalization, which has increased the interconnectivity of markets, enhanced capital flows, and led to the development of complex financial instruments. Globalization has expanded the scope of financial trading beyond national borders, leading to the emergence of a truly global financial market. This interconnectedness has brought numerous benefits, including greater market efficiency, diversified investment opportunities, and improved access to capital. However, it has also introduced challenges such as increased market volatility, regulatory complexities, and systemic risks. This transformation has necessitated robust institutional and legal frameworks to ensure market stability, investor protection, and fair-trading practices [90].

This section examines the institutional and legal frameworks that govern financial trading in the global context. By analysing key regulatory bodies, market structures, and legal provisions, this study aims to elucidate how globalization has reshaped financial trading practices and the implications for market participants and draws on extensive literature to provide a comprehensive overview and further explores emerging trends and future directions.

The evolution of financial trading has been marked by significant historical milestones. Table 2.1 shows six key historical periods that have shaped the current financial trading landscape in order to explore them in depth.

Table 2.1

Main events in the historical development of financial trading

Period	Year	Main events
I. Early financial markets	1602	The Amsterdam Stock Exchange was founded
	1792	The Buttonwood Agreement formed the NYSE
	1801	The London Stock Exchange was established
II. Industrial Revolution	1913	The Federal Reserve System was created
	1933	The Glass-Steagall Act was passed
III. Post-war financial expansion	1944	The IMF and World Bank were established
	1971	NASDAQ was launched
IV. Deregulation and financial liberalization	1986	The UK passed the Financial Services Act
	1992	Globex electronic trading platform was introduced
V. Global financial crisis	2007	The global financial crisis began
	2010	The Dodd-Frank Act was enacted
VI. The period after 2010 till nowadays	After 2010	New trading technology regulations were introduced

Source: [90]

The first period was Early Financial Markets, which occurred in the 17th - 19th century. During this period, the establishment of early stock exchanges marked the beginning of organized financial trading. One of the earliest and most influential was the Amsterdam Stock Exchange, established in 1602 by the Dutch East India Company (VOC) to facilitate the trading of its shares. This was the world's first official stock exchange which introduced many concepts that are now fundamental to modern trading, such as the joint-stock company, dividends, and the limited liability of shareholders. The Amsterdam Stock Exchange's trading practices influenced the development of other stock exchanges, including the LSE, which was formally established in 1801 [90; 91, p.30-60; 92, p.70-110].

In the United States, the Buttonwood Agreement, signed by 24 stockbrokers under a buttonwood tree on Wall Street in 1792, laid the foundation for what would become the NYSE. The NYSE formalized trading practices and established rules that promoted fair and orderly markets [93, p.40-70]. By the 19th century, it had become the dominant securities market in the U.S., supporting the country's rapid economic growth. During this period, trading was characterized by face-to-face interactions, open outcry auctions, and the physical delivery of stock certificates. The primary participants were individual investors, wealthy merchants, and institutional investors such as banks and insurance companies. The absence of regulatory oversight often led to market manipulation and speculation, exemplified by events such as the South Sea Bubble in 1720 and the Panic of 1837 [90; 94, p.1-25].

Next, the second period was Industrial Revolution and Financial Innovation, which occurred in the 19th - early 20th century. The Industrial Revolution, spanning from the late 18th century to the early 20th century, brought profound changes to economies worldwide, necessitating significant capital investments to finance industrial expansion. This era saw the rise of investment banks, which played a crucial role in underwriting securities and facilitating mergers and acquisitions. Firms like J.P. Morgan & Co. and Goldman Sachs emerged as dominant players in the financial markets [90; 95, p.250-270].

The introduction of new financial instruments during this period revolutionized financial markets. Corporate bonds became a primary means for companies to raise capital. Preferred stocks, offering fixed dividends and priority over common stocks in the event of liquidation, provided a safer investment alternative, appealing to more conservative investors. The widespread issuance of these instruments by corporations facilitated large-scale infrastructure projects such as railways, telegraph networks, and urban utilities [90; 96, p.120-180].

The formalization of trading practices and the establishment of financial regulations began to take shape during this period. The formation of the Federal Reserve System in 1913 was a pivotal development aimed at providing a safer, more flexible, and stable monetary and financial system in the United States. The Glass-Steagall Act of 1933, enacted in response to the stock market crash of 1929, separated commercial banking from investment banking to reduce the risk of financial speculation [90; 97, p.230-235].

Then, the third period was Post-War Financial Expansion, which occurred during 1945 - 1970s. The Post-World War II era was characterized by rapid economic growth, technological advancements, and the expansion of global trade. The Bretton Woods

Conference in 1944 established a new international monetary system with the creation of the IMF and the World Bank. These institutions aimed to promote international monetary cooperation, facilitate the expansion and balanced growth of international trade, and provide resources to member countries experiencing balance of payments difficulties [90; 98, p.4-8].

During this period, the U.S. dollar became the dominant global currency, and the fixed exchange rate system provided stability for international trade and investment. The Marshall Plan, an American initiative to aid Western Europe's economic recovery, further stimulated global economic growth and increased international capital flows [90; 99, p.5-15].

Financial markets experienced significant innovations, including the development of the Eurodollar market, which allowed for the lending of U.S. dollars outside the United States, primarily in Europe. This market provided multinational corporations with an alternative source of funding and contributed to the growth of international banking [90; 100, p.225-230].

The introduction of electronic trading systems in the 1960s, such as the NASDAQ in 1971, revolutionized financial markets by providing a centralized and automated platform for trading securities. NASDAQ became the world's first electronic stock market, facilitating greater market transparency and efficiency [90; 101, p.1462–1464].

The fourth period was Deregulation and Financial Liberalization, which occurred during the 1980s - 1990s. The 1980s and 1990s were characterized by significant deregulation and financial liberalization, driven by the belief that free markets could allocate resources more efficiently than government intervention. This era witnessed the dismantling of capital controls, the deregulation of financial markets, and the advent of new financial products such as derivatives. In the United States, the Reagan administration implemented policies aimed at reducing government intervention in the economy [90; 102, p.15-25].

The Financial Services Act of 1986 in the UK, part of the Thatcher government's broader program of economic liberalization, restructured financial regulation and led to the "Big Bang" deregulation of financial markets. This event abolished fixed commission charges and allowed foreign firms to own UK brokers, transforming the City of London into a global financial centre [90; 103, p.400-430].

The rise of electronic trading platforms revolutionized the trading landscape. The introduction of the Globex electronic trading platform by the Chicago Mercantile Exchange in 1992 enabled round-the-clock trading of futures contracts, increasing market liquidity and accessibility [90; 104, p. 50-100].

The development of complex financial derivatives, including options, futures, and swaps, allowed market participants to hedge risks and speculate on price movements. The Commodity Futures Trading Commission (CFTC) and the Securities and Exchange Commission (SEC) played critical roles in overseeing these markets and ensuring their integrity [90; 105, p.27-30].

Further, the short fifth period was the Global financial crisis and regulatory reforms, which occurred during 2007-2010. The global financial crisis of 2007-2008 exposed significant weaknesses in the financial system, leading to a wave of regulatory reforms aimed at enhancing market stability and protecting investors. The crisis was triggered by the collapse of the subprime mortgage market in the United States, which led to a severe liquidity crisis and the failure of major financial institutions such as Lehman Brothers [90; 106, p. 30-50].

The Dodd-Frank Wall Street Reform and Consumer Protection Act, enacted in 2010, was a comprehensive regulatory response to the crisis in the United States. It aimed to reduce systemic risk, increase transparency, and protect consumers. Key provisions of the Dodd-Frank Act included the establishment of the Financial Stability Oversight Council (FSOC) to monitor systemic risks, the Volcker Rule to restrict proprietary trading by banks, and the creation of the Consumer Financial Protection Bureau (CFPB) to protect consumers from abusive financial practices [90; 107, p. 160-190].

Internationally, the Basel III framework was introduced to strengthen the regulation, supervision, and risk management of banks. Basel III increased capital requirements, introduced new liquidity standards, and enhanced the overall resilience of the banking sector. These reforms aimed to prevent a recurrence of the financial instability experienced during the crisis [90; 108, p.160-180].

The European Union also implemented significant regulatory reforms, including the Capital Requirements Directive IV (CRD IV) and the European Market Infrastructure Regulation (EMIR). These regulations aimed to enhance the stability and transparency of the financial system by imposing stricter capital and liquidity requirements on banks and improving the oversight of over-the-counter derivatives markets [90; 109, p.4-6].

At this stage, the institutional and legal provisions governing financial trading under globalization has gradually improved to a mature and stable level. These institutional and legal provisions focus on the following aspects [90]. For institutional frameworks, the institutional landscape of financial trading comprises various entities that regulate, facilitate, and oversee market activities. These include central banks, securities commissions, and international regulatory bodies. Key institutions include:

Firstly, international regulatory bodies, play a crucial role in harmonizing regulatory standards across jurisdictions. They help to ensure that financial markets operate smoothly and transparently. Some of the key international regulatory bodies are [90]:

- International Organization of Securities Commissions (IOSCO): IOSCO is a global organization that brings together the world's securities regulators. It aims to establish and maintain standards for the securities industry to ensure fair, efficient, and transparent markets. IOSCO's principles are widely adopted by its member organizations, which include the SEC, FCA, and other national regulators [90; 110, p. 1-2].
- Basel Committee on Banking Supervision (BCBS): The BCBS sets global standards for the regulation of banks. Its Basel III framework, introduced after the 2008 financial crisis, aims to strengthen bank capital requirements and improve risk management. The Basel standards are implemented by national regulators worldwide [90; 111, p.1-2].
- Financial Stability Board (FSB): The FSB coordinates the work of national financial authorities and international standard-setting bodies at the international level. It works to develop and promote the implementation of effective regulatory, supervisory, and other financial sector policies in the interest of financial stability [90; 112, p.1].

- IMF and World Bank: These institutions provide financial assistance and policy advice to countries facing economic instability. They also play a role in the development of global financial standards and practices [90; 113, p.1-2].

Secondly, national regulatory agencies, usually enforce domestic regulations while aligning with international standards. Some of the prominent national regulatory agencies are [90]:

- U.S. Securities and Exchange Commission: The SEC oversees securities markets in the United States, enforcing laws that protect investors, maintain fair and efficient markets, and facilitate capital formation. The SEC's regulations are often considered a benchmark for other countries [90; 114, p.1].

- Financial Conduct Authority (FCA) in the UK: The FCA regulates financial firms providing services to consumers and maintains the integrity of the financial markets in the UK. It operates independently of the UK government and is financed by charging fees to the firms it regulates [90; 115, p.1].

- European Securities and Markets Authority (ESMA): ESMA is an independent EU Authority that contributes to safeguarding the stability of the EU's financial system by enhancing the protection of investors and promoting stable and orderly financial markets [90; 116, p.1].

- China Securities Regulatory Commission (CSRC): The CSRC is the national regulatory body overseeing securities and futures markets in China. It aims to protect investors, ensure fair market practices, and promote the healthy development of the securities market [90; 117].

Thirdly, exchanges and trading venues provide the infrastructure for securities trading, ensuring transparency and liquidity. These institutions are:

- NYSE and NASDAQ: these are two of the largest stock exchanges in the world, providing platforms for trading a wide range of securities. They ensure high levels of market transparency and liquidity [90; 118].

- Alternative Trading Systems (ATS): ATSs are non-exchange trading venues that match buyers and sellers of securities. They often offer advantages such as lower fees and greater anonymity compared to traditional exchanges [90; 119].

- European Stock Exchanges (e.g., Euronext, Deutsche Börse): these exchanges provide trading platforms for European securities and play a crucial role in the integration of European financial markets [90; 120].

For legal provisions, legal frameworks governing financial trading are designed to protect investors, maintain market integrity, and prevent financial crimes. Key legal provisions include:

Firstly, securities laws regulate the issuance, trading, and disclosure requirements of securities. They are fundamental to maintaining investor confidence and market integrity [90]. Key securities laws are:

- U.S. Securities Act of 1933 and Securities Exchange Act of 1934: These laws regulate the initial issuance of securities and the trading of securities in the secondary market, respectively. They require companies to provide significant information about their business and securities to the public [90; 121, p. 1].
- EU Markets in Financial Instruments Directive (MiFID II): MiFID II is a comprehensive regulatory framework that governs the provision of investment services across the European Economic Area. It aims to increase transparency and investor protection [90; 122].
- Sarbanes-Oxley Act (SOX) of 2002: Enacted in response to corporate scandals, SOX introduced significant changes to financial practice and corporate governance to improve the accuracy and reliability of corporate disclosures [90; 123].
- Dodd-Frank Wall Street Reform and Consumer Protection Act: This act was introduced after the 2008 financial crisis to reduce risks in the financial system. It includes provisions for increased transparency, consumer protection, and systemic risk oversight [90; 124].

Secondly, anti-money laundering regulations (AML), prevent the use of financial systems for illicit activities [90]. Key AML regulations are:

- Financial Action Task Force (FATF): The FATF sets international standards for combating money laundering and terrorist financing. Its recommendations are adopted by member countries and guide national AML regulations [90; 125].

- Bank Secrecy Act (BSA) and USA PATRIOT Act: These U.S. laws require financial institutions to assist in the detection and prevention of money laundering and terrorist financing through record-keeping and reporting requirements [90; 126].

- EU Anti-Money Laundering Directives: These directives establish a framework for preventing the use of the EU financial system for money laundering and terrorist financing. The 6th Anti-Money Laundering Directive (AMLD6) enhances the regulatory framework by introducing stricter rules and increasing cooperation between member states [90; 127].

Thirdly, market abuse regulations address insider trading, market manipulation, and other fraudulent activities. Key regulations are:

- EU Market Abuse Regulation (MAR): MAR aims to enhance market integrity and investor protection by establishing a common regulatory framework for preventing market abuse in the EU [90; 128].

- U.S. Insider Trading Sanctions Act of 1984 and Insider Trading and Securities Fraud Enforcement Act of 1988: These acts enhance penalties for insider trading and provide the SEC with greater authority to enforce insider trading laws [90; 129].

- UK Criminal Justice Act 1993 (Part V: Insider Dealing): This act criminalizes insider dealing and outlines the penalties for such offenses in the UK [90; 130].

Until now, the period after 2010 has seen significant advancements in trading technologies and the implementation of new regulatory frameworks to address the challenges posed by these technologies [90]. Key developments include:

1) Algorithmic and HFT. Algorithmic trading and HFT have revolutionized financial markets by enabling the rapid execution of trades based on pre-programmed strategies. These technologies have increased market efficiency but also introduced new risks such as market manipulation and flash crashes [90]. Regulatory responses to these developments are mainly:

- Regulation National Market System (Reg NMS): implemented by the SEC, Reg NMS aims to modernize and strengthen the U.S. equity markets by ensuring fair and efficient access to market data and execution services. It addresses issues related to HFT and seeks to prevent market fragmentation [131].

- EU Markets in Financial Instruments Regulation (MiFIR): MiFIR complements MiFID II by establishing a comprehensive framework for the regulation of trading venues, including those employing HFT strategies. It requires trading venues to implement systems and controls to prevent market abuse and ensure fair and orderly trading [132, p.1].

- Dodd-Frank Act Provisions on HFT: the Dodd-Frank Act includes provisions aimed at increasing transparency and oversight of HFT activities. It mandates the registration of HFT firms and requires them to maintain detailed records of their trading activities [133].

2) Blockchain and Distributed Ledger Technology. Blockchain and DLT have the potential to transform financial markets by enhancing transparency, reducing settlement times, and lowering transaction costs [90]. Key regulatory initiatives related to blockchain and DLT include:

- European Blockchain Partnership (EBP): the EBP is an initiative of the European Commission to develop a pan-European blockchain infrastructure. It aims to promote the adoption of blockchain technology across various sectors, including finance, by ensuring interoperability and regulatory compliance [134].

- SEC's FinHub: The SEC established the Strategic Hub for Innovation and Financial Technology (FinHub) to facilitate engagement with market participants on emerging technologies such as blockchain and DLT. FinHub provides guidance on regulatory issues and promotes innovation in financial markets [135].

- Financial Conduct Authority's Regulatory Sandbox: the FCA's Regulatory Sandbox allows fintech firms to test innovative products and services in a controlled environment. It includes blockchain-based solutions, enabling firms to assess the regulatory implications and operational feasibility of their technologies [136].

3) AI Technologies in Financial Trading. Artificial Intelligence has revolutionized the landscape of financial trading by introducing advanced algorithms, machine learning models, and big data analytics. These technologies enable faster and more accurate decision-making, predictive analytics, and automated trading systems. The integration of AI in financial trading has led to significant improvements in market efficiency, risk

management, and trading strategies. However, the rise of AI also brings new regulatory challenges and legal considerations to ensure fair and transparent markets [90]. The main AI technology applications in financial trading are:

- Algorithmic Trading. Algorithmic trading involves the use of computer algorithms to execute trades based on predefined criteria. These algorithms can analyse vast amounts of data at high speeds, enabling traders to capitalize on market opportunities in milliseconds. Algorithmic trading strategies include arbitrage, trend following, and market making. The use of AI in algorithmic trading enhances the ability to identify patterns and optimize trading strategies in real-time [137, p.20-30].

- Machine Learning and Predictive Analytics. Machine learning models are used to analyse historical market data and predict future price movements. These models can identify complex patterns and correlations that are not apparent to human analysts. Predictive analytics helps traders develop strategies based on anticipated market trends and improve the accuracy of their forecasts. Machine learning algorithms can also adapt to changing market conditions, providing a dynamic approach to trading [138, p.25-40].

- Natural Language Processing (NLP). NLP technologies enable the analysis of unstructured data such as news articles, social media posts, and financial reports. By processing and understanding the sentiment and context of this information, NLP can provide insights into market sentiment and potential market-moving events. Traders use NLP to enhance their decision-making process and gain a competitive edge in the market [139].

- Robotic Process Automation (RPA). RPA involves the use of software robots to automate repetitive and rule-based tasks in trading operations. This includes order execution, trade settlement, and compliance reporting. RPA improves operational efficiency, reduces human error, and allows traders to focus on more strategic activities. The automation of back-office processes also enhances the overall efficiency of financial institutions [140].

- Big Data Analytics. Big data analytics involves the processing and analysis of large datasets to extract valuable insights. In financial trading, big data analytics is used to analyse market data, transaction records, and customer behaviour. This information helps traders make informed decisions, identify market trends, and manage risks more effectively [141]. The ability to analyse vast amounts of data in real-time is a significant advantage in the fast-paced trading environment [142].

Besides these main AI technology applications in financial trading, there are also some related regulations and legal provisions that regulate these financial trading AI technologies. They are:

1. The first is the regulation of algorithmic and High-Frequency trading. The rise of algorithmic and HFT has prompted regulators to implement measures to ensure market stability and prevent market abuse. Key regulations include:

- MiFID II and MiFIR: the MiFID II and the MiFIR require trading venues to implement systems and controls to manage the risks associated with algorithmic trading. These regulations mandate the registration of algorithmic trading firms and impose requirements for testing and monitoring algorithms to prevent market abuse [132].

- Reg NMS: in the United States, Reg NMS aims to modernize and strengthen equity markets by ensuring fair and efficient access to market data and execution services. It addresses issues related to algorithmic trading and seeks to prevent market fragmentation [131].

- Dodd-Frank Act Provisions: the Dodd-Frank Act includes provisions aimed at increasing transparency and oversight of HFT activities. It mandates the registration of HFT firms and requires them to maintain detailed records of their trading activities [133].

2. The second is the data privacy and protection. The use of AI and big data analytics in financial trading involves the processing of vast amounts of personal and financial data. Ensuring data privacy and protection is crucial to maintaining investor trust and compliance with legal requirements. Key regulations include:

- General Data Protection Regulation (GDPR): the GDPR sets out the legal framework for data protection and privacy in the European Union. It imposes strict requirements on the processing, storage, and transfer of personal data. Financial institutions using AI technologies must ensure compliance with GDPR to protect the privacy of their clients [143].

- California Consumer Privacy Act (CCPA): the CCPA is a data privacy law in the United States that provides California residents with the right to know what personal data is being collected, the purpose of collection, and the ability to access, delete, and opt-out of the sale of their data. Financial institutions must comply with CCPA when using AI technologies that process personal data [144].

3. The third is the fairness and transparency in AI algorithms. Ensuring fairness and transparency in AI algorithms is essential to prevent discrimination and maintain market integrity. Regulators have introduced guidelines to promote ethical AI practices:

- OECD Principles on AI: the Organization for Economic Co-operation and Development (OECD) has developed principles to promote the responsible development and use of AI. These principles emphasize transparency, accountability, and fairness in AI systems. Financial institutions using AI technologies should adhere to these principles to ensure ethical practices [145].

- Ethics Guidelines for Trustworthy AI: the European Commission's High-Level Expert Group on AI has published guidelines for trustworthy AI. These guidelines outline key requirements for AI systems, including transparency, accountability, and non-discrimination. Financial institutions should incorporate these guidelines into their AI development and deployment processes [146].

4. And the fourth is cybersecurity regulations. The increasing reliance on AI and digital technologies in financial trading heightens the importance of robust cybersecurity measures. Key regulations include:

- National Institute of Standards and Technology (NIST) Cybersecurity Framework: the NIST Cybersecurity Framework provides guidelines for managing cybersecurity risks. It emphasizes the importance of identifying, protecting, detecting, responding to, and recovering from cybersecurity incidents. Financial institutions using AI technologies must implement robust cybersecurity measures to protect against cyber threats [147].

- Financial Services Sector Cybersecurity Regulations: various jurisdictions have introduced specific cybersecurity regulations for the financial services sector. For example, the New York Department of Financial Services (NYDFS) Cybersecurity

Regulation requires financial institutions to implement comprehensive cybersecurity programs to protect customer data and ensure the integrity of their systems [148].

Table 2.2 shows the impact of main regulatory frameworks on financial trading under globalization after 2010.

Table 2.2

Impact of regulatory frameworks on financial trading (Post-2010)

Regulatory framework	**Region**	**Year of implementation**	**Key focus**	**Impact on financial trading**
Reg NMS	USA	2020	Equity Market Modernization	Improved market efficiency, mitigated fragmentation risks.
MiFIR	EU	2020	Regulation of Trading Venues and HFT	Ensured fair and orderly trading, addressed HFT market abuse.
Dodd-Frank Act Provisions on HFT	USA	2010	Transparency and Oversight of HFT	Increased transparency, improved HFT activity monitoring.
GDPR	EU	2016	Data Protection and Privacy	Protected personal data, enhanced investor trust.
Basel III Framework	Global	2017	Banking Regulation and Risk Management	Strengthened bank resilience, improved transparency.

Source: author’s own generalisation based on [90; 111; 131; 132; 133; 143]

To summarise, table 2.3 shows the characteristics of the institutional and legal provision of financial trading in the six stages from the emergence of financial trading to the present.

At the same time, current globalization has significantly transformed financial trading by increasing the interconnectivity of global markets, facilitating cross-border capital flows, and fostering the development of complex financial instruments. The multifaceted impact of globalization on financial trading, concentrates on international actions, the development of AI technologies, and ESG considerations [149].

The aspects of international actions are mainly reflected in regulatory harmonization cooperation, trade agreements and economic integration. Globalization has necessitated greater regulatory harmonization and cooperation among countries to ensure stable and efficient financial markets [149]. Key international actions include:

Table 2.3

Comparative summary of the institutional and legal provisions of financial trading across the main historical periods of its development

Period	Key Features	Major Developments	Impacts on Financial Trading
I. Early financial markets (17th – 19th century)	Establishment of stock exchanges	Amsterdam Stock Exchange, Buttonwood Agreement	Formalized trading practices, early market regulation
II. Industrial revolution (19th – early 20th century)	Rise of investment banks, new financial instruments	Corporate bonds, preferred stocks, Federal Reserve	Increased capital for industrial projects, formalized regulations
III. Post-War financial expansion (1945–1970s)	Economic growth, technological advancements	Bretton Woods Conference, Marshall Plan	Stabilized international trade, growth in global markets
IV. Deregulation and financial liberalization (1980s–1990s)	Market deregulation, rise of electronic trading	Financial Services Act, introduction of Globex	Increased market liquidity, introduction of complex derivatives
V. Global financial crisis (2007–2010)	Financial instability, regulatory reforms	Dodd-Frank Act, Basel III framework	Enhanced market stability, increased regulatory oversight
VI. The period after 2010 till nowadays	Significant advancements in trading technologies	MiFID II, MiFIR, Dodd-Frank Act	Limits the adverse impact of trading technology development on the market

Source: author's own generalisation based on [90; 91; 92; 95; 98; 99; 102; 103; 106; 107; 108; 109; 111; 112; 124]

- Basel III Framework: the Basel Committee on Banking Supervision (BCBS) introduced Basel III to strengthen regulation, supervision, and risk management within the banking sector. Basel III aims to improve the banking sector's ability to absorb shocks arising from financial and economic stress, improve risk management and governance, and enhance banks' transparency and disclosures [111].
- International Financial Reporting Standards (IFRS): the IFRS, developed by the International Accounting Standards Board (IASB), provide a common global language for business affairs so that company accounts are understandable and comparable across international boundaries. Adoption of IFRS promotes transparency and efficiency in financial markets globally [150].

The following trade agreements and economic integration have facilitated the growth of cross-border financial activities:

- North American Free Trade Agreement (NAFTA): NAFTA, and its successor, the United States-Mexico-Canada Agreement (USMCA), have promoted trade and investment between the USA, Canada, and Mexico by reducing tariffs and other trade barriers. These agreements have also enhanced the financial linkages and investment flows among the member countries [151].
- European Union (EU) Single Market: the EU Single Market allows for the free movement of goods, capital, services, and people within the EU. This integration has created a larger, more efficient financial market, enabling easier access to capital and investment opportunities across member states [152].

The aspects of AI technology development are mainly reflected in enhanced trading strategies and risk management [149]. The development of AI technologies has revolutionized trading strategies by providing advanced tools for data analysis and decision-making. On the one hand, Machine learning models can analyse vast amounts of historical and real-time data to identify patterns and predict market movements. These algorithms enhance trading strategies by providing insights that are beyond human capabilities, thus improving the accuracy of predictions and trading decisions [138]. On the other hand, AI-powered sentiment analysis tools evaluate market sentiment by analysing news articles, social media posts, and other unstructured data. Traders use those insights to gauge market mood and make informed decisions about buying or selling securities [139; 149].

At the same time, AI technologies have improved risk management in financial trading by providing more accurate and timely risk assessments. Predictive analytics models assess potential risks by analysing historical data and identifying patterns that may indicate future market movements. These models help traders and financial institutions mitigate risks and make proactive decisions [142]. And AI algorithms detect fraudulent activities by analysing transaction data for anomalies and patterns indicative of fraud. This enhances the security of financial transactions and protects investors from potential losses [149; 153].

The last aspects of ESG considerations under globalization are mainly reflected in the incorporation of ESG criteria, ESG reporting, and disclosure [149]. Globalization has driven the adoption of ESG criteria in investment decisions as investors and institutions increasingly recognize the importance of sustainable and responsible investing:

- Environmental considerations: investors are factoring in environmental risks and opportunities, such as climate change, resource scarcity, and environmental regulations, into their investment decisions. This shift promotes the allocation of capital to environmentally sustainable projects and companies [154].

- Social considerations: social factors, including labour practices, human rights, and community relations, are becoming critical in investment analysis. Companies with strong social practices are often seen as less risky and more likely to generate long-term value [155].

- Governance considerations: good governance practices, such as board diversity, executive compensation, and shareholder rights, are essential for sustainable business operations. Investors are increasingly scrutinizing governance structures to ensure accountability and transparency [156].

The growing importance of ESG considerations has led to enhanced reporting and disclosure requirements:

- Global Reporting Initiative (GRI): the GRI provides a comprehensive framework for sustainability reporting, enabling companies to measure and communicate their ESG performance. This transparency helps investors make informed decisions based on ESG criteria [157, p.2-3].

- Task Force on Climate-related Financial Disclosures (TCFD): the TCFD offers recommendations for climate-related financial disclosures, helping companies provide clear, comparable, and consistent information about climate-related risks and opportunities [158, p.1-2].

With the rise of ESG considerations around the world, the concept of sustainable investment is becoming increasingly important. Sustainable investment, from a scientific and financial perspective, is an evolving approach focused on integrating ESG factors into investment strategies. This practice aims to not only generate financial returns but also contribute to long-term societal and environmental goals. According to the Principles for Positive Impact Finance, sustainable investment is essential in bridging the $5-7 trillion annual funding gap to achieve the United Nations' Sustainable Development Goals (SDGs) by 2030. This involves a holistic appraisal of sustainability, where positive impacts on the economy, society, and the environment are maximized, and potential negative impacts are minimized through rigorous frameworks, transparency, and assessment mechanisms. Similarly, the Principles for Responsible Investment emphasize the necessity for a sustainable financial system that fosters long-term value creation while addressing global challenges like climate change and inequality. Responsible investors are encouraged to actively incorporate ESG issues into decision-making processes, ownership practices, and to collaborate for systemic changes in market practices. In essence, sustainable investment is not just a financial strategy but a scientific and social responsibility to foster inclusive, resilient economies [159; 160]. At the same time, the Sustainable Stock Exchanges (SSE) Initiative is now a critical United Nations platform promoting peer learning and collaboration among stock exchanges, investors, regulators, and companies. Its primary focus is enhancing corporate transparency and performance on ESG issues, which is crucial for fostering sustainable investments. The SSE Initiative plays a pivotal role in aligning stock exchange activities with the SDGs, particularly in areas like climate action, green finance, and ESG disclosures. It is recognized globally for driving sustainability in capital markets [161].

Financial trading in Ukraine has also evolved considerably over the past three decades, transitioning from a centrally planned economy to an open market system integrated into the global financial market. This transformation necessitated the development of a robust institutional and legal framework to ensure the stability of financial markets, protect investors, and facilitate the efficient allocation of capital [162]. Ukraine's financial sector reforms, particularly after 2014, have been driven by the need to align with international standards and enhance market transparency, they are mainly institutional frameworks:

- National Securities and Stock Market Commission (NSSMC): the NSSMC regulates Ukraine's capital markets, including the issuance and trading of securities, the activities of stock exchanges, and the protection of investors' rights. The NSSMC is responsible for developing and enforcing regulations that govern the securities market, aiming to align Ukraine's practices with those of the EU [163, p.1-2].

- National Bank of Ukraine (NBU): the NBU plays a central role in regulating Ukraine's banking and non-banking financial services markets, overseeing monetary policy, and ensuring financial stability. It regulates the banking sector, manages the country's currency, and implements monetary policy. Since 2015, the NBU has implemented a flexible exchange rate regime and inflation targeting, which has helped stabilize the economy [164, p.1-2].

- Anti-Monopoly Committee of Ukraine (AMCU): the AMCU ensures fair competition within the financial markets, preventing monopolistic practices and promoting transparency. It plays a critical role in overseeing mergers and acquisitions, especially those involving large financial institutions, to prevent market concentration and ensure a competitive environment [165, p.1-2].

- State Financial Monitoring Service (SFMS): the SFMS is the primary body responsible for combating money laundering and terrorist financing in Ukraine. It operates under the Financial Action Task Force (FATF) recommendations and works closely with international partners to enhance the integrity of Ukraine's financial system [166, p.1].

- Deposit Guarantee Fund (DGF): the DGF ensures the protection of depositors' funds in the event of bank insolvency. It plays a vital role in maintaining public confidence in the banking system, especially during periods of economic instability [167, p.1].

And also, the legal provisions of financial trading in Ukraine include:

- Law on Capital Markets and Organized Commodity Markets: enacted in 2020, this law represents a significant overhaul of Ukraine's financial market regulations, aligning them more closely with EU directives, particularly MiFID II. The law introduces comprehensive rules for the operation of capital markets, including the regulation of investment firms, trading venues, and market participants. It also sets out clear guidelines for the issuance and trading of securities, derivatives, and other financial instruments [168].

- Law on Prevention and Counteraction to Legalization (Laundering) of the Proceeds from Crime: this law, amended in 2020, strengthens Ukraine's anti-money laundering framework by incorporating the latest FATF recommendations. It imposes stringent due diligence requirements on financial institutions and introduces measures to prevent the financing of terrorism. The law also enhances cooperation with international financial intelligence units, facilitating the exchange of information on suspicious transactions [169].
- Law on the National Bank of Ukraine: the law defines the NBU's mandate, including its independence, objectives, and functions. It is pivotal in ensuring the central bank's autonomy, allowing it to implement effective monetary policy and oversee financial stability without political interference [170].
- Law on Joint Stock Companies: the law regulates the formation, operation, and dissolution of joint-stock companies in Ukraine. It sets out the rights and obligations of shareholders, the procedures for holding general meetings, and the requirements for financial reporting and disclosure. This law is crucial for the governance of companies listed on Ukrainian stock exchanges, ensuring transparency and protecting minority shareholders [171].

On the other hand, Ukraine's integration into the global financial system has been facilitated by its association with the European Union and adherence to international financial standards. The EU-Ukraine Association Agreement, which includes a Deep and Comprehensive Free Trade Area (DCFTA), has been a key driver of regulatory convergence between Ukraine and the EU. Under this agreement, Ukraine has committed to aligning its financial regulations with EU directives, particularly in areas such as securities regulation, AML/CFT, and corporate governance [172, p.1].

The IMF and World Bank have also played significant roles in supporting Ukraine's financial sector reforms. The IMF's Extended Fund Facility (EFF) program, launched in 2015, has provided Ukraine with financial assistance to stabilize its economy and implement structural reforms. These reforms have included measures to strengthen the independence of the NBU, improve the regulatory framework for financial institutions, and enhance the transparency of public finances [173; 174].

Ukraine's institutional and legal framework for financial trading has undergone significant transformation in recent years, driven by the need to align with international standards and integrate into the global financial system. The development of robust regulatory institutions and the implementation of comprehensive legal provisions have played a crucial role in enhancing market stability, protecting investors, and fostering economic growth. Despite the progress made in recent years, Ukraine's financial trading sector faces several challenges. These include the need to further strengthen the legal framework to address issues such as insider trading, market manipulation, and the enforcement of shareholders' rights. Additionally, the ongoing conflict in Eastern Ukraine and the geopolitical tensions with Russia pose significant risks to the stability of the financial markets. Looking forward, Ukraine's financial trading sector is poised for further growth, supported by continued regulatory alignment with EU standards, increased foreign investment, and the development of new financial instruments. The adoption of digital technologies, such as blockchain and artificial intelligence, could also enhance the efficiency and transparency of financial markets, providing new opportunities for market participants. As Ukraine continues to face challenges, including geopolitical risks and the need for further legal reforms, Ukraine's financial trading sector remains on a path of positive development, with promising prospects for the future.

The evolution of financial trading under the influence of globalization has been profound, marked by significant advancements and challenges. This study has examined the institutional and legal frameworks, historical milestones, technological innovations, and the multifaceted impact of globalization on financial trading.

In conclusion, the integration of global markets has led to unprecedented levels of market efficiency, diversified investment opportunities, and enhanced access to capital. However, it has also introduced complexities such as regulatory divergence, increased market volatility, and systemic risks. The role of robust institutional and legal frameworks remains critical in ensuring market stability, protecting investors, and promoting fair trading practices. The historical context highlights the cyclical nature of financial crises and the subsequent regulatory responses aimed at safeguarding the financial system.

The advancements in AI and other technologies have transformed trading strategies, risk management, and operational efficiency, offering significant benefits but also posing new regulatory and ethical challenges. As financial markets continue to evolve, the importance of balancing innovation with effective oversight cannot be overstated. The development of regulatory frameworks that can adapt to the rapid pace of technological change is essential. Looking ahead, several research areas warrant further attention:

- Regulatory harmonization: enhanced international cooperation and harmonization of regulatory standards will be crucial in managing the complexities of global financial trading. Efforts to align regulations can help mitigate systemic risks and promote stability.

- Sustainable and responsible investing: the increasing focus on ESG criteria reflects a broader shift towards sustainable and responsible investing. Developing comprehensive frameworks for ESG reporting and disclosure will support this trend and enable investors to make informed decisions.

- Technological integration and cybersecurity: the continued integration of AI, blockchain, and other emerging technologies will drive further innovation in financial trading. Concurrently, robust cybersecurity measures will be essential to protect market integrity and investor data.

- Market inclusivity and access: expanding market access and inclusivity, particularly in emerging markets, can foster greater global economic integration and provide new opportunities for investment and growth.

- Adaptive regulatory frameworks: regulators must remain agile, developing frameworks that can adapt to technological advancements and evolving market conditions. This includes proactive measures to address potential risks associated with new financial instruments and trading strategies.

In essence, the future of financial trading under globalization will be shaped by the interplay between innovation, regulation, and market dynamics. A concerted effort from regulators, market participants, and other stakeholders will be required to navigate this complex landscape, ensuring that the benefits of globalization are realized while mitigating.

2.2. Tendencies of global financial trading

Global financial markets form a complex, interconnected system that mirrors the economic conditions of regions across the world. The interactions between North American, European, Asian, and emerging markets generate a constantly evolving environment in which capital flows, investor sentiment, and geopolitical developments continuously reshape trading behaviour and financial outcomes. Building on the foundations of technological transformation and evolving regulatory responses discussed in the previous study, this section examines how globalization has further intensified market interdependence, influenced cross-border investment behaviour, and contributed to the convergence of trading practices. A detailed analysis of financial market performance through the end of 2024 is presented, focusing on indicators such as market capitalization, trading volumes, international capital mobility, and volatility patterns. Comparative data and visualizations are used in order to highlight regional dynamics and reveal broader structural trends in global financial trading. The main regional financial markets globally are the U.S., European and Asian markets.

The first main financial market all over the world is the North American financial markets, led by the United States, which have remained dominant in the global arena. The NYSE and Nasdaq continue to be the largest stock exchanges by market capitalization globally, with the U.S. dollar maintaining its status as the world's primary reserve currency [175; 176]. Table 2.4 shows the main characteristics of the U.S. financial markets including different financial market segments and their global impacts.

Table 2.4

Main characteristics of the U.S. financial markets

Financial market segment	Market overview	Drivers and trends	Notable players/institutions	Global impact
1	2	3	4	5
Equity markets	U.S. stock markets are led by the NYSE and Nasdaq, driven by corporate earnings, economic indicators, and monetary policy	Surge in retail trading due to trading apps (e.g., Robinhood); digital platforms continue to drive trading growth	NYSE, Nasdaq, Robinhood, Apple, Microsoft, Tesla	The U.S. equity market remains the largest globally, influencing global capital allocation and investment trends
Bond markets	The largest and most liquid bond market in the world, including government, corporate, and municipal bonds.	Federal Reserve's monetary policy (rate changes, quantitative tightening) influences yields; continued rise in green bonds	U.S. Treasury, Federal Reserve, green bonds issuers	Treasury bonds remain a global safe haven, shaping interest rates and investment strategies worldwide
Derivatives markets	Extensive use of futures, options, and swaps for hedging and speculation. Regulatory oversight remains high post-Dodd-Frank Act	Record volumes in interest rate derivatives; continued growth in automated trading platforms	CME Group, Dodd-Frank regulators, institutional investors	U.S. derivatives markets are critical for global risk management and pricing in commodities, interest rates, and currencies
Foreign exchange markets (FX)	The U.S. dollar (USD) dominates global FX trading, serving as the primary reserve currency	USD strength impacted global trade, investment flows, and commodities in 2024	USD, Federal Reserve, European Central Bank, Bank of Japan	The USD's reserve status shapes trade balances, global liquidity, and currency valuations

Source: author's own generalisation based on [177; 178; 179; 180; 181; 182; 183]

The table 2.4 provides a comprehensive analysis of the U.S. financial markets, highlighting their core segments, equities, bonds, derivatives, and foreign exchange and their global influence as of 2024. In the equity markets, the USA continues to dominate, led by the NYSE and Nasdaq, driven by strong corporate earnings, economic indicators, and Federal Reserve policy. The rise of retail trading platforms like Robinhood and the growth of tech giants such as Apple, Microsoft, and Tesla have played a major role in boosting market capitalization beyond $45 trillion [177].

The bond market, anchored by USA Treasuries, remains the world's largest and most liquid. Yields were shaped by continued Federal Reserve tightening, with the 10-year yield hovering around 4.1% by the end of 2024 [179]. Green bond issuance also gained momentum, reflecting the rise of sustainable finance. In the derivatives market, the CME Group led record-breaking volumes, especially in interest rate futures and options, amid policy uncertainty and rising automation in trading [180].

In the FX market, the U.S. dollar retained its role as the dominant reserve and transaction currency. Fluctuations in its value significantly impacted global trade and capital flows, with central bank policies playing a key role in 2024's currency dynamics. Overall, the table illustrates how the U.S. financial markets continue to set the tone globally, shaping investment flows, risk management, and benchmark pricing across all asset classes.

North America's financial markets, beyond the USA, are led by Canada and Mexico, both of which contribute significantly to regional liquidity and financial diversity through advanced infrastructure and active capital markets. Canada's Toronto Stock Exchange (TSX) is heavily weighted toward resource-based firms, while Mexico's BMV supports equities trading in Latin America's second-largest economy. Bond markets in both countries attract foreign investment, with Canada known for its stable government and corporate bonds, and Mexico showing growth in sovereign debt. The Canadian dollar (CAD) and Mexican peso (MXN) are actively traded currencies, strongly influenced by commodity prices and trade relations, particularly under the USMCA agreement. Canada exports key resources like oil and minerals, while Mexico is a major silver and oil producer. Both nations are also developing derivatives markets – Canada through the Montreal Exchange and Mexico through expanding hedging instruments for currency and interest rate risks.

The second main financial market around the world is the European financial markets. Europe's financial markets are diverse, with key financial centres in London, Frankfurt, Paris, and Zurich. The EU and the Eurozone significantly influence the region's financial dynamics. The European financial landscape has been shaped by a series of regulatory reforms aimed at promoting financial stability and market integration. The European Securities and Markets Authority play a crucial role in overseeing the functioning of Europe's financial markets. Table 2.5 below shows the main characteristics of the main European financial markets including different financial market segments and their global impacts.

The table 2.5 on the European financial markets provides a structured overview of the region's four major market segments, stock markets, bond markets, foreign exchange markets, and derivatives markets, highlighting their current structure, key trends, influential institutions, and global relevance as of 2024.

In stock markets, major financial centres such as London, Frankfurt, Paris, and Zurich anchor trading activities. Post-Brexit, there has been a shift in trading volume toward continental hubs like Amsterdam and Paris, with increasing market integration through exchanges like Euronext. The Euro Stoxx 50 remains the main benchmark for Eurozone blue-chip equities, and regulatory divergence between the UK and the EU is reshaping the landscape.

The bond markets are crucial for both sovereign and corporate financing. German Bunds are still considered the benchmark for safety and pricing within the Eurozone, while peripheral bonds from countries like Italy and Spain offer higher yields. The ECB plays a key role in managing yields through monetary policy, especially with recent rate hikes aimed at addressing inflation. Green bonds have seen rapid growth, supporting Europe's leadership in sustainable finance.

In the FX markets, the euro is the second most traded currency globally, influenced heavily by ECB policy and Eurozone macroeconomic performance. The British pound (GBP) and Swiss franc (CHF) also play critical roles, with the GBP affected by UK-EU economic relations post-Brexit and the CHF acting as a stable safe-haven currency backed by Switzerland's independent monetary policy.

Table 2.5

Key characteristics of the main European financial markets

Financial market segment	**Market overview**	**Drivers and trends**	**Notable players/institutions**	**Global impact**
Stock markets	Diverse equity markets with major centres in London, Frankfurt, Paris, and Zurich. The Euro Stoxx 50 index tracks leading Eurozone companies	Regulatory divergence post-Brexit; integration of exchanges; Amsterdam and Paris growing in volume	LSE, Deutsche Börse, Euronext, Euro Stoxx 50, Paris Bourse	Brexit reshaped European finance, redistributing trading across the EU. Interconnected markets influence global capital flows
Bond markets	Critical for sovereign and corporate financing. German Bunds are the safest, while peripheral bonds offer higher yields	ECB policy remains the key driver; green bonds grow rapidly; interest rates increased in response to inflation	ECB, German Bunds, EIB, green bond issuers, UK Gilts	Bond markets attract global investors via stability (Bunds), yield (periphery), and sustainability (green bonds)
FX markets	The euro (EUR) is the second most traded currency globally; GBP and CHF are also significant	EUR driven by ECB policy and growth; GBP impacted by post-Brexit trade; CHF remains a haven	ECB, Bank of England, SNB, FX platforms	EUR remains critical to global trade; GBP and CHF also affect commodity and capital markets
Derivatives markets	Eurex and Euronext lead in product variety and volume; UK remains central despite Brexit	Shifts in clearing from London to EU; MiFID II drives transparency; automation rises	Eurex, Euronext, MiFID II, UK FCA	Europe's derivatives markets support global hedging strategies; UK maintains relevance post-Brexit

Source: author's own generalisation based on [184; 185; 186; 187; 188; 189; 190; 191; 192; 193]

The derivatives markets are highly developed, with exchanges like Eurex and Euronext offering a wide array of products. While Brexit caused some clearing and trading operations to move from London to EU-based venues, London remains a dominant force, especially in OTC derivatives. Regulatory frameworks like MiFID II continue to enhance transparency, investor protection, and risk oversight across these markets.

Overall, it shows the strategic importance of Europe's financial system, the ongoing effects of Brexit, the role of regulatory reforms, and how these factors collectively position Europe as a key player in shaping global financial dynamics.

Next, the third main financial market around the world is the Asian financial markets. Asian financial markets have grown rapidly over the past few decades, with key financial hubs in Tokyo, Hong Kong, Shanghai, and Singapore. These markets are diverse, reflecting varying levels of development and regulatory environments. The region's rapid economic expansion, coupled with increasing integration into the global financial system, positioned Asia as a critical player in global finance [194; 195]. Table 2.6 below shows the main characteristics of the main Asian financial markets in details of different financial market segments and their global impacts.

The table 2.6 provides a comprehensive overview of the main characteristics of Asia's financial markets across four critical segments: stock markets, bond markets, foreign exchange, and derivatives. It highlights Asia's growing role in global finance, driven by expanding capital markets, regional integration efforts, and increasing foreign participation.

In stock markets, major financial hubs such as Tokyo, Hong Kong, Shanghai, and Singapore anchor trading activity, with a rising presence from India's BSE and NSE. The region's equity markets are increasingly shaped by the technology and Internet sectors, particularly in China and India, and by initiatives like Stock Connect, which facilitate cross-border investments between mainland China and Hong Kong. These developments have positioned Asian stock exchanges as pivotal players in global capital flows, especially in tech IPOs and multinational listings.

Asia's bond markets, particularly in Japan and China, are essential for regional financing and attract substantial global investor interest. Programs such as Bond Connect in China and the Asian Bond Markets Initiative (ABMI) have enhanced accessibility and integration. While Japanese Government Bonds (JGBs) are known for their low yields and safety, Chinese and Indian bond markets offer higher returns and growth potential. The region is also seeing strong momentum in green bond issuance, supporting sustainable development and climate-related infrastructure financing.

Table 2.6

Main characteristics of the Asian financial markets

Financial market segment	Market overview	Drivers and trends	Notable players/institutions	Global impact
Stock markets	Major hubs include Tokyo, Hong Kong, Shanghai, and Singapore; rising prominence in India	Tech and internet firms drive market growth; Stock Connect boosts cross-border trading	TSE, HKEX, SSE, BSE, NSE	Asian markets significantly shape global capital flows, especially via tech IPOs and regional integration
Bond markets	Key financing sources, led by Japan and China; foreign access increasing	Bond Connect, low rates, and the ABMI promote market development; green bond growth accelerates	JGBs, China Bond Connect, ABMI, RBI	Asian bond markets provide attractive yields and diversification, drawing international investment
FX markets	JPY, CNY, and INR are vital to global FX trades	China's managed float and CNY internationalization are strategic; Asia-wide currency management supports macro stability	CNY, JPY, INR, SGD, KRW, RBI	Asia's currencies affect trade and investment globally, with CNY's role expanding via IMF SDR inclusion
Derivatives markets	Fast-growing, led by JPX, HKFE, SGX, KRX	Regulatory reforms increase transparency; derivatives support hedging/speculation in commodities and indices	JPX, HKFE, SGX, KRX	Asian derivatives increasingly shape global trading trends, especially in energy and equity-linked products

Source: author's own creation based on [194; 195; 196; 197; 198; 199; 200; 201]

In the FX markets, key Asian currencies, Japanese yen (JPY), Chinese yuan (CNY), Indian rupee (INR), Singapore dollar (SGD), and Korean won (KRW), play significant roles in global currency trade. China's managed float regime and the gradual internationalization of the yuan continue to shape regional FX dynamics. The CNY's inclusion in the IMF's SDR basket underscores its growing prominence, while other currencies remain critical to trade and investment strategies across Asia and beyond.

The derivatives markets in Asia are expanding rapidly, driven by increased use for both hedging and speculative purposes. Major exchanges like the Japan Exchange Group (JPX), Hong Kong Futures Exchange (HKFE), Singapore Exchange (SGX), and Korea Exchange (KRX) are enhancing their offerings across equities, interest rates, and commodities. Regulatory reforms in China and India are also contributing to improved transparency and investor confidence, positioning Asian derivatives markets as influential players in global risk management.

Besides, the cryptocurrency markets have also emerged as a significant player in the global financial system, characterized by its decentralized nature, high volatility, and rapid innovation [202]. Since the launch of Bitcoin in 2009, the market has expanded to include thousands of cryptocurrencies, with a total market capitalization exceeding $1.7 trillion as of late 2024 [203; 204]. By the end of 2024, Bitcoin's market capitalization hovered around $850 billion, while Ethereum's market capitalization was approximately $280 billion. Daily trading volumes for Bitcoin often exceeded $30 billion, reflecting the market's liquidity and the high level of investor interest. The rise of digital assets such as Bitcoin (BTC), Ethereum (ETH), and stablecoins like Tether (USDT) has led to the development of a parallel financial system [205; 206] that operates largely outside traditional regulatory frameworks.

The growth of cryptocurrencies is fuelled by demand for decentralized finance, blockchain innovations, and increasing institutional interest, particularly as a hedge against inflation and economic uncertainty. Operating 24/7, cryptocurrency markets differ from traditional finance in their decentralized, lightly regulated structure and global exchange ecosystem (e.g., Binance, Coinbase, Kraken). While major cryptocurrencies like Bitcoin and Ethereum enjoy high liquidity, smaller assets face wider spreads and volatility due to limited trading volume. Price discovery occurs across fragmented exchanges, often resulting in discrepancies mitigated by arbitrage, though the absence of centralized pricing still presents efficiency challenges.

The global nature of cryptocurrencies presents significant challenges for regulators. Cryptocurrencies operate across borders, often circumventing traditional financial systems and regulations. This has led to a patchwork of regulatory approaches worldwide, ranging from outright bans to full legalization and integration into existing financial systems. The main regulatory approaches in major economies are:

- the USA: the USA maintained a fragmented regulatory approach in 2024, with agencies such as the SEC, Commodity Futures Trading Commission (CFTC), and the IRS playing overlapping roles. The SEC intensified enforcement, classifying several tokens as securities and targeting unregistered offerings and platforms.

- the European Union: the Markets in Crypto-Assets (MiCA) regulation officially came into effect in 2024, creating a unified legal framework for crypto across the EU. MiCA aims to ensure consumer protection, operational clarity for businesses, and broader market stability.

- Asia: regulatory strategies in Asia remained mixed. China sustained its bans on trading and mining, while Japan strengthened its crypto laws to enhance transparency and consumer protection. Singapore introduced clearer licensing requirements and stablecoin regulation to maintain its role as a crypto-friendly hub.

However, the absence of a unified global regulatory framework poses significant challenges to the integration of cryptocurrency markets worldwide. Divergent regulatory environments not only create arbitrage opportunities but also heighten risks associated with compliance, fraud, and market manipulation.

At the same time, stablecoins - cryptocurrencies pegged to fiat values - have gained prominence for facilitating transactions with reduced volatility. USDT and USD Coin (USDC) remain dominant, serving as on-ramps to the crypto economy. Regulatory attention to stablecoin reserves and disclosures intensified in 2024, as concerns about de-pegging and systemic impact grew.

Central Bank Digital Currencies (CBDCs) also advanced rapidly. These digital versions of sovereign currency, issued by central banks, aim to merge digital efficiency with national control. China's Digital Yuan expanded trials to more regions and international pilots. Sweden's e-Krona entered public testing, and nations like India, Brazil, and the UK unveiled frameworks for CBDC rollouts in the coming years. These developments are expected to reshape retail payments, financial inclusion, and the relationship between public and private digital money [207; 208].

The introduction of CBDCs could reduce reliance on private stablecoins while promoting the integration of digital currencies into the traditional financial system, especially for cross-border settlements.

The global adoption of cryptocurrencies accelerated in 2024, with growing interest from both retail and institutional investors. Major financial players, including BlackRock, Fidelity, Visa, and PayPal, continued to develop crypto-related products and services. Companies such as Tesla and MicroStrategy maintained significant Bitcoin holdings, reinforcing confidence in crypto as a long-term store of value.

Institutional integration is also reflected in the creation of Bitcoin ETFs, crypto futures, and other derivatives. The USA SEC's approval of additional spot and futures Bitcoin ETFs in 2024 marked a new milestone [209], expanding access to regulated crypto investment vehicles and encouraging further institutional involvement.

The discussion now turns to Ukraine's financial markets. Ukraine's financial markets have undergone a significant transformation in the context of globalization, marked by increased integration with global financial systems and the adoption of international standards.

The Ukrainian stock market has seen substantial growth, with the Ukrainian Exchange (UX) and the PFTS Stock Exchange serving as primary platforms for equity trading. The UX, established in 2008, offers a range of financial instruments, including equities and derivatives, and has implemented advanced trading technologies to enhance market efficiency. The PFTS Stock Exchange, operating since 1997, has also contributed to the development of Ukraine's securities market by providing a platform for trading government and corporate bonds. Both exchanges have played pivotal roles in attracting domestic and foreign investment, reflecting Ukraine's commitment to integrating with global financial markets.

Ukraine's bond market features a variety of instruments, including government securities and corporate bonds. The government regularly issues domestic and international bonds to finance budgetary needs, with maturities ranging from short to long term. Corporate bonds, though being less prevalent, are utilized by Ukrainian companies in order to raise capital. Efforts have been made to improve the transparency and reliability of the bond market, aligning with international best practices to attract a broader investor base.

The Ukrainian hryvnia (UAH) operates under a managed float exchange rate system, with the National Bank of Ukraine (NBU) intervening to stabilize the currency as needed. The NBU's policies aim to balance exchange rate stability with inflation targeting, considering the significant impact of foreign exchange dynamics on the economy. The central bank's interventions and regulatory measures are designed to mitigate excessive volatility and maintain economic stability.

Ukraine is a major player in global commodity markets, particularly in agriculture, where it ranks among the top exporters of wheat and corn. The country's fertile land and favourable climate conditions have positioned it as a key supplier in global food security. Additionally, Ukraine has significant reserves of natural resources, including iron ore and coal, contributing to its export economy. The nation's commodity markets are integral to its financial system, with prices influenced by both domestic factors and global market trends.

The development of Ukraine's derivatives market is ongoing, with the Ukrainian Exchange offering futures and options contracts. While the market is still in its nascent stages compared to more developed economies, there is a growing interest in using derivatives for hedging and speculative purposes. Regulatory frameworks are being strengthened to support market growth and ensure financial stability.

Overall, Ukraine's financial markets are evolving within the global financial landscape, striving to adopt international standards and practices. Ongoing reforms and technological advancements aim to enhance market efficiency, transparency, and integration, bolstering Ukraine's position in the global economy.

Ukraine's financial markets, particularly its trading ecosystem, are progressively adapting to the challenges and opportunities presented by globalization. The integration of international standards and the increasing role of technology in financial trading are pivotal in this transformation. Under the framework of Ukraine's Law on Financial

Services and Financial Companies and the Law on Capital Markets and Organized Commodity Markets, financial trading in Ukraine encompasses several core activities such as currency trading, securities trading (stocks and bonds), and derivatives, which are essential for market liquidity and growth. The National Securities and Stock Market Commission play a critical regulatory role, ensuring that the financial markets operate transparently and fairly in accordance with global best practices.

Globalization has allowed Ukraine's financial markets to connect with international capital markets, enhancing cross-border investments and trade. Ukrainian companies, particularly in sectors such as energy, agriculture, and technology, increasingly seek capital from foreign investors through Eurobond issuances and listings on international exchanges. This alignment has fostered deeper liquidity and diversified investor bases, helping Ukraine position itself as an emerging market with significant growth potential.

Moreover, the influence of international financial bodies such as the IMF, the World Bank, and the European Bank for Reconstruction and Development (EBRD) has been instrumental in guiding Ukraine's financial reforms, particularly in ensuring macroeconomic stability and implementing regulatory frameworks conducive to foreign investments. Ukraine's gradual adoption of global financial trading standards, such as the European Union's MiFID II, has helped harmonize its trading practices with those of the EU. This alignment promotes greater investor confidence, especially among European partners, by improving transparency and reducing market manipulations.

Similar to the global trends, financial trading in Ukraine is increasingly digitalized. The adoption of algorithmic trading, blockchain technology, and artificial intelligence in financial markets has brought higher efficiency, reduced transaction costs, and improved market access. Ukraine's exchanges and financial institutions have begun to utilize HFT and automated trading systems that allow trades to be executed in milliseconds, improving market liquidity and narrowing spreads. Blockchain technology, in particular, is gaining traction in Ukraine's financial sector, providing enhanced transparency in trading operations and enabling secure transactions without intermediaries.

Despite notable progress, Ukraine's financial market is still subject to several challenges and risks. One of the primary concerns is geopolitical instability, particularly in the context of the ongoing conflict with Russia. This has led to market volatility and capital outflows, with investors seeking safer, more stable markets. The reliance on foreign capital for market liquidity also exposes Ukraine to global financial fluctuations and external shocks. In times of international financial crises, the COVID-19 pandemic, Ukraine's financial markets have experienced significant disruptions, similar to other emerging markets, as global risk aversion rises and foreign investments decline.

Additionally, while Ukraine is aligning with international regulations, the country still faces issues with regulatory fragmentation and enforcement. Ensuring compliance by market participants with the stringent requirements of global financial standards, including anti-money laundering regulations and reporting obligations, continues to pose a significant challenge. Strengthening enforcement mechanisms and creating a unified regulatory environment are critical for attracting sustained foreign investment.

Besides, a growing trend in Ukraine's financial markets is the emphasis on sustainable finance and responsible investing. Influenced by the European Union directives and ESG principles, Ukraine is seeing increased issuance of green bonds and socially responsible investment products. The European Green Deal has also spurred interest in financing projects that contribute to environmental sustainability, and Ukraine's role as an energy transit hub makes it a crucial player in the region's energy security strategy.

Green bonds and other sustainable finance instruments are gaining popularity as Ukraine seeks to rebuild its infrastructure post-conflict and transition to a more sustainable economy. These instruments not only attract environmentally conscious investors but also align with global efforts to combat climate change. Sustainable finance has the potential to reshape Ukraine's capital markets by driving investment toward renewable energy, energy efficiency projects, and other initiatives aimed at reducing carbon emissions.

International organizations have also played a key role in shaping Ukraine's financial trading environment. The International Monetary Fund, through various loan programs and financial assistance packages, has helped stabilize Ukraine's economy and provided crucial liquidity during periods of economic turbulence. The European Bank for Reconstruction and Development has been actively involved in financing Ukrainian infrastructure and energy projects, while the World Bank has provided both technical assistance and capital to foster sustainable development.

The adoption of the Basel III framework by Ukrainian financial institutions is another sign of the country's growing integration with international financial standards. This framework ensures that Ukrainian banks maintain adequate capital reserves, reduce risk exposure, and improve their resilience to market shocks, thus contributing to the overall stability of Ukraine's financial trading system.

Looking ahead, Ukraine's financial markets are poised to benefit from increased integration into the global financial system, particularly as the country continues to implement structural reforms and attract foreign direct investment (FDI). The continued modernization of trading technologies, greater transparency, and the expansion of sustainable financial products are likely to make Ukraine an attractive destination for global investors. Furthermore, Ukraine's strategic location and its role as a key transit hub for energy and commodities position it as an important player in the global supply chain.

However, realizing this potential will require sustained political stability, comprehensive regulatory reforms, and a commitment to aligning more closely with international financial standards. As Ukraine strengthens its market infrastructure and enhances its regulatory framework, its financial markets are likely to emerge as a key player in the global financial ecosystem, providing attractive opportunities for both domestic and international investors.

Fig. 2.1 offers a decade-long comparative view of financial market development across major regions, North America, Europe, Asia, the Cryptocurrency market, and Ukraine, and key financial instruments: stocks, bonds, and derivatives. It highlights shifts in capital concentration, structural strengths, and regional momentum in a globally interconnected financial system.

From fig. 2.1 it is clear, that North America remains the undisputed global leader in financial markets, with stock and bond market capitalizations each reaching $38 trillion by 2024, and derivatives climbing to $47 trillion. The steady growth over the decade reflects the region's institutional depth, technological advancement in trading platforms, and dominance in dollar-denominated global transactions. Derivatives trading in particular saw continuous expansion, fuelled by innovation in risk management instruments and macroeconomic hedging.

Fig. 2.1. Heatmap of global market capitalization ($T) by region and instrument (2015–2024)

Source: [210; 211; 212; 213; 214]

Europe, while expanding at a more moderate pace, consistently maintained a diversified and stable financial market. By 2024, stock markets grew to $13 trillion, bonds to $15 trillion, and derivatives to $18 trillion [211]. European financial infrastructure benefitted from post-Brexit adjustments, increased regional exchange integration (e.g., Euronext), and harmonized regulation via MiFID II. German Bunds and other core sovereign bonds remain benchmarks for security and yield in a diversified portfolio, and Europe's derivatives growth reflects a maturing post-crisis financial system.

Asia demonstrated the strongest growth trend among traditional financial markets.

Its stock market capitalization rose from $8 trillion in 2015 to $13.2 trillion in 2024, driven by rapid economic development and robust IPO activity, especially in China and India. Bond markets expanded to $12.5 trillion, with increased foreign investor access through mechanisms like Bond Connect. Derivatives also saw consistent expansion, hitting $14 trillion, as markets in Japan, Singapore, and South Korea introduced more sophisticated instruments and attracted regional and global hedgers [212].

The Cryptocurrency market has witnessed exponential growth since 2009, led by the adoption of Bitcoin, Ethereum, and crypto derivatives. Although structurally different from traditional asset classes, crypto's rise underscores a parallel evolution in decentralized financial systems and digital asset investment. Derivatives volumes, particularly on exchanges like CME and Binance, have added to market sophistication.

Ukraine, while smaller in absolute scale, reflects an emerging financial market undergoing modernization and reform. By 2024, stock market capitalization reached $0.06 trillion, and bonds totally $0.03 trillion, with most instruments focused on public debt financing and reconstruction support. Ukraine's derivatives and cryptocurrency market remains nascent, but steadily evolving, offering new tools for risk management as the country aligns with EU standards and international investor expectations [215].

In summary, the heatmap underscores North America's dominance, Europe's regulatory-driven stability, Asia's momentum as a growth engine, crypto's disruptive rise, and Ukraine's gradual but strategic transformation. The decade from 2015 to 2024 reveals increasing global financial integration, regional specialization in capital formation, and a broader toolkit for managing economic uncertainty through capital markets.

Fig. 2.2 illustrates the heatmap of global financial market trade volumes from 2015 to 2024 across major regions and instruments.

From fig. 2.2 we can conclude that North America consistently leads in trading volumes across all instruments, particularly in equities ($3T) and derivatives ($3.2T). Europe and Asia follow closely, with strong activity in bonds, FX, and derivatives. Emerging regions like the Middle East, Latin America, and Africa show growing participation, especially in FX and commodities, indicating regional diversification and rising global integration. The future direction suggests increasing convergence in FX and derivative markets, with digital platforms expected to boost volumes in underrepresented regions.

Fig. 2.2. Heatmap of global financial markets trade volume by region and instrument (2015–2024)

Source: [210; 211; 212; 213; 214]

Fig. 2.3 visualizes the key features of global financial markets from 2015 to 2024. From fig. 2.3 we can see:

1. Volatility Index (VIX Equivalent): highlights market uncertainty. Crypto remains highly volatile (65+), while traditional markets (North America, Europe, Asia) show spikes during crisis years like 2020. Traditional markets showed relative stability in the pre-pandemic years, followed by a sharp spike in 2020 due to COVID-19, and a gradual normalization thereafter. Volatility averaged around 18–20 for North America and Asia, and slightly lower for Europe (~16.5). In stark contrast, the cryptocurrency market exhibited extreme volatility, peaking at 110 in 2020 and tapering to 65 by 2024, underscoring its speculative nature and sensitivity to sentiment and regulation.

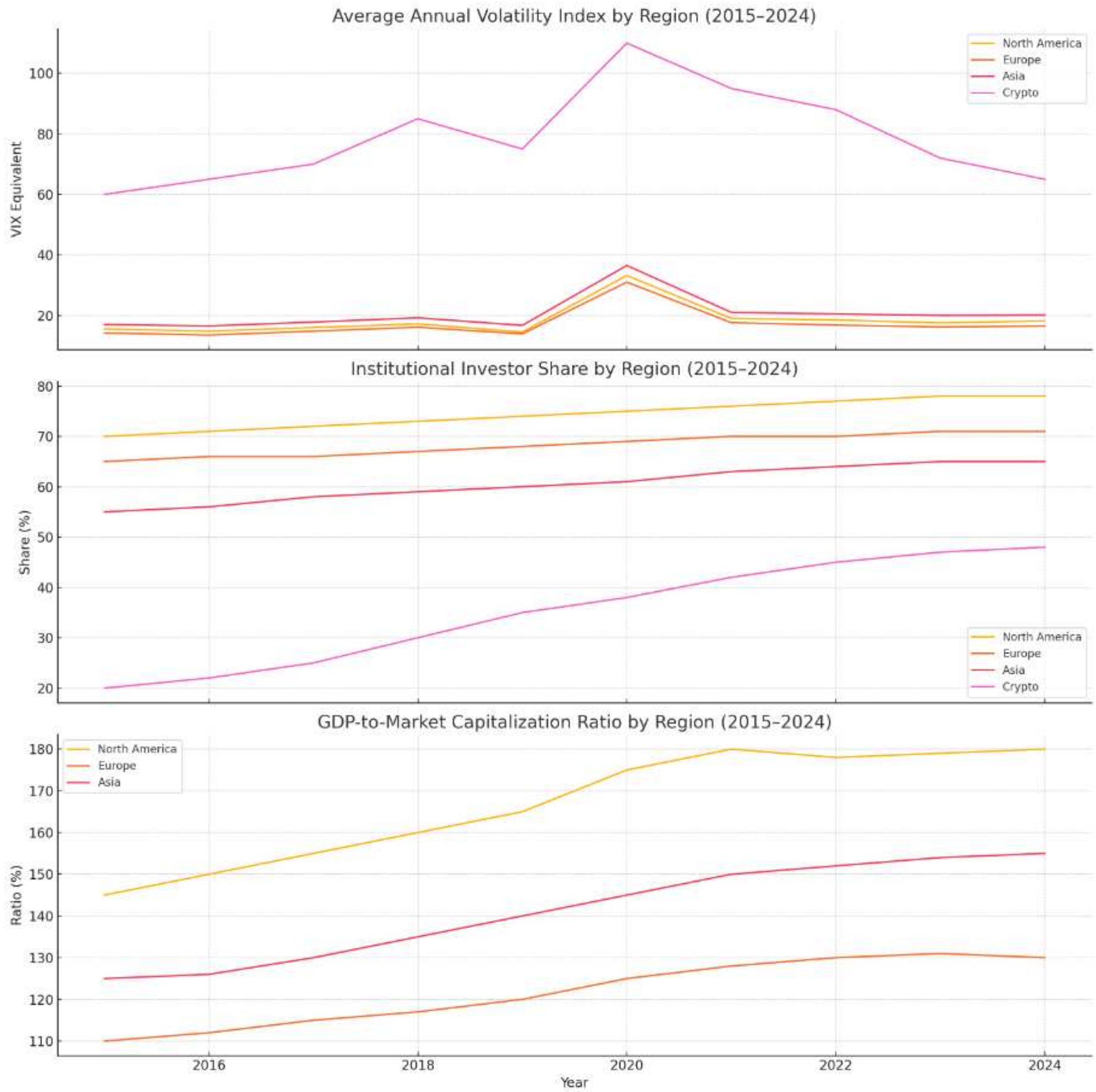

Fig. 2.3. Key features of global financial markets from 2015 to 2024

Source: [216; 217; 218; 219]

2. Institutional Investor Share (% of total market ownership): measures the level of professional, long-term investment participation. North America leads (~78%), while Asia and Crypto show rising trends, reflecting maturing investor bases. North America leads with a consistently high institutional ownership, rising to 78% by 2024, reflecting the strength of pension funds, mutual funds, and sovereign wealth involvement. Europe follows at 71%, while Asia's share grew from 55% to 65%, indicating rapid financial deepening. Crypto, which started with only 20% institutional participation in 2015, has now reached 48%, signalling growing institutional confidence and regulatory maturation.

3. GDP-to-Market Capitalization Ratio (%): gauges whether markets are over- or undervalued. North America shows a persistently high ratio (~180%), suggesting market expansion outpacing GDP. This metric shows how the size of financial markets relates to economic output. North America's ratio soared to 180%, reflecting asset price inflation and deep capital markets. Europe remained balanced at ~130%, while Asia's ratio climbed steadily to 155%, showing accelerated financial development. The crypto market was excluded here due to the absence of GDP equivalency but would show hyper-capitalization relative to economic activity if token-based economies were accounted for.

For the future tendency of the global main financial markets, North America is likely to maintain high institutional penetration and deep markets but may face periodic corrections as asset valuations outpace GDP. Focus will shift toward AI-led investment strategies and green finance integration. Europe is expected to stabilize further, with a strong ESG and regulatory edge. Market growth may remain moderate but balanced, supported by MiFID III evolution and deeper capital market union initiatives. Asia will likely continue converging with developed market norms, with rising institutional share and capital efficiency. China's gradual liberalization, India's retail-investor boom, and ASEAN market integration will be key drivers. Cryptocurrency markets are poised for transformation. As volatility normalizes and institutional participation crosses 50%, more hybrid financial instruments, regulated exchanges, and tokenized real-world asset (RWA) trading can be expected. Yet, volatility risks remain amid evolving global regulation and CBDC competition.

Globalization has profoundly influenced financial markets, intertwining economies and amplifying the impact of economic cycles across borders. The integration of global markets means that financial cycles are no longer confined to individual countries but are part of a broader, interconnected system. As a result, economic events in one region can trigger ripple effects across the global financial system, intensifying the impact of both booms and busts. To further examine these ripple effects, a cycle-based analysis focusing on financial globalization is conducted in Annex B.

Globalization has made a great progress since the end of World War II. The KOF Globalization Index measures the economic, social and political dimensions of globalization [224]. Globalization in these fields has been on the rise since the 1970s, receiving a particular boost after the end of the Cold War. The fig. 2.4 shows the regional levels of globalization and financial globalization levels (in fact and in law) between the years 1970 and 2024 [225; 226].

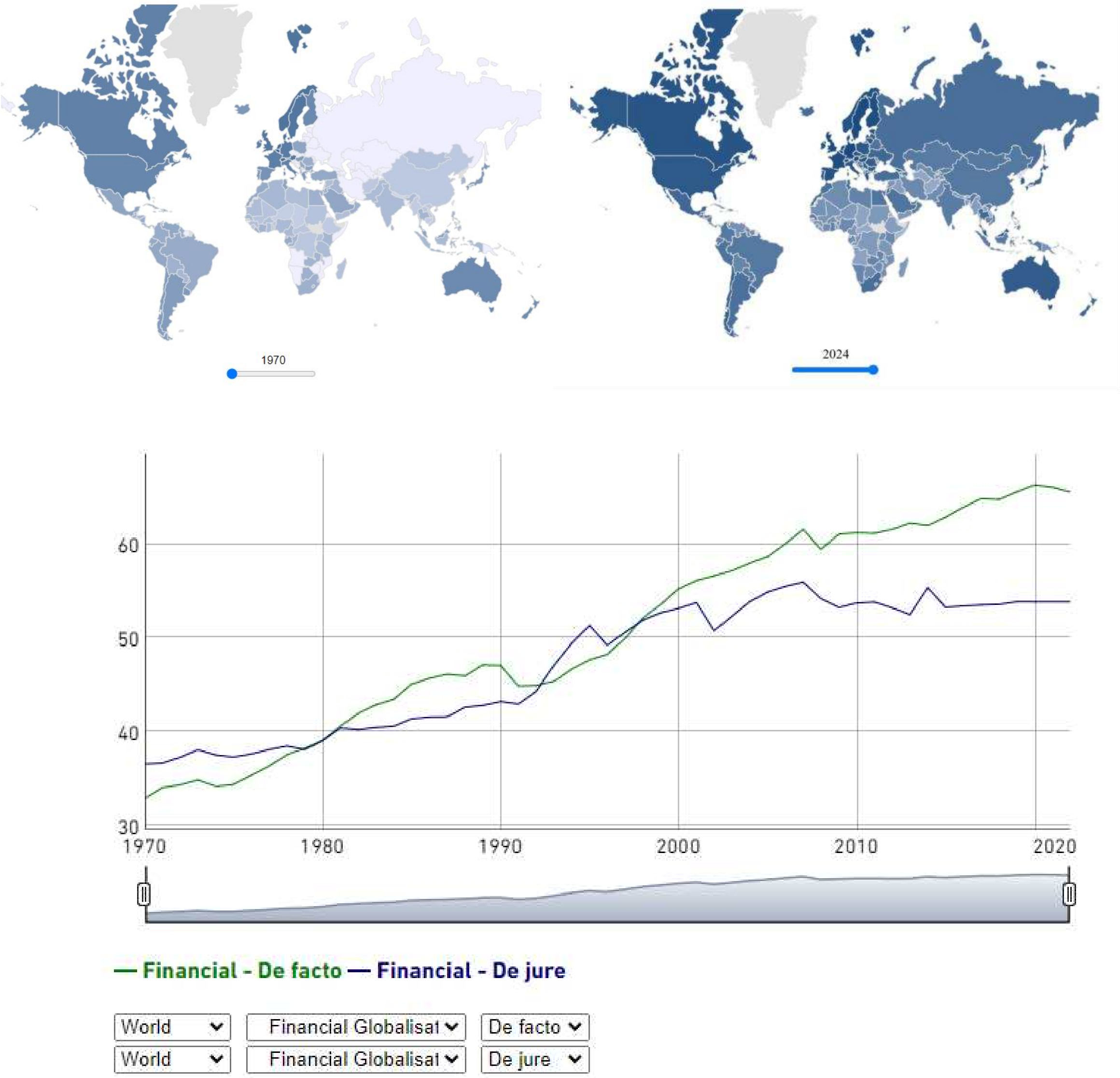

Fig. 2.4 Regional levels of globalization and financial globalization levels between the years 1970 and 2024

Source: [224]

The comparison shows a marked increase in the level and spread of globalization from 1970 to 2024, with many more countries becoming deeply integrated into the global economy. Regional financial markets are interconnected, with correlations between asset prices and market movements. Understanding these relationships helps identify risk transmission channels and potential spillover effects from one market to another. The global financial crisis of 2008 demonstrated how financial shocks in one region can rapidly spread to others, highlighting the importance of monitoring these correlations.

Risk transmission mechanisms include contagion effects, where financial distress in one market spreads to others, and feedback loops, where market reactions amplify initial shocks. Identifying these mechanisms is crucial for maintaining financial stability. The role of global financial institutions, such as banks and investment funds, in transmitting risks across borders is significant.

The interconnectedness of banks through the interbank lending market and their exposures to global financial markets can lead to the rapid transmission of financial stress. During the European sovereign debt crisis, concerns about the solvency of European banks spread to global markets, affecting banks and financial institutions worldwide.

Policymakers need to consider the interconnectedness of financial markets when designing regulatory frameworks and intervention strategies. Coordinated international efforts are essential to address global financial challenges and enhance market resilience. The G20 and the Financial Stability Board (FSB) play crucial roles in promoting global financial stability and regulatory cooperation.

For instance, the Basel III regulatory framework, developed by the Basel Committee on Banking Supervision, aims to strengthen bank capital requirements and improve risk management practices. This framework has been adopted by countries worldwide to enhance the stability of the global banking system. Additionally, international cooperation on anti-money laundering and combating the financing of terrorism is critical for maintaining the integrity of the global financial system.

The global financial trading system is a complex and dynamic network of regional markets and participants. Understanding the interactions and dependencies among these markets is crucial for effective risk management, policy formulation, and investment decision-making. Continued research and monitoring of these markets are essential to navigate the challenges and opportunities in the global financial landscape. The intricate relationships among North American, European, and Asian financial markets underscore the importance of a coordinated and comprehensive approach to financial regulation and market oversight.

In order to further study the cyclicality of financial markets in different regions under globalization, here raises an explanation of “lag cycle of regional financial trading market cycles under globalization” which addresses the interdependent nature of financial markets in developed countries and emerging economies. The explanation posits that market cycles in these two regions are intrinsically linked, with emerging markets typically lagging behind developed markets by one phase. This creates a dynamic where shifts in developed markets often trigger corresponding changes in emerging markets, albeit with a delay. The explanation encompasses four main phases: Accumulation, Growth, Distribution, and Correction, and details the interplay between these phases across the two market types [61]:

1) Phase I. Accumulation phase (developed markets) and correction phase (emerging markets):

- Developed markets: the accumulation phase in developed markets follows a period of correction. During this phase, institutional investors begin to accumulate undervalued assets as market sentiment shifts from bearish to cautious optimism. There is typically low volatility, and market activity is driven by smart money positioning for the next growth phase [61].

- Global impact: as developed markets begin to stabilize, emerging markets are often still in their Correction Phase, dealing with the fallout from previous market excesses. The stability in developed markets can lead to a stabilization of capital outflows from emerging markets, providing a foundation for their recovery [61].

-Emerging markets: in the correction phase, emerging markets experience significant declines in asset prices and economic slowdown. High volatility and currency devaluation are common, as is capital flight. The phase is often marked by attempts to stabilize the economy through policy interventions or external support (e.g., IMF loans) [61].

- Global impact: the stabilization and gradual recovery in developed markets create conditions for emerging markets to begin accumulating, as the economic environment improves and capital begins to return [61].

2) Phase II. Growth phase (developed markets) and accumulation phase (emerging markets):

- Developed markets: the growth phase in developed markets is characterized by increasing investor confidence, rising asset prices, and economic expansion. There is broad participation in the market, with retail and institutional investors driving up valuations. Economic indicators like GDP growth and consumer spending show marked improvements [61].

- Global impact: the growth in developed markets fuels increased demand for commodities and products from emerging markets, leading to an inflow of capital into these regions. This influx helps emerging markets transition from their Correction Phase into their own Accumulation Phase [61].

- Emerging markets: in the accumulation phase, emerging markets benefit from capital inflows and improved economic conditions driven by demand from developed markets. Investors begin to see value in these markets, leading to a gradual increase in asset prices and a more stable economic environment [61].

- Global impact: the improving conditions in emerging markets contribute to global growth, reinforcing the positive momentum in developed markets and leading to increased international trade and investment [61].

3) Phase III. Distribution phase (developed markets) and growth phase (emerging markets):

- Developed markets: the distribution phase in developed markets occurs as smart money begins to take profits. Asset prices start to level off, and market sentiment becomes increasingly cautious. There is often a peak in market valuations, followed by increased volatility as uncertainty grows [61].

- Global impact: the cooling of developed markets often redirects investment capital toward emerging markets, which are still in their Growth Phase. This capital shift can amplify the growth in emerging markets, even as developed markets begin to face downward pressures [61].

- Emerging markets: during their growth phase, emerging markets experience rapid economic expansion, high capital inflows, and significant increases in asset prices. This phase is often more volatile than in developed markets, driven by higher risks and returns. Economic indicators in these markets show robust improvement, supported by global demand and investment [61].

- Global impact: the continued growth in emerging markets provides a buffer against the Distribution Phase in developed markets, sustaining global economic activity even as developed markets begin to cool [61].

4) Phase IV. Correction phase (developed markets) and distribution phase (emerging markets):

- Developed markets: the correction phase in developed markets is marked by significant declines in asset prices, economic slowdown, and increased market volatility. Investors rush to sell overvalued assets, leading to sharp market downturns. Central banks and governments may intervene with stimulus measures to prevent a prolonged recession [61].

- Global impact: the correction in developed markets often triggers the Distribution Phase in emerging markets, as investors become risk-averse and begin to withdraw capital. The economic slowdown in developed markets reduces demand for emerging market exports, further exacerbating the downturn in these regions [61].

- Emerging markets: the distribution phase in emerging markets is characterized by profit-taking, market saturation, and rising volatility. Asset prices peak and then begin to decline as capital outflows increase and economic growth slows. Emerging markets, heavily dependent on external capital and demand, face significant challenges as developed markets correct [61].

- Global impact: the simultaneous downturn in both developed and emerging markets can lead to a global economic slowdown, with spillover effects such as reduced trade, lower commodity prices, and increased financial instability [61].

In summary, table 2.7 shows the main features of the cyclicality of financial trading in the developed and emerging financial markets.

Table 2.7

Cyclicality of financial trading in the developed and emerging financial markets

Phase	**Developed markets**	**Emerging markets**	**Global impact**
Phase I	Accumulation Phase (Smart money starts reinvesting after a downturn)	Correction Phase (Emerging markets still experience downturns and capital outflows)	Capital stability begins in developed markets, but emerging markets remain volatile
Phase II	Growth Phase (Rising asset prices, economic expansion)	Accumulation Phase (Capital starts returning, asset prices stabilize)	Developed market recovery boosts investor confidence in emerging markets
Phase III	Distribution Phase (Smart money starts profit-taking, market valuations peak)	Growth Phase (Strong capital inflows, market gains peak)	Investors shift capital from developed to emerging markets
Phase IV	Correction Phase (Market downturn, economic slowdown)	Distribution Phase (Profit-taking, slowing growth, capital outflows)	Global economic slowdown, capital outflows from emerging markets

Source: author's own generalisation based on [61]

The explanation of regional financial transaction market cycles under globalization highlights the interconnectedness of developed and emerging markets. The one-phase lag between the cycles in these markets creates a feedback loop that can either amplify global growth or exacerbate global downturns. Understanding these dynamics is crucial for policymakers and investors as they navigate the complexities of a globalized financial system:

- investors can leverage the cyclical lag to diversify portfolios, shifting capital between developed and emerging markets depending on the phase of the cycle;
- coordinated policy responses between developed and emerging markets can help mitigate the negative impacts of these cycles, especially during downturns;
- ensuring global financial stability requires recognizing the cyclical interdependence of markets and taking proactive measures to manage risks associated with these cycles.

This explanation provides a framework for understanding the cyclical nature of financial trading in the financial markets in the context of globalization, offering insights into the timing and interaction of phases across different regions. The global financial trading landscape is a complex and interconnected system that has been shaped by globalization. The interactions among North American, European, and Asian financial markets, along with emerging markets, have become deeper and more intertwined, reflecting the increasing integration of global economies. This interconnectedness has both benefits and challenges, as financial shocks and market movements can quickly spread across regions, necessitating careful risk management and regulatory oversight [61]. Globalization has significantly influenced the structure and dynamics of global financial trading. The broader participation and deeper integration of countries into the global economy have led to increased interconnectedness and correlation among regional financial markets. Risk transmission mechanisms and policy implications need to be carefully considered to maintain financial stability and market resilience. Coordinated international efforts, such as regulatory frameworks and cooperation, are essential for addressing global financial challenges and ensuring the integrity of the global financial system [61].

In addition, for further studying the cyclicality of financial trading in the financial markets in different regions under globalization, this research raises an explanation of "lag cycle of regional financial trading market cycles under globalization" which addresses the interdependent nature of financial markets in developed countries and emerging economies. This explanation also provides a framework for understanding the cyclical nature of financial markets in the context of globalization, offering insights into the timing and interaction of market phases across different regions [61].

Overall, understanding the complex interactions and dependencies among regional financial markets is crucial for effective risk management, policy formulation, and investment decision-making in the global financial landscape. Continued research, monitoring, and international cooperation are necessary to navigate the challenges and opportunities in the global financial trading system.

2.3. Assessment of financial trading efficiency

This section integrates the preceding discussions on technological innovation and structured data frameworks to evaluate the financial trading efficiency using a dynamic metric, denoted as ($\varepsilon(t)$). The financial trading efficiency is a foundational concept in the study of financial markets. Efficient trading is crucial for the optimal functioning of capital markets, ensuring that prices reflect all available information, transaction costs are minimized, and markets are liquid enough to accommodate large trades without significant price changes. This concept is not only central to financial theory but also to the practical operations of global financial markets.

This section aims to provide a comprehensive analysis of financial trading efficiency, exploring its theoretical underpinnings, empirical measurements, and real-world applications. This study will examine the various dimensions of trading efficiency, including operational efficiency, transaction costs, liquidity and volatility and will consider the role of regulatory frameworks and international comparisons, highlighting how different markets exhibit varying levels of trading efficiency.

To study financial trading efficiency, it is necessary to start from the financial market, as the Efficient market hypothesis is a cornerstone of modern financial theory, originally proposed by Eugene Fama in the 1970s [227]. The hypothesis asserts that financial markets are "informationally efficient", meaning that asset prices fully reflect all available information at any given time. EMH is categorized into three forms:

- Weak form: prices reflect all past market data, such as historical prices and trading volumes.
- Semi-strong form: prices reflect all publicly available information, including financial statements, news releases, and economic data.
- Strong form: prices reflect all information, both public and private, including insider information [227].

The implications of EMH are profound, suggesting that it is impossible to consistently achieve returns higher than the market average without taking on additional risk. This hypothesis underpins much of the academic research in finance, influencing investment strategies and the development of financial instruments.

Despite its widespread acceptance, the EMH has been challenged by numerous market anomalies and the field of behavioural finance. Behavioural finance explores how cognitive biases and emotional reactions can lead to irrational financial decisions, resulting in market inefficiencies. Common examples include:

- The momentum effect: the tendency for stocks that have performed well in the past to continue performing well in the short term, contradicting the weak form of EMH.
- The January effect: a seasonal anomaly where stock prices tend to increase more in January than in other months, potentially due to tax-related selling in December [228].

Behavioural finance has led to a more nuanced understanding of market efficiency, recognizing that while markets may generally be efficient, they are not perfect. Psychological factors, market sentiment, and investor behaviour can all lead to temporary mispricings.

In EMH theory, informationally efficient markets should also exhibit high levels of transactional and operational efficiency. Whereas the presence of significant inefficiencies in the trading process not only increases costs for investors but also raises questions about the absolute validity of the EMH in a practical context. This involves evaluating the practical efficacy and cost-effectiveness of the trading process through empirical metrics such as transaction costs (bid-ask spreads, commissions), market impact, slippage, and liquidity depth. For investors in practice, a better market environment means lower transaction costs, reduced slippage, and the capacity to confidently execute complex strategies at scale, thereby improving risk-adjusted returns. Under globalization, highly efficient financial markets are more attractive to global investors, as they enhance financial trading efficiency itself. This appeal draws greater capital and sophisticated participants, fostering a virtuous cycle of deeper liquidity and sharper price discovery. Therefore, this study also employs quantitative models, including ARIMA analysis to test for return predictability and GARCH models to assess volatility clustering, to gauge these market inefficiencies that financial trading strategies must navigate.

The pursuit of higher performance and profitability in global financial markets necessitates a clear understanding of the determinants of financial trading efficiency. Financial trading efficiency is determined by multiple factors, their dimensions usually divided into:

1) Firstly, the transaction costs and market frictions. Transaction costs are a critical factor in assessing financial trading efficiency. These costs include both explicit costs, such as broker fees, commissions, and taxes, and implicit costs, such as bid-ask spreads and market impact costs [229]. High transaction costs can hinder market efficiency by discouraging trading and leading to less accurate price discovery.

Bid-ask spread: it is the difference between the highest price a buyer is willing to pay and the lowest price a seller is willing to accept. A narrower spread indicates a more efficient market, as it suggests higher liquidity and lower transaction costs. In highly liquid markets, such as major currency pairs in the foreign exchange market or large-cap stocks in the equity markets, bid-ask spreads are typically very narrow, often just a few basis points [230].

Market impact and slippage (a difference between estimated and actual costs): market impact refers to the effect that a large trade has on the price of an asset. Large orders can move the market, causing the trader to receive a worse price than expected – a phenomenon known as slippage. Reducing market impact and slippage is essential for maintaining trading efficiency, particularly in markets with lower liquidity.

2) Secondly, liquidity as a measure of the market efficiency. Liquidity is a key indicator of the market efficiency, reflecting the ease with which assets can be bought or sold without significantly affecting their price. A highly liquid market allows for large transactions with minimal price disruption, facilitating better price discovery and lower transaction costs.

Trading volume and market depth: trading volume is often used as a proxy for liquidity. High trading volumes indicate that a market is active and can handle large trades without significant price changes. The market depth, which refers to the volume of orders available at different price levels, is another important measure of liquidity. Deeper markets are more resilient to large orders and tend to be more efficient [231].

The role of market makers: market makers play a crucial role in maintaining liquidity by continuously providing buy and sell quotes for assets. By doing so, they help narrow the bid-ask spread and ensure that markets remain liquid even in times of low trading activity. The presence of active market makers is often associated with the higher market efficiency [232].

3) The third dimension is an information processing and a price discovery. An efficient market quickly incorporates all available information into the asset prices, a process known as a price discovery. The speed and accuracy with which new information is reflected in prices are crucial indicators of the market efficiency.

Event studies and information efficiency: event studies are a common method for analysing how quickly and accurately markets respond to new information. These studies typically examine the price reaction to specific events, such as earnings announcements, mergers, or macroeconomic data releases. A rapid adjustment of prices to new information suggests a high level of information efficiency [233].

High-frequency trading: HFT involves the use of advanced algorithms to execute trades at extremely high speeds. HFT firms contribute to price discovery by rapidly arbitraging away mispricings, thereby enhancing the market efficiency. However, HFT also raises concerns about market stability and fairness, as it can lead to flash crashes and increased volatility [234].

4) The fourth and last dimension is the regulatory impact on the market efficiency. Regulatory frameworks play a significant role in shaping the market efficiency. Regulations can either enhance efficiency by promoting transparency and competition or hinder it by imposing unnecessary burdens on market participants.

The role of financial market regulation: financial markets are subject to various regulations aimed at protecting investors, maintaining market integrity, and promoting fair competition. For example, the implementation of the Markets in Financial Instruments Directive in the European Union has significantly impacted the trading efficiency by increasing transparency and competition among trading venues [235].

Impact of transaction taxes: transaction taxes, such as the financial transaction tax (FTT) proposed in the European Union, can affect financial trading efficiency by increasing trading costs. While such taxes are intended to curb excessive speculation and stabilize markets, they can also reduce liquidity and widen bid-ask spreads, ultimately decreasing financial trading efficiency [236].

In real-world financial trading, there is substantial empirical evidence regarding the efficiency of different financial instruments, they are mainly:

1) First, the efficiency in equity markets: equity markets are often considered the most efficient financial markets due to their high liquidity, a large number of participants, and rapid information processing. However, empirical studies have identified various factors that can impact the efficiency of equity markets.

Algorithmic trading and its effect on the efficiency: the rise of algorithmic trading has had a profound impact on financial trading efficiency. Studies have shown that algorithmic trading reduces transaction costs, improves liquidity, and enhances price discovery by quickly arbitraging away mispricing. However, the increased reliance on algorithms has also raised concerns about market stability, particularly during periods of high volatility [237].

Market anomalies and behavioural biases: despite the general efficiency of equity markets, various anomalies persist. For example, the January effect, where stock prices tend to rise more in January than in other months, challenges the notion of the market efficiency. Behavioural biases, such as overconfidence and herding, also contribute to temporary mispricing, highlighting the limitations of the EMH [238].

The efficiency of equity markets varies significantly across different regions. The developed markets, such as those in the United States, Europe, and Japan, generally exhibit higher efficiency levels due to their deep liquidity, a large number of participants, and advanced technological infrastructure. In contrast, emerging markets, while rapidly developing, often face challenges related to lower liquidity, higher transaction costs, and less transparency.

The U.S. equity market is often cited as one of the most efficient in the world, with narrow bid-ask spreads, high liquidity, and rapid information processing. The European equity market, while also efficient, tends to have slightly wider spreads and lower liquidity, particularly in smaller markets [239].

The emerging markets, such as those in China, India, and Brazil, are characterized by higher volatility, wider bid-ask spreads, and a greater susceptibility to market anomalies. However, as these markets continue to develop and attract more international investors, their efficiency is expected to improve [240].

2) Second, the efficiency in fixed-income markets: fixed-income markets, particularly government and corporate bond markets, are generally less liquid than equity markets, which can lead to inefficiencies. However, recent developments in electronic trading and data analytics have enhanced the efficiency of these markets.

Liquidity in corporate bond markets: it is often lower than in equity markets, leading to wider bid-ask spreads and higher transaction costs. However, the introduction of electronic trading platforms has helped narrow these spreads and increase liquidity, making the market more efficient [241].

Price discovery in government bond markets: government bond markets are generally considered efficient, particularly for major economies like the United States, Germany, and Japan. The presence of large institutional investors and active trading by central banks contribute to rapid price discovery and narrow bid-ask spreads in these markets [242].

The efficiency of fixed-income markets also varies across regions. Developed economies, with their established financial systems and large institutional investor base, tend to have more efficient bond markets. In contrast, emerging economies often face challenges related to lower liquidity, higher transaction costs, and less developed regulatory frameworks.

In developed markets, government bonds are typically very liquid, with narrow bid-ask spreads and active trading by central banks and institutional investors. These markets are considered highly efficient, particularly for major economies like the United States, Germany, and Japan [240].

Corporate bond markets in emerging economies are generally less liquid and more fragmented, leading to wider spreads and less efficient price discovery. However, efforts to develop local currency bond markets and attract foreign investors are gradually enhancing the efficiency of these markets [243].

3) Thirdly, the efficiency in foreign exchange markets: the FX market is one of the

largest and most liquid financial markets in the world. It is generally considered to be highly efficient, particularly in major currency pairs such as EUR/USD, USD/JPY, and GBP/USD.

The impact of central bank interventions: central bank interventions can temporarily distort the efficiency of the FX markets by artificially altering supply and demand dynamics. However, such interventions are typically short-lived, and the market quickly reverts to the efficiency as traders arbitrage away any mispricing [244].

The role of HFT in FX markets: high-frequency trading plays a significant role in enhancing the efficiency of the FX markets. HFT firms use sophisticated algorithms to exploit small price discrepancies across different trading venues, thereby contributing to price discovery and reducing bid-ask spreads [245].

The foreign exchange market is generally efficient, particularly for major currencies. However, the efficiency of the FX market can vary significantly between major and minor currencies.

Major currency pairs, such as EUR/USD, USD/JPY, and GBP/USD, are highly liquid and efficient, with narrow bid-ask spreads and rapid price discovery. These markets benefit from the presence of large institutional investors, central banks, and high-frequency traders [246].

Emerging market currencies tend to be less liquid and more volatile, leading to wider spreads and less efficient price discovery. These currencies are also more susceptible to external shocks, such as changes in global risk sentiment or commodity prices, which can further impact their efficiency [247].

4) Fourth, the efficiency in cryptocurrency markets: cryptocurrency markets have rapidly evolved and present unique challenges and opportunities in terms of the market efficiency. While these markets are relatively new, they have grown significantly in liquidity and participation, particularly for major cryptocurrencies like BTC and ETH.

Volatility and liquidity in cryptocurrency markets: cryptocurrency markets are known for their high volatility, which can be attributed to several factors, including speculative trading, regulatory uncertainty, and the relatively smaller market capitalization compared to traditional assets. High volatility often leads to wider bid-ask spreads and can create temporary inefficiencies. However, as the market matures and more institutional investors participate, liquidity has improved, contributing to better price discovery [248].

The impact of decentralized exchanges (DEXs) on the market efficiency: the rise of decentralized exchanges has introduced new dynamics in cryptocurrency trading. DEXs operate without a central authority, allowing for peer-to-peer trading directly on the blockchain. While this enhances transparency and reduces the risk of centralized failures, the lack of centralized order books can lead to fragmentation in liquidity and discrepancies in pricing across platforms. However, arbitrageurs actively trade across DEXs and centralized exchanges (CEXs) to exploit these inefficiencies, thereby contributing to the overall market efficiency [249].

Market anomalies in cryptocurrency trading: despite the advancements, cryptocurrency markets are still prone to certain anomalies, such as flash crashes and pump-and-dump schemes, which challenge the notion of the market efficiency. These anomalies are often driven by the relatively unregulated nature of the market and the influence of large holders (whales) who can manipulate prices. Efforts to introduce more robust regulation and surveillance are ongoing, aiming to mitigate these inefficiencies [250].

Developed economy financial markets and emerging economy financial markets often behave very differently due to the influence of these multi-dimensional factors. To compare the financial trading efficiency among the Standard & Poor’s 500 (S&P 500), FTSE 100 (London), and Shanghai Composite Index, here takes a time series analysis with Autoregressive Integrated Moving Average Model (ARIMA) and GARCH models to assess the predictability of returns and the volatility clustering in these indices. Here is a step-by-step guide to design and execute this analysis in R (Version 4.41) by the software Rstudio (Version 2024.04.2) [251]. All steps of the analysis are:

The first step is data acquisition, by downloading the year 2010-2023 historical data of S&P 500, FTSE 100, and Shanghai Composite Index from Investing.com [252].

Then the second step is a model selection, which are the following:

1. ARIMA Model: the ARIMA model will help assess the predictability of the returns, providing insight into the weak-form market efficiency. The steps for ARIMA analysis are mainly:

- Identify the order of differencing (d): since using log returns, differencing should not be necessary (d = 0).
- Identify the AR (p) and MA (q) orders: use ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots to identify the orders.
- Fit the ARIMA model: fit the ARIMA model using the identified parameters.
- Evaluate the model: analyse the residuals to check if they are white noise (no autocorrelation), which indicates a good fit.

2. GARCH Model: GARCH models assess the volatility clustering in the returns, providing insight into how volatility behaves over time in these markets. The steps for GARCH analysis are:

- Specify GARCH (1,1) model: this is the most common specification where both AR and MA terms are 1.
- Evaluate the model: examine the conditional volatility and residuals to assess the model fit.

The third step is to obtain the results. Across all the models, the ARIMA components help assess predictability, while GARCH components capture volatility clustering. These analyses provide insight into the market efficiency and volatility of the respective financial indices. For each index, the figures mentioned (fig. 2.5-2.13) present the model fit results and residual analysis, giving a visual representation of the model's performance. For every model:

1) S&P 500 close price return Time Series Analysis (fig. 2.5, fig. 2.6, fig. 2.7).

With the Time Series Analysis model – ARIMA (4,0,4) component:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} + \phi_4 y_{t-4} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \theta_3 \epsilon_{t-3} + \theta_4 \epsilon_{t-4} \tag{2.1}$$

ARIMA(4,0,4) with non-zero mean Coefficients:

	ar1	ar2	ar3	ar4	ma1	ma2	ma3	ma4	mean
	-0.2111	0.7742	-0.2899	-0.7965	0.1250	-0.7238	0.3279	0.6778	4e-04
s.e.	0.0461	0.0579	0.0600	0.0420	0.0534	0.0655	0.0663	0.0467	2e-04

sigma^2 = 0.0001174: log likelihood = 10940.38

AIC=-21860.76 AICc=-21860.7 BIC=-21799.1

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	8.361395e-07	0.01082224	0.007315428	NaN	Inf	0.6765913	-0.009512629

Ljung-Box test data: Residuals from ARIMA(4,0,4) with non-zero mean

Q* = 10.524, df = 3, p-value = 0.0146

Model df: 8. Total lags used: 11

Fig. 2.5. Results of ARIMA (4,0,4) model analysis of S&P 500 returns

Source: author’s own calculation

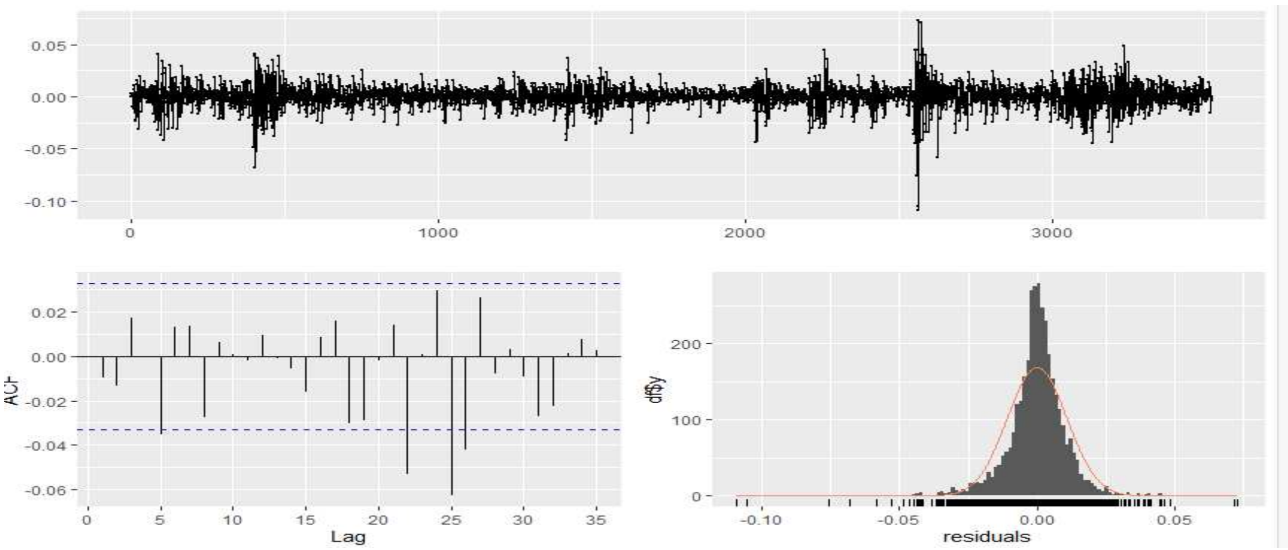

Fig. 2.6. Residual diagnostics of ARIMA (4,0,4) model analysis of S&P 500 returns

Source: author’s own calculation

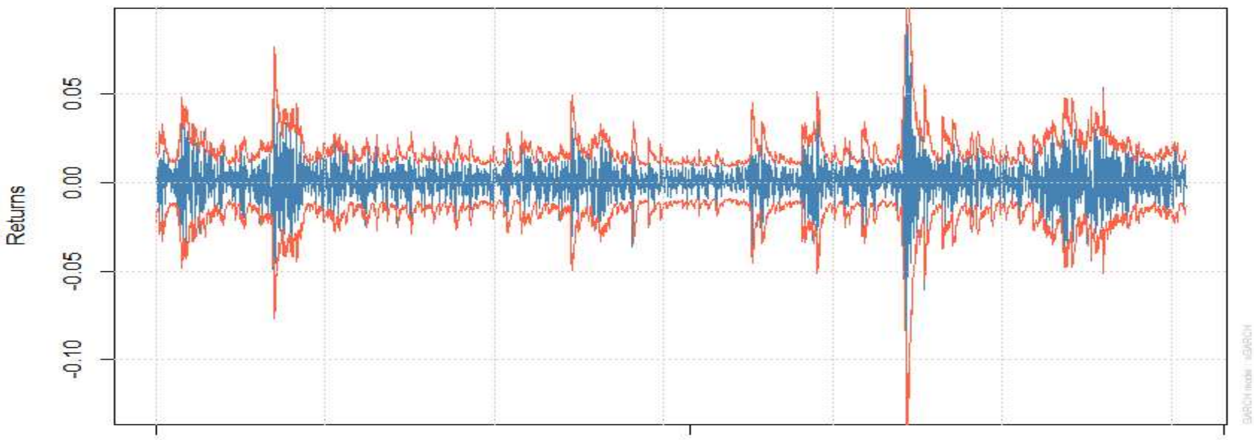

Fig. 2.7. Conditional volatility of ARIMA (4,0,4) model analysis of S&P 500 returns

Source: author's own calculation

And GARCH (1,1) component:

$$\epsilon_t = \sigma_t z_t \tag{2.2}$$

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{2.3}$$

Fig. 2.5 - 2.7 show the S&P 500 ARIMA(4,0,4) model has 4 autoregressive (AR) terms and 4 moving average (MA) terms with non-zero mean. The ARIMA analysis reveals that the AR and MA coefficients exhibit notable values, with an overall log likelihood of 10940.38, AIC = -21860.76, and a BIC = -21799.1. The training set error measures indicate a small root mean square error (RMSE) of 0.0108 and a low mean absolute error (MAE) of 0.0073. The residuals show signs of autocorrelation with a Ljung-Box test p-value of 0.0146, indicating some unexplained autocorrelation in the data.

2) FTSE 100 (London) close price return Time Series Analysis (fig. 2.8, fig. 2.9 and fig. 2.10).

With the Time Series Analysis model – ARIMA (4,0,3) component:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} + \phi_4 y_{t-4} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \theta_3 \epsilon_{t-3} \tag{2.4}$$

ARIMA(4,0,3) with zero mean Coefficients:

ar1 ar2 ar3 ar4 ma1 ma2 ma3

-0.6788 0.8591 0.7540 -0.0310 0.6861 -0.8709 -0.7640

s.e. 0.0777 0.0350 0.0659 0.0208 0.0760 0.0362 0.0667

sigma^2 = 0.0001021: log likelihood = 11220.83

AIC=-22425.65 AICc=-22425.61 BIC=-22376.3

Training set error measures:

ME RMSE MAE MPE MAPE MASE ACF1

Training set 0.000176894 0.01009348 0.007025722 NaN Inf 0.6997989 0.0003045757

Ljung-Box test data: Residuals from ARIMA(4,0,3) with zero mean

Q* = 7.4954, df = 3, p-value = 0.05768

Model df: 7. Total lags used: 10

Fig. 2.8. Results of ARIMA (4,0,3) model analysis of FTSE 100 (London) returns

Source: author’s own calculation

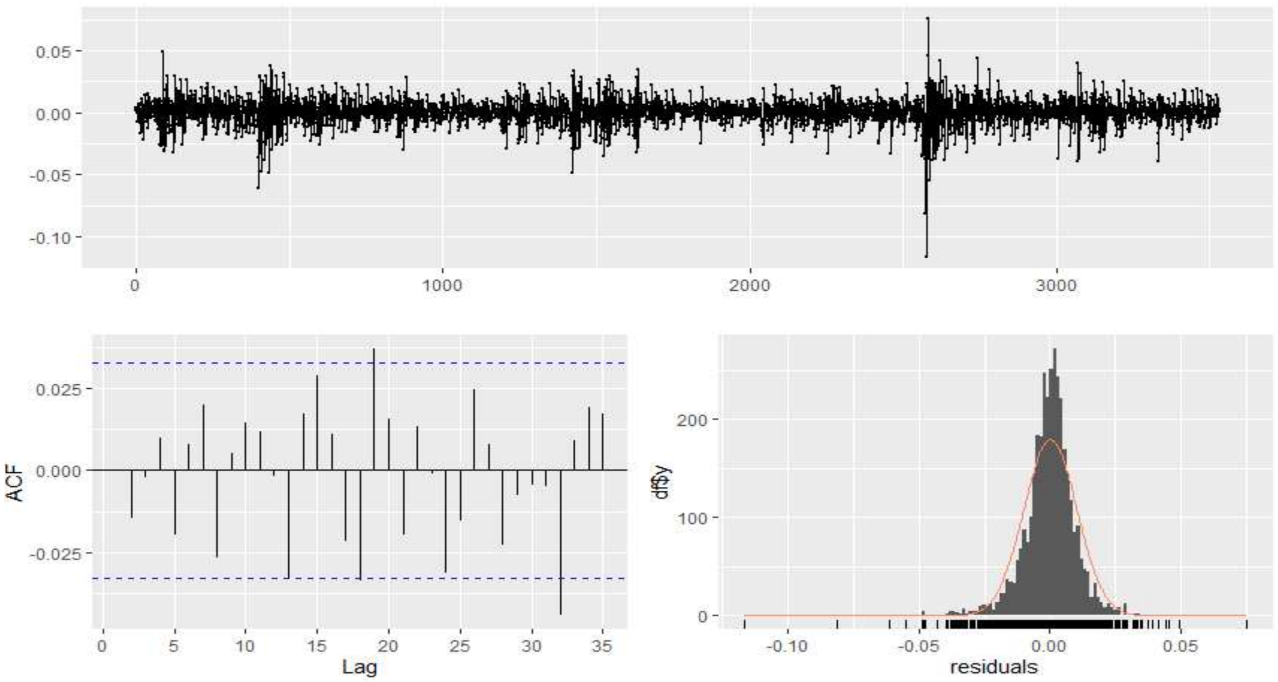

Fig. 2.9. Residual diagnostics of ARIMA (4,0,3) model analysis of FTSE 100 (London) returns

Source: author’s own calculation

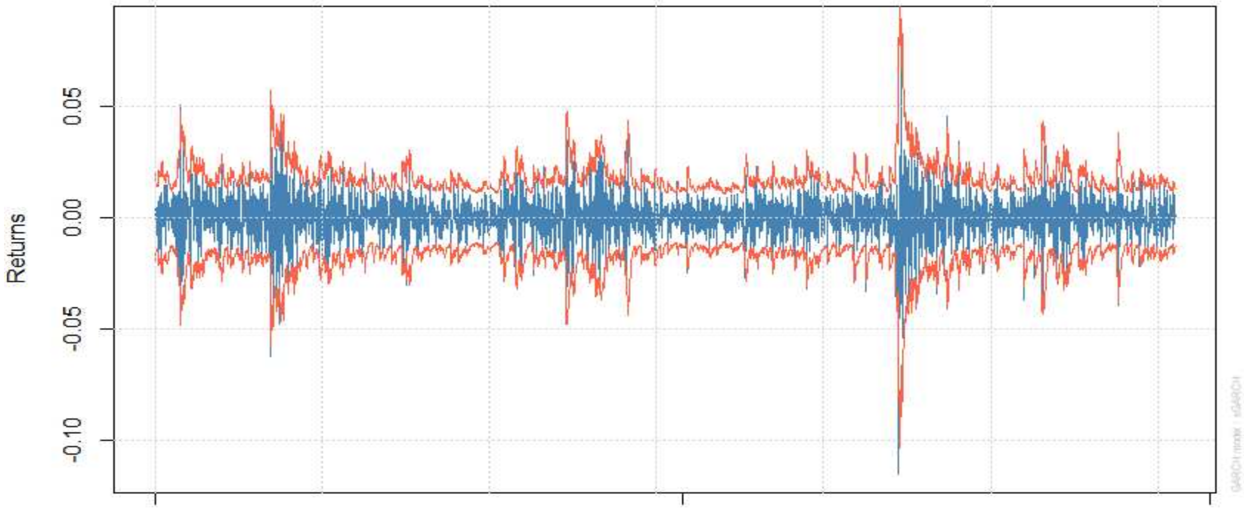

Fig. 2.10. Conditional volatility of ARIMA(4,0,3) model analysis of FTSE 100 (London) returns

Source: author's own calculation

And GARCH(1,1) component:

$$\epsilon_t = \sigma_t Z_t \tag{2.5}$$

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{2.6}$$

Figures 2.8-2.10 show the FTSE 100 ARIMA (4,0,3) model also captures autoregressive and moving average components, though with 4 AR terms and 3 MA terms. The log likelihood here is 11220.83, AIC = -22425.65, and BIC = -22376.3, indicating a slightly better model fit compared to the S&P 500. The RMSE is 0.01009, and the MAE is 0.00703. The residuals, however, show better behaviour, with a p-value of 0.057 from the Ljung-Box test, implying that the residuals are closer to white noise, indicating a better fit for this model.

3) Shanghai Composite Index close price return Time Series Analysis (fig. 2.11, fig. 2.12 and fig. 2.13).

With the Time Series Analysis model - ARIMA(2,0,3) component:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \theta_3 \epsilon_{t-3} \tag{2.7}$$

ARIMA(2,0,3) with zero mean

Coefficients:

	ar1	ar2	ma1	ma2	ma3
	0.1549	-0.9461	-0.1245	0.9163	0.0565
s.e.	0.0257	0.0166	0.0306	0.0200	0.0178

sigma^2 = 0.0001613: log likelihood = 10025.52

AIC=-20039.04 AICc=-20039.01 BIC=-20002.25

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	-2.454788e-05	0.01269206	0.008690591	Inf	Inf	0.682808	5.766164e-05

Ljung-Box test data: Residuals from ARIMA(2,0,3) with zero mean

Q* = 8.9594, df = 5, p-value = 0.1107

Model df: 5. Total lags used: 10

Fig. 2.11. Results of ARIMA (2,0,3) model analysis of Shanghai Index returns

Source: author's own calculation

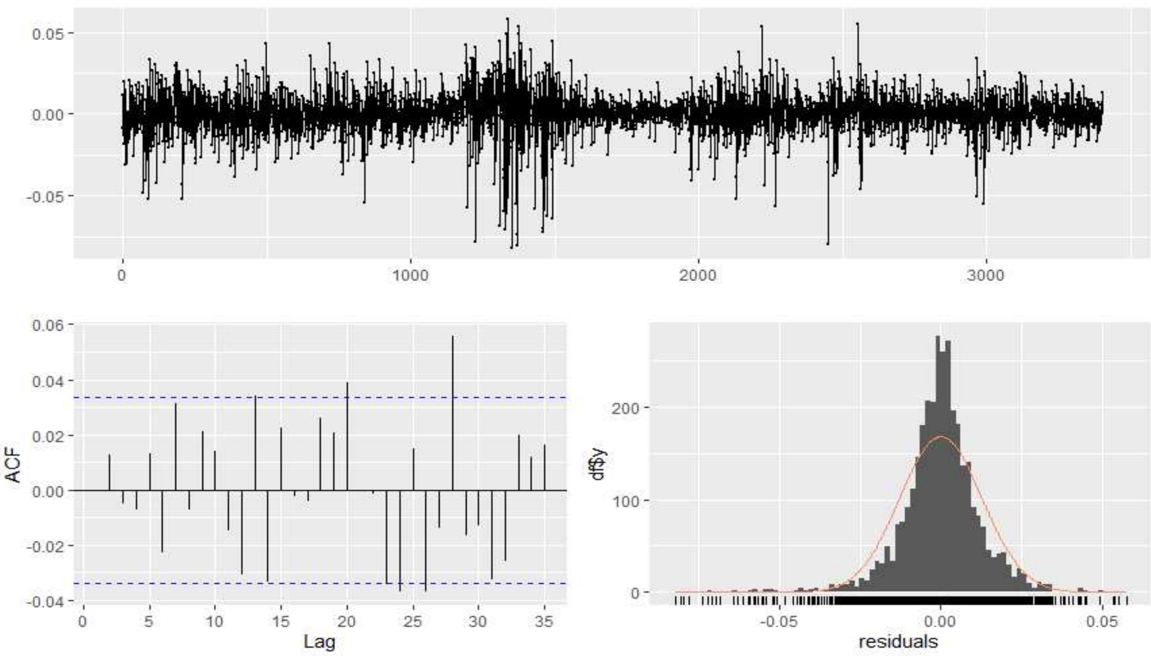

Fig. 2.12. Residual diagnostics of ARIMA (2,0,3) model analysis of Shanghai Index returns

Source: author's own calculation

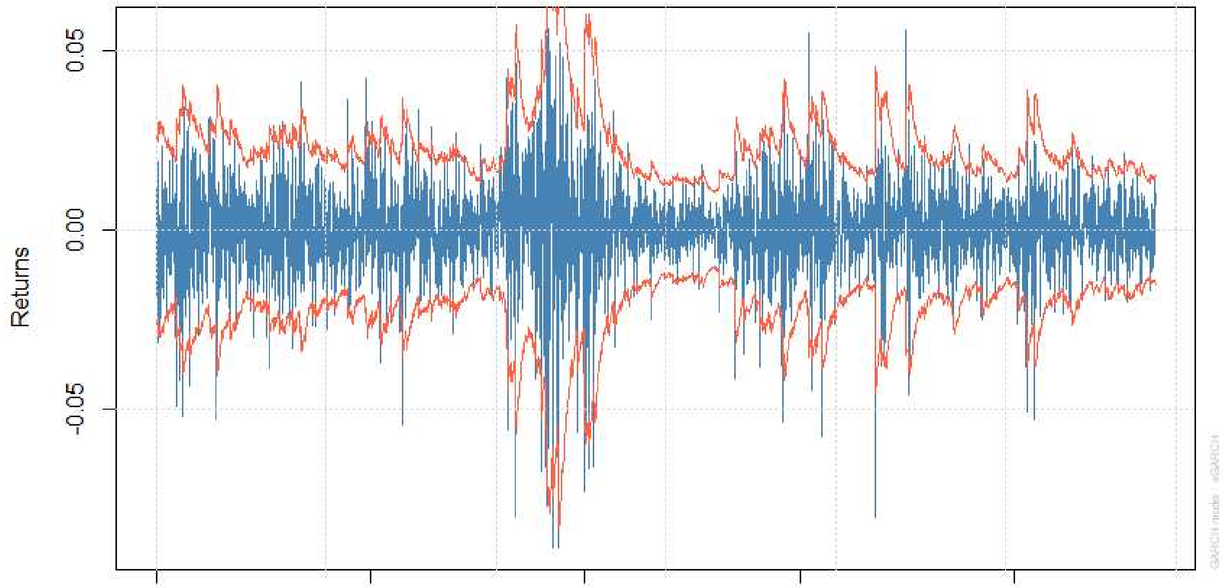

Fig. 2.13. Conditional volatility of ARIMA (2,0,3) model analysis of Shanghai Index returns

Source: author's own calculation

And GARCH(1,1) component:

$$\epsilon_t = \sigma_t z_t \tag{2.8}$$

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{2.9}$$

Figures 2.11-2.13 show the Shanghai Composite Index ARIMA(2,0,3) model has 2 AR terms and 3 MA terms. The log likelihood is 10025.52, AIC = -20039.04, and BIC = -20002.25. The RMSE is slightly higher at 0.01269, and the MAE is 0.00869, suggesting that this index exhibits slightly more volatility compared to the S&P 500 and FTSE 100. The residuals, with a Ljung-Box test p-value of 0.1107, suggest that the model adequately captures the data, as residuals are close to white noise. Then the last step is to analyse the results, they are mainly:

1. ARIMA Model Results:

- SP500: if the ARIMA model for the S&P 500 shows insignificant autocorrelation in the residuals, it suggests that past returns do not predict future returns, supporting the weak-form efficiency.

- FTSE: similar results for the FTSE would indicate that the UK market is also weak-form efficient. Differences might suggest inefficiencies.

- Shangzheng: emerging markets like the Shanghai Composite might show more significant autocorrelation, suggesting potential inefficiencies.

2. GARCH Model Results:

- SP500: the GARCH model for the S&P 500 is expected to show lower volatility clustering, indicative of a more efficient and stable market.

- FTSE: the UK market might show moderate volatility clustering, depending on the economic and political environment (e.g., post-Brexit).

- Shangzheng: the Shanghai Composite is likely to exhibit significant volatility clustering, reflecting higher market risks and inefficiencies.

Comparing the ARIMA and GARCH models across the three indices can draw conclusions about the relative efficiency of the S&P 500, FTSE 100, and Shanghai Composite. The analysis reveals that developed markets like the USA and the UK are more efficient, with lower predictability of returns and less volatility clustering. In contrast, the Shanghai Composite may exhibit higher predictability and volatility clustering, indicating potential inefficiencies typical of emerging markets.

To summarize, financial trading efficiency is a critical aspect of financial markets that impacts price discovery, transaction costs, liquidity, and information processing. The EMH provides a theoretical foundation for understanding market efficiency, but it has been challenged by behavioural finance and market anomalies.

In order to further evaluate the financial trading market efficiency, a mathematical model is proposed here that integrates multiple real-world factors. This model focuses on evaluating the efficiency of practical financial trading markets. It is built upon a modified Price stochastic model by integrating multiple realistic macroeconomic factors such as market volatility, information flow, transaction costs, and liquidity dynamics. The model attempts to quantify efficiency based on how well prices reflect available information. To fulfil the targets, here the following components are introduced:

- Market price equation: captures price dynamics using a stochastic differential equation (SDE).

- Efficiency index: measures the market efficiency based on price deviations and volatility.

- Market liquidity and transaction costs: integrated to reflect real-world trading frictions.

- Information flow rate: a dynamic factor reflecting the impact of new information.

The foundation of the model is a SDE, which captures the dynamics of the market price $P(t)$:

$$dP(t) = \mu(t)P(t)dt + \sigma(t)P(t)dW(t), \tag{2.10}$$

where:

- $\mu(t)$: Drift term, representing the expected return or trend of the asset price. It accounts for factors like interest rates and market sentiment.

- $\sigma(t)$: Volatility term, representing the market risk or price variability. It is time-dependent and may vary based on market conditions.

- $dW(t)$: Brownian motion, modelling the random shock or noise in the price dynamics.

This equation models the continuous evolution of the asset price. It incorporates both deterministic trends $\mu(t)$ and stochastic components $\sigma(t)dW(t)$. It is also a foundation for developing trading algorithms that require a realistic model of asset price movements.

Then the Efficiency Index $E(t)$ is designed to quantify how closely the observed market price $P(t)$ aligns with the fundamental price $P^*(t)$, which represents the intrinsic value of the asset:

$$E(t) = exp\left(-\alpha\left|\frac{P(t)-P^*(t)}{P^*(t)}\right|\right), \tag{2.11}$$

where:

- α : Sensitivity parameter, controlling how strongly deviations from the fundamental price affect the efficiency index.

- $P^*(t)$: Fundamental price, which is an estimate of the asset's true value based on factors such as earnings, dividends, and macroeconomic indicators.

Properties:

$E(t)$ ranges from 0 to 1:

- $E(t) = 1$: The market is perfectly efficient, and the observed price equals the fundamental price.

- $E(t) = 0$: The market is completely inefficient, and there is a significant deviation from the fundamental price.

In practical scenarios, the Efficiency Index can be used by market analysts to evaluate the efficiency of specific asset markets (e.g., stocks, commodities). It helps identify periods when the market may be overvalued (bubble) or undervalued (crash), providing signals for investment decisions.

Market liquidity also significantly impacts the trading efficiency. Here we introduce $L(t)$, the liquidity factor, modelled as:

$$L(t) = \frac{V(t)}{\lambda(t)}, \tag{2.12}$$

where:

- $V(t)$: Trading volume, representing the total quantity of the asset traded within a given time period.

- $\lambda(t)$: Bid-ask spread, indicating the difference between the highest price a buyer is willing to pay (bid) and the lowest price a seller is willing to accept (ask).

Properties:

- Higher $L(t)$ indicates better liquidity, as high trading volume and low bid-ask spread suggest a more efficient market. Low $L(t)$ reflects poor liquidity, making the market more prone to inefficiencies and price distortions.

At the same time, transaction costs play a significant role in determining the market efficiency. Let $C(t)$ be the transaction cost per a unit of the traded volume. The adjusted price dynamic, incorporating costs, becomes:

$$d\tilde{P}(t) = dP(t) - C(t)dV(t), \tag{2.13}$$

The transaction cost model can be further specified as:

$$C(t) = \beta\sqrt{\lambda(t)}, \tag{2.14}$$

where:

- β: Cost coefficient, reflecting market conditions and the impact of trading fees.

- $\lambda(t)$: Bid-ask spread, indicating the market friction.

Properties:

- The transaction cost function is nonlinear, increasing with the square root of the spread. This captures the real-world observation that larger trades or trades in less liquid markets incur disproportionately higher costs.

Then we model the rate at which information enters the market using an exponential decay function:

$$I(t) = \eta e^{-\gamma t}, \tag{2.15}$$

where:

- η: Initial information flow rate, representing the intensity of information release (e.g., earnings reports, news).

- γ: Decay rate, indicating how quickly the relevance of the information diminishes over time.

Properties:

- $I(t)$ decreases exponentially, reflecting the diminishing impact of old information as new data becomes available.

At last, the combined efficiency metric $\varepsilon(t)$ reflects how well the market price aligns with the fundamental price, adjusted for liquidity, transaction costs, and information flow. It integrates these components:

$$\varepsilon(t) = E(t) \cdot \frac{L(t)}{1+C(t)} \cdot I(t), \tag{2.16}$$

Explanation:

- $E(t)$: Captures the deviation of the observed price from the fundamental price.

- $\frac{L(t)}{1+C(t)}$: Adjusts the efficiency metric for liquidity and transaction costs. Higher liquidity and lower costs increase the efficiency.

- $I(t)$: Modulates the metric based on the rate of information flow, reflecting the dynamic nature of information assimilation.

Properties:

- $\varepsilon(t)$ ranges from 0 to 1, with values closer to 1 indicating a more efficient market.

In practical application, the assessment model can be used by analysts, traders, and risk managers as follows:

Step 1. Define Input Parameters.

For a target asset or market, they include:

- P(t): Observed market price at time t;

- $P_f(t)$: Estimated fundamental price at time t;

- V(t): Trading volume at time t;

- $S(t)$: Bid-ask spread at time t;
- TC: Transaction cost per unit traded;
- $\lambda(t)$: Information flow rate.

Step 2. Calculate Liquidity Factor L.

Step 3. Calculate the Efficiency Index E.

Step 4. Calculate Combined Efficiency Metric $\varepsilon(t)$.

The Combined Efficiency Metric can be applied to some practical research purposes:

1. Market monitoring and analysis: financial institutions can use $\varepsilon(t)$ as a real-time indicator of the market efficiency. During periods of high $\varepsilon(t)$, the market is deemed efficient, suggesting that prices reflect all available information. Low values of $\varepsilon(t)$ may signal inefficiency, providing opportunities for arbitrage trading or indicating potential market stress.
2. Trading strategy development: the combined metric can be integrated into algorithmic trading systems. For example, if $\varepsilon(t)$ falls below a certain threshold, the system might execute trades designed to exploit temporary inefficiencies. High-frequency traders can use changes in $\varepsilon(t)$ to adjust their trading algorithms, reducing exposure when the market is less efficient and more prone to price distortions.
3. Risk management: risk managers can utilize $\varepsilon(t)$ to assess the market conditions and adjust portfolio positions accordingly. During periods of the low market efficiency, they may opt to increase cash holdings or hedge positions to mitigate the risk of price shocks. The model can also help in stress testing by simulating scenarios with varying liquidity and information flow, allowing for better preparation against adverse market movements.

This model integrates multiple real-world factors that influence financial trading efficiency, such as information flow, transaction costs, and liquidity dynamics. Traditional models often focus narrowly on price dynamics or information asymmetry. By considering these additional parameters, the proposed model offers a more comprehensive view of trading behaviour and its efficacy, making it suitable for analysing various market conditions, including high-frequency trading environments and periods of market stress. The model bridges the gap between microeconomic market microstructure (e.g., transaction costs, bid-ask spreads) and macroeconomic factors (e.g., information dissemination, systemic shocks). This dual-layer approach allows for a deeper understanding of how individual trading behaviours and broader economic conditions collectively shape the efficiency of the trading process itself. At the same time, using an Efficiency Index $E(t)$ and a combined metric $\varepsilon(t)$, the model provides a quantitative measure of financial trading efficiency, which enables policymakers, analysts, and traders to assess its degree dynamically, facilitating better decision-making.

The assessment model proposed in this study introduces novel elements that expand traditional approaches to evaluating financial trading efficiency. Unlike classical models focusing purely on price dynamics or static information assumptions, this model integrates:

- Dynamic Information Flow Rate ($\lambda(t)$): modelled using an exponential decay function, it reflects the realistic diminishing impact of information over time, addressing a major gap in traditional models that assume constant information assimilation rates.

- Liquidity Factor (L): defined as a function of trading volume and bid-ask spreads, it quantitatively captures market depth and friction, enabling refined insights into real-time market operability.

- Adaptive Sensitivity Parameter (α) in the Efficiency Index: Allows analysts to adjust the model to market-specific efficiency precision levels, supporting applications across highly efficient developed markets and less efficient emerging markets.

- Integrated Transaction Cost Function (TC): modelled nonlinearly with the square root of bid-ask spreads, this element captures the reality that larger trades or trades in illiquid markets incur disproportionately higher costs.

- Combined Efficiency Metric ($\varepsilon(t)$): by integrating price deviation from fundamental value (usually as present or intrinsic value of a financial asset), liquidity, transaction costs, and information flow into a single metric, this model provides a holistic and dynamic quantification of the market efficiency.

Overall, these novel elements advance existing literature by bridging micro-level market microstructure factors (transaction costs, spreads) with macro-level dynamics (information flow, systemic liquidity), thus enabling a more accurate, operationally meaningful, and adaptive assessment of financial trading efficiency under real-world market conditions.

On the other hand, there are also some shortcomings of the efficiency model:

- assumptions of stationarity and simplified dynamics: the model assumes certain parameters (e.g., volatility $\sigma(t)$, trading volume $V(t)$) are either constant or follow predictable patterns. In reality, financial markets are highly non-stationary, and these variables may exhibit abrupt changes due to macroeconomic events or market sentiment shifts. This limitation may reduce the model's predictive power during periods of extreme market volatility;

- simplification of transaction costs: while the model includes a transaction cost component, in practice, transaction costs can vary significantly based on the order size, market depth, and the presence of high-frequency trading algorithms. More complex transaction cost models may be necessary for certain applications. The innovative features of this model open up several avenues for future research and potential enhancements:

1. Empirical testing and calibration:

a. Real-world validation: one of the primary future research directions is the empirical testing of the model using real market data. By calibrating the model parameters (e.g., α, β, γ) with historical price and volume data, researchers can assess its predictive accuracy and refine its components.

b. Cross-sectional analysis: applying the model across different markets (e.g., developed vs. emerging markets) and asset classes (e.g., stocks vs. bonds) will help validate its robustness and identify market-specific adjustments.

2. Policy and Regulatory Implications:

a. Impact analysis of financial regulations: the model can be used to simulate the effects of various regulatory measures (e.g., transaction taxes, short-selling restrictions) on the market efficiency. Researchers can explore how changes in transaction costs or market liquidity, driven by policy interventions, affect the overall efficiency metric $\varepsilon(t)$.

b. Systemic risk and market stability: by analysing periods of low efficiency, the model can help identify potential systemic risks. This can be a valuable tool for central banks and regulatory bodies in monitoring and mitigating financial instability.

In summary, financial trading efficiency is a critical aspect of financial markets that impacts price discovery, transaction costs, liquidity, and information processing.

Transaction costs and market frictions play a crucial role in assessing the trading efficiency, with bid-ask spreads and market impact costs being important measures. Liquidity is another key indicator, reflecting the ease of buying and selling assets without significantly affecting prices. Market makers and high-frequency trading contribute to liquidity and price discovery, but they also raise concerns about market stability and fairness.

Information processing and price discovery are essential for the market efficiency, with event studies and high-frequency trading playing significant roles. Regulatory frameworks can either enhance or hinder the market efficiency, depending on their impact on transparency and competition. Transaction taxes, while intended to stabilize markets, can reduce liquidity and market efficiency.

Empirical evidence suggests that equity markets, particularly in developed economies, are generally more efficient compared to fixed-income and foreign exchange markets. However, efficiency levels can vary across different regions and currencies due to factors such as liquidity, market depth, and regulatory frameworks.

Statistical analysis using ARIMA and GARCH models can provide insights into the predictability of returns and volatility clustering, further assessing the market efficiency. These analyses can help market participants and regulators better understand the relative efficiency of different markets and make informed decisions.

At the same time, the proposed mathematical model offers a comprehensive framework for assessing financial trading efficiency, integrating realistic factors that influence price dynamics. Its innovative approach provides a solid foundation for academic research and practical applications in trading, policy analysis, and risk management. However, its reliance on certain assumptions and simplified components highlights the need for further refinement and empirical testing, particularly in the context of rapidly evolving financial markets. This analysis underscores the model's potential as a valuable tool for understanding financial trading efficiency but also emphasizes areas where future research can enhance its applicability and accuracy.

In addition, there are some implications for market participants:

- implications for traders: traders operating in highly efficient markets face intense competition and must leverage advanced technology and data analytic to achieve above-average returns. Strategies such as algorithmic trading, high-frequency trading, and quantitative analysis are increasingly necessary to gain an edge in these markets;

- implications for regulators: regulators must balance the need for efficient markets with the need to protect investors and maintain market integrity. The rise of HFT and algorithmic trading presents challenges, including the potential for flash crashes and market manipulation. Regulators must ensure that markets remain fair and transparent while fostering innovation and efficiency.

In conclusion, understanding and enhancing financial trading efficiency is crucial for the optimal functioning of capital markets. Market participants, including traders and regulators, need to adapt to technological advancements, leverage data analytics, and strike a balance between efficiency and market integrity.

CONCLUSIONS TO CHAPTER II

The institutional and legal provisions governing financial trading were generalized. The multilevel structure of regulation was revealed, covering international, regional, and national frameworks. Their interaction was systematized in order to highlight both common features and divergences in approaches to the regulation of markets. The significance of this finding is that it ensures a more structured understanding of the institutional environment of financial trading, which contributes to the harmonization of rules, greater transparency of processes, and the creation of a more stable and predictable financial market system.

The tendencies of global financial trading were examined. It was established that the main vectors of development are linked to the rapid growth of digital platforms, the active implementation of algorithmic and high-frequency trading, and the integration of artificial intelligence technologies. The strengthening of globalization processes and the expansion of cross-border financial flows were revealed. The importance of this result lies in the identification of the transformation drivers in global financial markets, which makes it possible to understand future development trajectories and to prepare strategic responses to technological and institutional challenges. The "lag cycle" was suggested to explain the financial trading cyclicality in the emerging and developed financial markets. It means that emerging markets' financial cycles typically lag behind those of developed financial markets by one phase (accumulation, growth, distribution, correction).

The dynamic model for assessing financial trading efficiency was developed. The efficiency criteria and indicators were structured not only in terms of profitability and risk but also in relation to institutional, infrastructural, and technological conditions. This broadened perspective made it possible to characterize efficiency as a multidimensional category, reflecting financial outcomes, system stability, and adaptability to global shocks. The value of this finding is the development of a more comprehensive assessment framework that can be used both by regulators and market participants to improve decision-making and strengthen financial trading efficiency under globalization.

To conclude, the obtained results include the systematization of institutional and legal provisions in a multilevel structure, the identification of global trends that determine technological and structural change in markets, and the construction of dynamic model to assessing financial trading efficiency. These achievements provide theoretical and practical foundations for further studies of financial trading.

CHAPTER III
PROSPECTIVE DIRECTIONS FOR THE DEVELOPMENT OF FINANCIAL TRADING UNDER GLOBALIZATION

3.1. Design of a financial trading risk management framework

Building on the summary of the financial trading risk categories, the identified challenges within institutional frameworks and the technological vulnerabilities inherent in modern trading systems discussed in the previous study, this section critically examines current risk management approaches and outlines a pathway toward their enhancement. The analysis leads to the development of an integrated global risk management framework for financial trading – one that addresses systemic exposures, adapts to technological disruption, and aligns with the principles of market efficiency. By synthesizing insights from regulatory structures, technological dynamics, and performance metrics in the previous study, the proposed framework offers a comprehensive and adaptive solution suited to the complexities of globalized financial markets.

In the context of financial trading, particularly as it pertains to the dynamics of globalization, various types of risks emerge. These risks arise from the complexities introduced by global financial integration, technological advancements, and the increased interdependence of financial markets. The financial trading risk management framework proposed in this study is designed to provide an integrated, systematic, and adaptive approach to managing the full spectrum of risks in modern financial markets. At its core, the framework aims to:

- identify and categorize risks systematically, ensuring no dimension of market, credit, operational, liquidity, or systemic risk is overlooked;
- integrate quantitative models with practical controls, bridging the gap between theoretical risk metrics and operational decision-making;

- enable adaptive and proactive management, responding dynamically to market changes, technological disruptions, and global interconnectedness.

Structurally, the framework is composed of five interlinked pillars, each targeting a specific risk dimension with scientifically validated models and mitigation tools. These include VaR and GARCH for market risk, Credit VaR and Copula for credit risk, Monte Carlo simulations and Risk Control Matrices for operational risk, Liquidity-Adjusted VaR and Market Depth Models for liquidity risk, and Network plus contagion models for systemic risk. By combining these models under a unified architecture, the design ensures that financial institutions can simultaneously monitor, quantify, and control each risk type, while also understanding their interdependencies. Moreover, the incorporation of AI enhancements further enables real-time monitoring, predictive insights, and automated mitigation, aligning the framework with the technological realities of modern trading environments.

In a global context, VaR models must consider the correlations between different asset classes and markets. For instance, the correlation between stock markets in developed and emerging economies can significantly affect the risk profile of a global portfolio. Key parameters include:

- global asset correlations: asset returns in different regions (e.g., Europe, Asia, North America) are correlated. Global financial integration often results in greater co-movements between markets. This requires the inclusion of correlation coefficients into the VaR model;

- currency and sovereign risk: the fluctuation of exchange rates is another significant risk factor in a globalized portfolio. A country's sovereign risk, political stability, and economic policies can drastically affect the returns on international investments;

- interest rates and global shocks: changes in interest rates set by central banks, as well as sudden macroeconomic shocks (e.g., financial crises or geopolitical events), can introduce significant volatility into financial markets.

At the same time, GARCH model is particularly important in global markets where volatility often clusters during crises or in response to macroeconomic news. In a globalized financial market, asset returns in different regions are often correlated. To capture these dependencies, multivariate models such as the Multivariate GARCH (MGARCH) model are used. These models allow for the estimation of the time-varying correlations between multiple assets or markets.

The Dynamic Conditional Correlation (DCC) model is a popular method for modelling time-varying correlations in multivariate settings [254, p.339-340]. The DCC model allows for the separation of modelling of the volatility dynamics and correlation dynamics, which are crucial when markets are globally interconnected. The theoretical underpinnings of the DCC model demonstrate its utility in capturing dynamic correlations between asset classes [254, p. 340-341]. This model has become a critical tool for managing risk in globalized financial markets, particularly for managing cross-market exposure. The application of multivariate volatility models in risk management also emphasized their importance in forecasting tail risks and co-volatility in international portfolios [255, p.150-170]. Key parameters are:

- cross-market volatility spillovers: the impact of volatility in one market on other markets is a crucial parameter in multivariate models. For example, a financial shock in the USA can spill over to European or Asian markets, leading to synchronized volatility increases;

- global market integration: the increasing integration of global financial markets means that correlations between markets have risen, especially during periods of market distress (e.g., 2008 financial crisis). This requires real-time monitoring and forecasting of inter-market correlations.

The advent of financial globalization has made it essential for risk models to account for factors that were once isolated to specific markets. Today, shocks in one region can rapidly propagate through interconnected financial systems. The presence of multinational banks, cross-border investments, and interconnected stock markets means that market risk is increasingly driven by global factors rather than localized ones. The role of financial globalization in transmitting market risk emphasizes how interconnected global financial markets have led to greater risk exposure, particularly during crises when liquidity is low [256, p. 50-62]. Further discussion on the impact of capital flows and global liquidity on market risk suggests that financial globalization has increased the transmission of risk across borders, requiring more integrated risk management strategies [257, p.18-24]. Globalization has introduced new elements into market risk models, such as:

- international capital flows: the flow of capital across borders impacts asset prices and can lead to increased market volatility. Global investors often react to regional economic policies and geopolitical events, causing shifts in asset prices;
- political risk: the political environment in one country can affect global markets, especially in emerging economies. Trade wars, sanctions, and political instability can trigger market movements that spread across borders;
- global monetary policies: central bank policies, particularly in large economies such as the USA, the Eurozone, and China, have global implications. Changes in interest rates, quantitative easing programs, and currency interventions can impact global asset prices and volatility.

The modelling of market risk in a globalized financial environment requires the integration of sophisticated mathematical models like VaR and GARCH, as well as the consideration of global risk factors such as exchange rate fluctuations, international capital flows, and geopolitical instability. As markets become more interconnected, it is crucial to continuously refine these models to account for the increased correlation between global asset classes and the complex interactions between national and international economic policies.

The second category is credit risk. In the context of a globalized financial market, credit risk is influenced not only by the individual creditworthiness of counterparties but also by a range of global factors including economic conditions, sovereign risk, and market-wide shocks**.** The Credit VaR model must also take into account the correlation between different credit assets and the likelihood of joint defaults, especially in a globalized context, where default events in one region can trigger defaults elsewhere.

Copula is especially important in a globalized financial system, where defaults in one region can increase the likelihood of defaults in other interconnected markets. To account for these, multi-factor models are used, where the default probabilities are influenced by several underlying factors. There are the key Indicators for Copula-based credit risk modelling in globalized financial markets as follows:

- credit default swap (CDS) spreads: measure market-implied default probabilities and capture changes in credit risk perception;
- bond yield spreads over risk-free rates: provide input for marginal default probabilities by reflecting the risk premium required for holding risky debt;
- equity market volatility (e.g., VIX): proxy for systemic stress; higher volatility increases correlations between defaults;
- sovereign risk indicators (sovereign spreads, ratings): reflect country-level credit risk, which can spill over into corporate and financial defaults;
- liquidity indicators (bid-ask spreads, trading volumes): signal market stress and contagion effects, amplifying default clustering in crises;
- macroeconomic indicators: capture systematic risk factors that drive joint default likelihood across regions.

One widely used model is the Merton model, which treats default as a function of the firm's asset value relative to its debt. In the multi-factor version, additional macroeconomic factors, such as interest rates, exchange rates, and commodity prices, are incorporated.

A more sophisticated model that can be used in the context of globalization is the Credits Risk model, which assumes a Poisson distribution for default events and incorporates the dependencies between defaults using a copula-based approach. This model can be applied to portfolios of credit derivatives, including CDOs, which are prevalent in the global financial system.

Credit VaR models, when combined with copula functions, can be used to assess the risk of large portfolios of loans, bonds, and other credit instruments. These models are particularly useful for institutions with global exposure to multiple asset classes across different countries and markets.

A typical implementation of the Credit VaR model in a globalized context involves:

- estimating the marginal default probabilities for each credit instrument in the portfolio using historical data, credit ratings, or market-implied probabilities;
- using a copula function to model the joint distribution of defaults across countries and industries, accounting for the fact that defaults in one region or sector can increase the likelihood of defaults in others;
- calculating the Credit VaR at a specified confidence level, which represents the maximum potential loss due to defaults over a given horizon.

Credit VaR and copula models are essential tools in managing credit risk, particularly in the context of a globalized financial environment. By incorporating default probabilities, recovery rates, credit spreads, and the dependencies between credit assets, these models help quantify the potential losses from credit events. The introduction of copulas allows for the modelling of more complex dependency structures, making it possible to assess systemic risk and joint default probabilities. However, the limitations of traditional models, such as the Gaussian copula, have led to the adoption of more advanced techniques to capture tail risks and contagion effects in a globally interconnected financial system.

Then, the third category is operational risk. In a globalized environment, operational risk is more complex due to several factors, including:

- technological integration: the increasing reliance on interconnected technologies and systems across borders increases the likelihood of system failures, cyber-attacks, and operational disruptions;
- global supply chains: organizations often rely on suppliers or partners in different countries, which may introduce risks such as geopolitical instability, currency fluctuations, or regulatory changes;
- legal and compliance risks: different regulatory environments across regions introduce the possibility of non-compliance, which can result in fines, legal costs, or reputational damage.

Monte Carlo simulations and RCM are especially useful in assessing these risks at a global level. For example, Monte Carlo simulations can be used to model the impact of a global cyber-attack, considering the different potential loss severities and the probability of multiple systems being affected across various regions. Similarly, RCMs can help assess the effectiveness of controls designed to manage global risks, such as compliance with GDPR in Europe or cybersecurity regulations in the USA.

Operational risk management using Monte Carlo simulations and RCM can be applied to various practical scenarios, including:

- IT system failures: Monte Carlo simulations can model the potential downtime and financial impact of system failures, while RCMs assess the effectiveness of backup systems, disaster recovery plans, and incident response protocols;
- fraud risk: simulations can estimate the frequency and severity of fraud events, while RCMs assess the effectiveness of fraud prevention measures such as employee background checks, transaction monitoring, and auditing processes;
- natural disasters: Monte Carlo simulations can be used to estimate the impact of natural disasters like earthquakes or floods on operations in different global regions, while RCMs can assess the adequacy of contingency plans and insurance coverage.

Both Monte Carlo simulations and RCM play a crucial role in managing operational risk in a globalized environment. Monte Carlo simulations provide a powerful tool for quantifying the uncertainty and variability in operational risk, while RCMs offer a structured approach to identify, assess, and mitigate risks. Together, these tools enable organizations to understand better the potential operational losses and improve their risk management processes. In an increasingly interconnected and dynamic global landscape, the ability to accurately model and control operational risks is more critical than ever.

The fourth category is liquidity risk. In global financial markets, liquidity risk is an essential factor to consider, as it can dramatically affect asset prices and trading strategies. L-VaR models and Market Depth Models are two key approaches for quantifying and managing liquidity risk. These models incorporate liquidity considerations into the traditional risk measurement framework, offering more accurate assessments in illiquid or volatile markets. The development of L-VaR, applied to the Indian debt market to adjust for liquidity risk, is based on bid-ask spreads and trading volumes. The study demonstrates the usefulness of L-VaR in markets with lower liquidity, highlighting the increased risk during periods of market stress [258]. The extended L-VaR model incorporates microstructural liquidity components, such as transaction costs and bid-ask spreads, into the risk measurement framework [259]. The research shows how these components improve the accuracy of liquidity risk assessments, particularly in markets with fluctuating liquidity conditions. The Market Depth Model examines the relationship between order size and price impact and provides a detailed analysis of how liquidity risk can be modelled by adjusting for market depth and trading volume [260]. This approach is particularly important when considering large trades in less liquid markets, such as emerging market assets or distressed securities. Further exploration of L-VaR and liquidity risk in traditional market risk models, where the authors discuss how incorporating liquidity risk into VaR frameworks can help financial institutions more accurately estimate potential losses during periods of market stress. The paper also highlights the role of transaction costs and market depth in liquidity risk modelling [261].

L-VaR integrates liquidity risk into traditional VaR frameworks, allowing for more accurate risk assessment, especially in volatile or thinly traded markets. Traditional VaR models typically assume that assets can be bought or sold at current market prices without any price impact. However, during times of financial stress, liquidity constraints can cause significant slippage between the expected and actual execution price.

The introduction of L-VaR allows for measuring market risk more comprehensively by adjusting for the liquidity premium and the market impact of trading. The liquidity premium refers to the additional cost of holding an illiquid asset, which is reflected in the broader bid-ask spread and market impact. Key considerations in L-VaR models:

- liquidity risk premium: when markets are illiquid, investors demand a higher return to compensate for the risk of being unable to execute trades at favourable prices;
- stress testing: L-VaR models can incorporate stress testing to simulate liquidity crises, allowing financial institutions to assess potential losses in extreme market conditions;

- transaction costs: L-VaR models account for transaction costs, including bid-ask spreads and market impact, which can substantially increase in illiquid markets.

In the context of a globalized financial market, liquidity risk is influenced by a range of external factors, such as international capital flows, central bank policies, and geopolitical events. For example, global financial crises can lead to a sudden drying up of liquidity, causing significant disruptions in asset prices and trading volumes. The global interconnectedness of markets means that liquidity risk in one region can quickly propagate to other regions, amplifying the impact on global portfolios.

The application of L-VaR and market depth models in a globalized context involves considering cross-border liquidity factors and the interconnectedness of financial markets. A global liquidity shock can significantly affect not just the domestic market but also international markets due to the spillover effects of capital movements and risk aversion.

L-VaR and Market Depth Models are critical tools for quantifying liquidity risk, especially in globalized financial markets. L-VaR extends traditional VaR models by incorporating the effects of liquidity constraints on asset prices, while market depth models quantify the relationship between trading volume, order size, and price movements. Both models are essential for assessing risk during periods of low liquidity, such as financial crises or market stress events. Incorporating liquidity risk into the traditional risk management framework allows for more accurate potential losses prediction, ultimately enabling better decision-making and more robust financial strategies in an interconnected global market.

Finally, the last category is systemic risk. In global financial markets, systemic risk is particularly important because the interconnectivity of financial institutions and markets means that the failure of one institution can cause cascading effects throughout the system [262]. Table 3.1 shows some typical systemic risk transmission pathways in global financial markets.

Table 3.1

Systemic risk transmission pathways in the global financial markets

Trigger event	Initial market impact	Cross-border contagion effect	Final global consequence
U.S. interest rate hike	Increased borrowing costs, stock market dip	Capital outflows from emerging markets	Currency depreciation, economic slowdown in developing nations
Major bank failure	Liquidity freeze in banking sector	Credit contraction in international markets	Global credit crunch, possible recession
Cyberattack on financial institution	Operational disruptions, data leaks	Loss of investor confidence, stock sell-offs	Increased volatility, potential financial panic
Geopolitical crisis (war, sanctions)	Market uncertainty, rising commodity prices	Supply chain disruptions, investment withdrawals	Inflation surge, slowdown in global trade

Source: author's own generalisation

Network models and contagion effects provide valuable frameworks for understanding and quantifying systemic risk, as they focus on the interdependencies between financial entities and the propagation of shocks through the system. The application of network models to financial contagion is extensively covered in [263], where they review different network-based approaches to modelling systemic risk. The authors explore how network structure influences the propagation of shocks and the vulnerability of the financial system to crises. Their work shows that certain types of networks (e.g., highly centralized networks) are more prone to contagion than decentralized networks.

In another study, the authors present a survey of contagion models in financial networks, discussing new methodologies for understanding the structural vulnerabilities of the financial sector. Their research highlights the importance of understanding the spatial and temporal dynamics of contagion and the role of network topology in the spread of financial shocks [264]. The next work [265] examines the role of shadow banking institutions in the propagation of systemic risk. The study emphasizes the importance of incorporating a broad range of financial entities, including hedge funds and pension funds, into network models of contagion to fully capture the complexities of modern financial systems. The following research takes an asset pricing perspective to model contagion in financial markets, inferring systemic risk dynamically based on network linkages [266]. The study focuses on how asset price movements and the strength of financial connections affect the propagation of risk in interconnected financial markets.

Further studies also provide detailed analyses of financial contagion and systemic risk in European financial networks, using network models to quantify spillover effects and the transmission of risk between institutions during times of financial crisis [267; 268].

In the context of systemic risk assessment under globalization, network models can be used to identify systemically important institutions (SIFIs) – financial institutions whose failure would cause widespread disruption to the system. By analysing the centrality and connectivity of nodes in a financial network, it is possible to identify institutions that are crucial for maintaining the stability of the system. Several measures of centrality can be used to quantify the importance of nodes:

- degree centrality: measures the number of direct connections (links) a node has to other nodes. A node with high degree centrality is well-connected and may play a critical role in the financial system;
- betweenness centrality: measures the number of shortest paths between pairs of nodes that pass through a given node. Institutions with high betweenness centrality are crucial for connecting different parts of the network and are more likely to act as conduits for contagion;
- eigenvector centrality: measures the influence of a node in a network by considering not just the number of direct connections, but the importance of the nodes it is connected to.

These centrality measures help identify the institutions or markets that, if disrupted, would have the most significant impact on the financial system.

Empirical studies of systemic risk have used network models to analyse historical financial crises, such as the 2008 global financial crisis and the European debt crisis. These studies often focus on how financial institutions' interconnectedness through derivatives, interbank lending, and asset holdings contributed to the spread of risk across borders. Network models have been applied to:

- assess the interdependence of major global financial markets and their vulnerability to external shocks;
- study the role of shadow banking institutions and their impact on systemic risk;
- examine the effects of market liquidity and how it amplifies contagion during periods of financial distress.

The results from these empirical studies have led to the development of macroprudential policies that aim to reduce the interconnectedness of financial institutions and increase the resilience of the financial system to contagion.

Network models and the study of contagion effects are essential for understanding systemic risk in modern financial markets. By modelling financial institutions as interconnected nodes in a network, it is possible to quantify the impact of shocks and identify key vulnerabilities in the financial system. Network centrality measures and contagion models provide insights into how risk propagates through interconnected markets and how policies can be designed to reduce the likelihood of widespread financial crises. These models are particularly relevant in a globalized financial system, where the failure of one institution can have far-reaching consequences.

To scientifically control the risks discussed, namely market risk, credit risk, operational risk, liquidity risk, and systemic risk, integrating scientific and mathematical approaches to risk management. In order to stably and permanently control the various risks of financial trading under globalization to a certain extent, this study proposes and recommends an integrated global financial trading risk management framework. To effectively implement this framework, there are some necessary solutions. These solutions aim to quantify and mitigate the various risks using advanced models, tools, and regulatory measures. These solutions aim to quantify and mitigate the various risks using advanced models, tools, and regulatory measures, they are mainly:

1) Firstly, scientific control market risk through VaR and GARCH Models. Market risk arises from fluctuations in asset prices, exchange rates, or interest rates. The scientific control of market risk is primarily achieved through advanced models such as

VaR and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. These models help institutions quantify potential losses, forecast volatility, and adjust portfolios accordingly.

VaR: VaR is used to estimate the potential loss in a portfolio under normal market conditions for a given confidence level. To scientifically control market risk, financial institutions must:

- use historical data for calibration: the VaR model should be regularly updated with historical data to ensure it reflects current market conditions. This includes incorporating stress scenarios (e.g., financial crises) to assess extreme loss potential;
- backtesting: financial institutions must backtest VaR models to ensure their predictions are accurate and to refine the model. Any discrepancies should lead to adjustments in risk exposure.

GARCH Models: GARCH models forecast market volatility, accounting for time-varying risk. To control market risk:

- use dynamic forecasting: institutions should update volatility forecasts dynamically, ensuring that volatility forecasts are responsive to market shocks;
- forecasting tail risks: GARCH models should be used to predict tail risks – extreme losses in the market. Monitoring these risks is essential to ensure preparedness during periods of market instability.

With regulatory and policy advice:

- Basel III: international financial institutions should adhere to Basel III regulations, which set out capital adequacy standards, liquidity requirements, and leverage ratios. Basel III emphasizes controlling market risk through stricter capital requirements, particularly during periods of volatility;
- stress testing requirements: regulators should enforce periodic stress testing for large financial institutions to assess their exposure to extreme market movements. This helps control market risk by ensuring that institutions remain resilient during crises;
- risk-based capital buffers: international regulators should consider risk-based capital buffers that adjust based on the volatility of market risks, increasing capital requirements when market conditions worsen.

2) Secondly, scientific control credit risk through Credit VaR and Copula models. Credit risk arises when a counterparty defaults on its financial obligations. To control credit risk, scientific models such as Credit VaR and copula models are employed to quantify and mitigate potential losses.

Credit VaR: such models assess the potential loss from defaults in a portfolio. To scientifically control credit risk:

- diversification: institutions must ensure that their credit portfolios are sufficiently diversified across different sectors, geographies, and counterparties to mitigate concentration risk;

- dynamic calibration: credit VaR models should be continuously calibrated using updated data on default probabilities and recovery rates.

Copula models: the correlation between different credit events. By using these models:

- joint default probabilities: institutions should use copulas to model the joint probability of defaults across counterparties and estimate systemic credit risk;

- interdependencies: copula models help institutions understand how the default of one institution can affect others. These insights are crucial for risk mitigation.

With regulatory and policy advice:

- Basel II & Basel III: regulators should ensure that banks adhere to Basel II and Basel III standards, which require the integration of credit risk in capital adequacy calculations;

- credit concentration limits: international regulators should set limits on credit concentrations, ensuring that financial institutions are not overly reliant on any single counterparty or sector;

- systemic risk monitoring: policymakers should use network-based models to monitor the interconnections between large financial institutions and ensure early identification of potential contagion effects.

3) Thirdly, scientific control operational risk through Monte Carlo simulations and Risk Control Matrices. Operational risk involves risks related to failed internal processes, systems, human errors, or external events. Scientific control of operational

risk is facilitated by tools like Monte Carlo simulations and RCM.

Monte Carlo Simulations: allow institutions to model a wide range of operational risk events and estimate the probability distribution of potential losses. To control operational risk:

- scenario-based modelling: institutions should run simulations for various operational failure scenarios, including IT system failures and fraud, to estimate potential financial losses and non-financial impacts;

- stress testing: simulations should be used to test the operational resilience under stressed conditions (e.g., simultaneous system failures or fraud cases).

Risk Control Matrices: RCMs are used to map risks against control measures. To control operational risk:

- evaluate control effectiveness: financial institutions should regularly assess the effectiveness of their controls and adjust them as necessary based on risk exposure;

- implement proactive mitigation: institutions should develop proactive risk management strategies based on RCM outputs, ensuring that new risks are addressed quickly.

With regulatory and policy advice:

- ISO 31000 standards: international institutions should follow ISO 31000 standards for risk management, which provide guidelines for identifying, assessing, and managing operational risks;

- regulatory requirements for operational risk reporting: regulators should enforce mandatory reporting of operational risk events, including near-misses, to help track trends and improve risk controls;

- resilience frameworks: policymakers should mandate the implementation of business continuity and disaster recovery plans, ensuring that organizations can continue operations during major disruptions.

4) Fourthly, scientific control liquidity risk through L-VaR and Market Depth models. Liquidity risk is the risk that an institution cannot meet its short-term obligations because it lacks sufficient cash or easily marketable assets. L-VaR and Market Depth Models are used to quantify liquidity risk.

L-VaR: L-VaR integrates liquidity into the VaR framework. To control liquidity risk:

- monitor bid-ask spreads: financial institutions should continuously monitor bid-ask spreads and adjust portfolios based on the liquidity of assets. In times of market stress, wider spreads indicate higher liquidity risk;

- maintain liquidity buffers: institutions should maintain liquidity buffers by holding liquid assets that can be easily converted into cash, reducing exposure to liquidity shortages.

Market depth models: help estimate the price impact of large transactions. To scientifically control liquidity risk:

- order execution strategies: institutions should optimize their order execution strategies by breaking large orders into smaller ones to avoid significant price impact in illiquid markets.

- model liquidity stress: financial institutions should use market depth models to simulate liquidity shocks, allowing them to assess the impact of large trades on their portfolios during times of market stress.

With regulatory and policy advice:

- Basel III liquidity standards: international regulators should enforce Basel III liquidity standards, including the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR), which ensure financial institutions maintain adequate liquid assets;

- stress testing for liquidity risk: regulators should require financial institutions to perform liquidity stress tests to simulate liquidity shortages under different market conditions and evaluate the adequacy of their liquidity buffers;

- central bank emergency liquidity support: policymakers should ensure that central banks have clear frameworks for providing emergency liquidity support during periods of market dysfunction.

5) Finally, scientific control systemic risk through Network models and Contagion effects. Systemic risk involves the risk of a breakdown in the financial system, which can be triggered by the failure of interconnected institutions. Network

models and contagion effects provide frameworks for understanding and controlling systemic risk.

Network models: map the interconnections between financial institutions. To control systemic risk:

- systemic risk monitoring: financial institutions and regulators should monitor the interconnectivity of financial institutions using network centrality measures to identify systemically important institutions;

- diversification: financial institutions should reduce their exposure to interconnected entities and diversify their portfolios to limit the impact of a single entity's failure on the broader system.

Contagion models: simulate how risks propagate through the network. To control systemic risk:

- contingent liquidity support: financial institutions should have access to contingent liquidity arrangements, such as lender-of-last-resort facilities, to prevent contagion from spreading across the system;

- early warning indicators: institutions should develop early warning systems based on contagion models to detect potential risks of systemic collapse.

With regulatory and policy advice:

- macroprudential policies: international regulators should implement macroprudential policies to limit systemic risk. This includes monitoring interconnectedness between institutions, implementing capital surcharges for SIFIs, and ensuring institutions have robust contingency plans;

- financial stability oversight council (FSOC): policymakers should empower international bodies, like the FSOC, to assess systemic risk on a global scale and to intervene when risks are identified that could lead to widespread financial instability;

- resolution plans (living wills): international institutions should require large financial institutions to develop living wills to ensure they can be resolved in an orderly manner without causing systemic disruptions.

Table 3.2 shows the description of the financial trading risk management framework.

Table 3.2

Description of the financial trading risk management framework

Risk type	**Description**	**Impact on financial stability**	**Examples**	**Estimation tools (models)**	**Traditional mitigation strategy**	**AI-driven enhancement**
Market risk	Price fluctuations in financial instruments	High	Stock market crashes, volatility spikes	VaR, GARCH, MGARCH, DCC	Diversification, stop-loss orders	AI-driven predictive analytics, algorithmic hedging
Liquidity risk	Inability to execute large trades without price impact	High	Flash crashes, bond market freezes	L-VaR, Market Depth Models	Holding cash reserves, central bank interventions	Real-time liquidity forecasting using deep learning
Credit risk	Counterparty default on financial obligations	Medium-high	2008 Lehman Brothers collapse	Credit VaR, Copula models, Merton model, Multi-factor credit models	Credit rating analysis, collateral requirements	Blockchain smart contracts for automated credit verification
Operational risk	System failures, cybersecurity threats, fraud	Medium	Algorithmic trading glitches, hacking incidents	Monte Carlo Simulations, RCM	IT security protocols, internal audits	AI-driven anomaly detection for fraud prevention
Systemic risk	Financial crises affecting the entire economy	Very high	Global banking crises, contagion effects	Network Models, Contagion Models, Centrality Measures	Capital adequacy regulations, stress testing	AI-based systemic risk simulations and contagion mapping

Source: author’s own generalisation

In summary, the effective management of market, credit, operational, liquidity, and systemic risk requires the integration of advanced mathematical models, sophisticated risk management techniques, and robust regulatory frameworks. By implementing resilient models such as VaR, Monte Carlo simulations, and network contagion models, financial institutions can better quantify, mitigate, and control risks. Additionally, international regulatory frameworks, macroprudential policies, and stress testing requirements, are essential for ensuring the stability of the global financial system. By adopting these scientifically grounded practices and policies, financial institutions can safeguard against potential risks and contribute to the overall stability of the financial markets.

On the other hand, the evolving landscape of global financial trading demands robust and adaptive risk mitigation strategies, and artificial intelligence is playing an increasingly vital role in enhancing traditional approaches. Market risk, typically managed through diversification and stop-loss orders, is now being addressed with AI-driven predictive analytics and algorithmic hedging techniques that dynamically adjust positions in response to real-time market data. For liquidity risk, traditional methods such as maintaining cash reserves and relying on central bank interventions are being supplemented by deep learning models capable of real-time liquidity forecasting, allowing institutions to proactively manage cash flow imbalances. Credit risk, long assessed via credit ratings and secured through collateral, is experiencing a transformation with the integration of blockchain-based smart contracts, enabling automated and transparent credit verification processes. Operational risk, traditionally mitigated by IT security protocols and regular internal audits, is now being significantly reduced through AI-powered anomaly detection systems that can identify and respond to fraudulent activities with greater speed and accuracy. Finally, systemic risk, often addressed through capital adequacy regulations and stress testing frameworks, is increasingly being managed with advanced AI simulations that model financial contagion and systemic interdependencies, offering regulators and institutions a more granular understanding of potential cascading effects in times of crisis. Together, these AI-driven enhancements are not only refining existing risk management strategies but are also reshaping the way the financial industry anticipates and responds to complex global threats.

In real-world financial institutions and trading operations, the proposed risk management framework can be applied through the following process:

Step 1. Risk identification and mapping:

Map all portfolio and trading exposures to the five risk categories: market, credit, operational, liquidity, and systemic.

For each exposure, identify relevant data inputs (e.g. asset prices, counterparty ratings, system performance metrics).

Step 2. Model calibration and integration:

Market Risk: Calibrate VaR and GARCH models using historical price data and real-time market feeds to set daily trading limits and portfolio stress tests.

Credit Risk: Apply Credit VaR models with Copula-based joint default estimations to quantify aggregated exposure, guiding counterparty concentration limits.

Operational Risk: Use Monte Carlo simulations to model operational event scenarios and Risk Control Matrices to align controls with identified risks.

Liquidity Risk: Calculate Liquidity-Adjusted VaR incorporating bid-ask spreads and use Market Depth Models to inform execution strategies for large orders.

Systemic Risk: Implement network models to monitor interconnected institutional exposures, identifying SIFIs and potential contagion pathways.

Step 3. Real-time monitoring and AI integration:

Integrate AI tools for anomaly detection (operational risk), real-time liquidity forecasting (liquidity risk), and market risk predictive analytics to automate alerts and enhance decision speed.

Step 4. Policy setting and actionable thresholds:

Define actionable thresholds for each risk metric. For example, if GARCH-predicted volatility exceeds a pre-set limit, trigger hedging strategies or reduce leverage.

Establish contingency protocols for systemic risk alerts, such as liquidity freeze plans or rapid collateral calls.

Step 5. Governance and reporting:

Embed framework outputs into risk dashboards for senior management, providing clear daily and weekly summaries across all five risk categories.

Use outputs for regulatory compliance reporting (e.g. Basel III LCR/NSFR for liquidity, stress testing results for market and credit risk).

By systematically applying each model within its respective risk category, integrating AI tools for dynamic monitoring, and aligning outputs with governance and regulatory processes, institutions can operationalize the framework to achieve robust, adaptive, and proactive financial risk management in complex global markets.

In conclusion, a comprehensive framework for financial trading risk management was created. Its foundation is built on the integration of classical and modern approaches, which ensures the balance between traditional tools of risk identification and the advanced methods of quantitative modelling. The framework systematizes risk types, links them to relevant assessment instruments, and provides a structured sequence for decision-making. The novelty of the framework lies in its multidimensional structure, which unites market, credit, liquidity, operational, and systemic risks into a single conceptual model. A distinctive feature is the inclusion of technological and informational dimensions, which reflect the realities of algorithmic, high-frequency, and digital platform-based trading. The value of the developed framework is its universality and adaptability. It can be applied both by regulators for systemic oversight and by market participants for internal risk control. Moreover, the model enhances the capacity to forecast potential vulnerabilities, to compare the efficiency of different trading strategies under risk exposure, and to strengthen the resilience of financial systems under conditions of volatility and uncertainty. It establishes the basis for a more reliable and transparent practice of financial trading risk management in a global and technology-driven environment.

3.2. Formation of a stable financial trading environment

This section intergrates perspectives on regulation, technological advancement and market efficiency discussed in the previous study to build a comprehensive understanding of financial market stability. The stability of financial trading is defined through key dimensions such as liquidity depth, coherence in regulatory practices, and the capacity of trading systems to withstand technological disruptions. By aligning these elements with the interconnected nature of global markets and the design of hierarchical financial trading information basis, the analysis of stability positions is not only a theoretical construct but also a practical imperative. This integrated approach offers a valuable tool for policymakers and institutional stakeholders seeking to foster resilient financial ecosystems amid increasing globalization and digital transformation.

Globalization has fundamentally reshaped the landscape of financial trading. The interaction of markets across different regions, time zones, and economic environments introduces complexities that go beyond traditional local trading. The globalization of financial markets has fundamentally transformed the dynamics of trading, creating an interconnected ecosystem where capital, information, and risks transcend national borders. Over recent decades, technological advancements, regulatory harmonization, and cross-border capital mobility have reshaped the efficiency, liquidity, and stability of global financial systems. Yet, these developments also introduce complexities, such as heightened volatility, systemic risks, and asymmetries in information and regulation. Understanding the conditions necessary for financial trading to thrive in this globalized context is critical to fostering resilient markets that balance innovation with stability.

This section will identify and analyse five foundational pillars that underpin effective financial trading in a globalized economy. Each condition is explored through theoretical models and empirical evidence, offering insights into their interdependence and collective impact on global financial systems. This work not only advances academic understanding of global financial systems but also offers actionable insights for policymakers, investors, and institutions navigating the challenges of 21st-century markets. The five main conditions are:

1. Market efficiency and information availability;
2. Cross-border capital flows and risk sharing;
3. Regulatory framework and institutional support;
4. Technological infrastructure and trading platforms;
5. Foreign exchange and currency market liquidity.

In detail, the first of the main conditions is market efficiency and information availability. The efficiency of financial markets is a fundamental concept in modern finance. The efficient market hypothesis suggests that asset prices reflect all available information at any given time. This concept is critical in understanding the dynamics of global financial trading, as the accessibility and speed with which information is disseminated across markets worldwide determine the potential for trading activity.

In the context of globalization, market efficiency extends beyond a single domestic market to encompass a global set of interconnected markets. With globalization, information travels much faster and more widely than before, which impacts asset prices and trading behaviour. A key condition for financial trading to occur in a globalized economy is the ability of markets to rapidly absorb and process information from various sources – economic reports, geopolitical events, corporate earnings, and even social media trends – across different regions. This can lead to a situation where information asymmetry is reduced, and asset prices adjust instantaneously to new information, thereby ensuring the efficiency of global markets.

The speed of information transmission and the degree of market integration (e.g., trading hours, availability of cross-border data) directly influence the market's efficiency. Without effective mechanisms for information dissemination and consumption, markets would become inefficient, leading to distortions in asset pricing and the potential for arbitrage opportunities. Therefore, market efficiency in a globalized context is characterized by:

- immediate reflection of information: as financial markets across borders become increasingly interconnected, information such as macroeconomic reports, changes in interest rates, or geopolitical instability quickly affects asset prices worldwide. An efficient global market adjusts prices in real-time, eliminating informational gaps that could otherwise create profitable opportunities for arbitrageurs [36];

- absence of barriers to information flow: in a globalized environment, information must flow freely across national borders. The regulatory barriers, technological infrastructure, and financial systems in different countries should facilitate the smooth dissemination of information without delays [270];

- reduction of transaction costs: the process of trading becomes more efficient when transaction costs are minimized. These costs could include bid-ask spreads, information acquisition costs, and other frictional costs in the process of trading internationally. Lower transaction costs mean that the market can more easily react to information and incorporate it into the asset prices [271];

- global network of traders: the integration of markets globally through technological advancements like algorithmic trading has also contributed to more efficient markets. These systems can digest information rapidly and make real-time adjustments to positions across different markets, further promoting efficiency.

This mathematical model can better capture the global dimensions of market efficiency and information availability. Let $P(t)$ represent the price of an asset at time t, and assume that price is a function of the information $I(t)$ from multiple global sources, including economic, financial, and geopolitical data. In a more complex global environment, this relationship can be captured by:

$$P(t) = \alpha \cdot E[I(t)] + \beta \cdot E[F(t)] + \delta \cdot E[G(t)], \tag{3.1}$$

where:

- α, β, and δ are scaling factors representing the sensitivity of the asset price to information from three sources: $I(t)$ (local information), $F(t)$ (global financial data), and $G(t)$ (geopolitical events or other external factors).

- $E[I(t)]$, $E[F(t)]$, and $E[G(t)]$ represent the expectations (or forecasts) of information availability at time t for local, financial, and global variables.

The efficiency of the market depends on the ability of traders and investors to rapidly process and incorporate this information. The model allows for the varying levels of influence of different types of information, reflecting how global news, regional economic reports, or international trade agreements can impact asset prices.

To model information asymmetry, here we introduce a measure of the discrepancy between the information available to different market participants. This can be represented by the following inequality:

$$Market\,Efficiency = \frac{P(t)}{I(t)} = 1, \text{ if information is symmetric.} \tag{3.2}$$

When information asymmetry exists (e.g., when one group has access to privileged information), the market will be less efficient, and prices will not fully reflect all available information.

To reinforce these theoretical constructs, empirical studies provide evidence supporting the relationship between market efficiency and information availability in a globalized context.

The EMH argues that in an efficient market, all available information should be incorporated into asset prices. This assumption holds for both local and global markets as long as the information is disseminated effectively across borders. Studies support the notion that markets are largely efficient, though they acknowledge anomalies that can arise in specific circumstances, such as during times of financial crises or significant market disruptions [270]. The ability to trade globally and access information in real-time significantly improves market efficiency. As markets become more interconnected, it is harder for mispricing to persist, as arbitrage opportunities disappear rapidly.

Then the second one of the main conditions is: cross-border capital flows and risk sharing. Under globalization, financial markets have become increasingly integrated, leading to greater cross-border capital flows. These flows are fundamental to the functioning of global financial markets and can serve to mitigate risk, diversify investments, and promote economic growth. For financial trading to occur effectively in such environment, it is essential to understand the dynamics of these capital flows, the mechanisms of risk sharing, and the implications for market efficiency.

Cross-border capital flows refer to the movement of funds between countries for the purpose of investment, lending, and trade. Globalization has facilitated these flows by reducing barriers to international trade, promoting free markets, and improving communication and transportation infrastructure. Cross-border capital flows can be classified into different forms, such as direct foreign investment, foreign portfolio investment, and debt flows. These types of capital flows are instrumental in the efficient allocation of capital across borders, leading to better resource allocation and diversification of risk.

The benefit of cross-border capital flows is most evident in the context of portfolio diversification. In a globalized financial market, investors can access a wide range of assets from different countries, industries, and regions, allowing them to spread their investments and reduce the overall risk of their portfolios. This ability to diversify is critical for improving financial stability, particularly when domestic markets face economic shocks. Moreover, countries that attract foreign investment benefit from increased capital, which can stimulate growth and development.

However, cross-border capital flows also come with potential risks, particularly in the form of capital flight or sudden withdrawals, which can destabilize financial markets. The balance between inflows and outflows is crucial for ensuring economic stability. In the absence of proper regulatory frameworks and institutional controls, volatile capital flows can lead to financial crises.

One of the primary reasons for the increased emphasis on cross-border capital flows in a globalized financial environment is the ability to share risk. Risk sharing allows investors to mitigate the adverse effects of localized economic shocks by spreading their investments across a broader set of markets. This enhances the overall stability of the global financial system. Financial markets that allow for risk sharing enable investors to pool risks and benefits, smoothing out the effects of economic fluctuations.

A critical component of capital market integration is the idea that as markets become more interconnected, financial assets become more correlated. For instance, economic events in one country, such as a change in monetary policy or a political crisis, can have widespread implications on asset prices across the globe. By sharing risks across different countries and regions, investors can reduce the likelihood of significant portfolio losses from any single market event. However, the degree of integration can also lead to the spread of economic crises across borders.

The global nature of financial markets means that investors have access to a much wider set of opportunities for risk diversification. Portfolio theory, as proposed by Markowitz [272, p. 77-78], highlights the benefits of holding a mix of assets with different risk-return characteristics. Global integration allows for the creation of portfolios that are less sensitive to local market conditions, enhancing overall stability. However, this integration also means that financial contagion can spread more easily, as seen in the global financial crisis of 2007-2008.

To model cross-border capital flows and risk sharing, here can use a portfolio optimization approach, considering multiple markets in a globalized context. Let the investor's total wealth $W(t)$ at time t be distributed across multiple countries, each with different economic conditions and risk profiles. The wealth invested in country j at time t is represented by $w_j(t)$, and the asset price in country j is denoted by $P_j(t)$. Thus, the total wealth of the investor is:

$$W(t) = \sum_{j=1}^{N} w_j(t) \cdot P_j(t), \tag{3.3}$$

where:

- $w_j(t)$ is the fraction of total wealth invested in market j at time t,

- $P_j(t)$ is the asset price in market j,

- N is the total number of markets in which the investor is exposed.

The investor's objective is to maximize the expected return while minimizing the variance of the portfolio, which represents the risk. The optimization problem can be expressed as:

$$Maximize \quad E\left[\sum_{j=1}^{N} w_j(t) \cdot r_j(t)\right], \tag{3.4}$$

subject to:

$$Var(R(t)) = \sum_{j=1}^{N} w_j^2 \cdot \sigma_j^2 + 2 \cdot \sum_{i \neq j} w_i w_j \cdot Cov(r_i(t), r_j(t)), \tag{3.5}$$

where:

- $r_j(t)$ is the return of asset j at time t,

- σ_j^2 is the variance of asset returns in country j,

- $Cov(r_i(t), r_j(t))$ is the covariance between returns in countries i and j, reflecting the degree of market integration.

This model enables the investor to allocate capital in a way that balances expected returns with the risk associated with different markets, as influenced by global economic conditions and the degree of integration between the markets.

Empirical studies provide significant evidence for the importance of cross-border capital flows and risk sharing in globalized financial markets. For example, studies highlight that international capital mobility allows countries to smooth consumption and invest in long-term growth projects [273]. Another study argues that financial integration improves the efficiency of capital allocation, leading to better resource distribution [274, p. 300-400].

On the other hand, the risks associated with cross-border capital flows are highlighted by studies demonstrating how sudden shifts in capital flows can lead to financial instability and crises [275]. These studies emphasize the importance of having proper mechanisms for managing and regulating cross-border capital flows to avoid financial contagion.

Next, the third main condition is the regulatory framework and institutional support.

In a globalized financial landscape, the regulatory environment plays a pivotal role in ensuring that financial markets function smoothly and efficiently. The framework within which financial markets operate not only influences the stability of the markets but also determines the level of confidence that investors and traders have when engaging in cross-border transactions. Effective regulatory oversight is essential for minimizing systemic risk, preventing market manipulation, and ensuring fair competition. In the context of globalization, a harmonized regulatory framework across countries is particularly important, as cross-border transactions and the flow of capital between markets require alignment between national regulations.

A regulatory framework encompasses the set of laws, rules, and regulations that govern financial markets and transactions. This framework ensures transparency, accountability, and fairness in the financial system. As markets become more interconnected globally, the coordination and standardization of financial regulations across different jurisdictions become increasingly important to prevent regulatory arbitrage, where market participants exploit differences in regulations to circumvent rules in one country by operating in another.

In a globalized world, financial regulations must not only address local market concerns but also consider the impact of cross-border transactions. International regulatory bodies like the International Monetary Fund, the World Bank, and the Financial Stability Board work to create standards and guidelines for regulatory practices across countries. However, the application of these standards often varies due to different legal frameworks and institutional capacities. Inadequate regulation can lead to situations where markets are vulnerable to shocks, as it was witnessed in the global financial crisis of 2007-2008. Financial institutions in some jurisdictions were able to take on excessive risk due to insufficient oversight, leading to widespread instability in global markets. Regulations in the context of globalized finance must address issues such as:

1. Market transparency: ensuring that market participants have access to accurate and timely information, especially with regard to securities, derivatives, and financial instruments traded globally.
2. Investor protection: safeguarding investors from fraudulent activities, market

manipulation, and excessive risk-taking by financial institutions.

3. Capital requirements: establishing minimum capital thresholds to ensure that financial institutions have sufficient resources to absorb losses and remain solvent during times of economic stress.

4. Cross-border enforcement: ensuring that regulations can be effectively enforced across jurisdictions, especially when dealing with multinational financial institutions and transactions.

In addition to regulatory frameworks, institutional support plays a crucial role in ensuring the smooth functioning of financial markets. Financial institutions, such as central banks, commercial banks, investment banks, and insurance companies, provide the necessary infrastructure for financial transactions. These institutions help create liquidity, facilitate the transfer of capital, and manage financial risks.

In a globalized economy, financial institutions must operate under a set of regulations that ensure they are resilient to external shocks and capable of supporting international trade and investment. Central banks play a key role in stabilizing the financial system by controlling money supply, regulating interest rates, and managing exchange rates. They also work to prevent excessive inflation or deflation, which can lead to economic instability. Financial markets infrastructure, including trading platforms, clearinghouses, and custodians, is vital in facilitating safe and efficient transactions between global participants. Exchanges like the New York Stock Exchange, the London Stock Exchange, and the Tokyo Stock Exchange provide a platform for the listing and trading of securities across borders.

Effective institutional support also includes providing financial products and services that enable risk management. Derivatives markets, for example, allow investors to hedge against risks associated with foreign exchange fluctuations, interest rates, or commodity prices. This is essential in a globalized trading environment, where such risks are magnified by the interconnectedness of international markets.

The role of international financial institutions is also important in providing institutional support for countries with developing economies. These institutions can offer loans, technical assistance, and advice on how to improve financial systems and regulatory frameworks to support financial market integration and stability.

To understand how regulatory frameworks and institutional support impact financial trading in a globalized economy, we extend the previous models of asset pricing and portfolio optimization. The risk-adjusted return of trading in a specific market j, considering the influence of regulatory stability, can be represented as:

$$R_j(t) = \frac{r_j(t)}{1+\rho_j(t)\cdot E[R_j]}, \tag{3.6}$$

where:

- $r_j(t)$ is the return on an asset in market j,

- $\rho_j(t)$ is the regulatory stability factor in market j,

- $E[R_j]$ is the expected regulatory cost or tax burden in market j.

In this model, the regulatory stability factor ρ_j reflects how well market regulations support financial activities. A higher ρ_j indicates a more stable regulatory environment, which enhances the attractiveness of the market for investors. Conversely, a lower ρ_j implies higher uncertainty, potentially reducing market participation.

Furthermore, the capital adequacy of financial institutions in a global context can be modelled as:

$$Capital\ Adequacy = \frac{K_j}{A_j} \geq \gamma, \tag{3.7}$$

where:

- K_j is the capital of financial institution j,

- A_j is the risk-weighted assets of financial institution j,

- γ is the minimum required capital adequacy ratio.

The capital adequacy ratio ensures that financial institutions have enough capital to cover potential losses, reducing the likelihood of insolvency in times of market stress. Regulatory bodies, such as the Basel Committee on Banking Supervision, set these standards, and their implementation is critical for the stability of global financial systems.

Numerous empirical studies have demonstrated the importance of effective regulation and institutional support in promoting financial stability and facilitating global financial trading. Studies show that countries with strong regulatory frameworks tend to attract more foreign direct investment and experience greater financial stability during periods of economic turbulence [276, p.1-5]. Furthermore, financial institutions that are subject to robust regulatory oversight are better positioned to withstand financial crises and continue providing services across borders [277, p.1-3].

The role of international regulatory bodies in harmonizing global standards has been highlighted by the research on the effects of cross-border regulatory cooperation [278]. Such cooperation helps mitigate the risk of regulatory arbitrage and ensures that global markets remain integrated and stable.

Move on, the fourth main condition is technological infrastructure and trading platforms. The technological infrastructure underlying financial markets plays a crucial role in the ability of financial trading to occur effectively, especially in the context of globalization. As financial markets become more interconnected and complex, the speed, security, and efficiency of transactions are increasingly dependent on advanced technological systems. Technological innovations, such as algorithmic trading, HFT, and blockchain technology, are transforming the way financial markets operate, making them more global, transparent, and efficient. At the same time, these advancements raise new challenges related to regulatory oversight, market stability, and cybersecurity.

The technological infrastructure of financial markets consists of the systems and platforms that facilitate the execution, clearing, and settlement of financial transactions. These systems include trading platforms, data centres, networking infrastructure, and financial market exchanges. As globalization has increased the number of participants in global markets, the demands on these systems have grown substantially. In order to handle large volumes of trade and data, technological systems must be capable of processing transactions in real-time and ensuring that trades are executed securely and efficiently. Key components of this infrastructure include:

1. Trading platforms: modern electronic trading platforms enable the buying and selling of financial assets, such as stocks, bonds, and derivatives, in real-time. These platforms provide a means for investors and traders to execute orders and manage their portfolios, often without the need for traditional intermediaries such as brokers. The growth of online trading platforms and direct market access allows investors to bypass traditional exchanges, making financial markets more accessible globally.
2. Algorithmic trading and high-frequency trading: algorithmic trading, which uses computer algorithms to execute trades based on pre-set criteria, has revolutionized the speed and efficiency of financial markets. In particular, high-frequency trading has become a significant feature of global financial markets. HFT involves executing large volumes of orders at extremely high speeds, often in milliseconds, to take advantage of small price discrepancies. The rise of HFT has contributed to more efficient price discovery, tighter bid-ask spreads, and greater liquidity. However, it has also raised concerns about market manipulation, fairness, and volatility.
3. Blockchain and distributed ledger technology: blockchain technology, a decentralized digital ledger, has the potential to transform the way financial transactions are executed, settled, and recorded. The transparency, security, and efficiency provided by blockchain can help reduce transaction costs, improve trust, and streamline cross-border payments. Cryptocurrencies such as Bitcoin and Ethereum leverage blockchain technology to facilitate peer-to-peer transactions without the need for intermediaries. While still emerging, blockchain has the potential to disrupt the traditional financial infrastructure by providing decentralized and immutable records of transactions.

In a globalized financial system, technological infrastructure serves as the backbone for connecting markets across borders. Without technological innovation, the growth of international trading and capital flows would be significantly constrained. The ability to conduct cross-border transactions in real-time is a direct result of improvements in technology that have enabled global financial integration.

The speed at which financial transactions occur has become a key feature of modern markets. In fact, many transactions are now executed within fractions of a second, allowing market participants to respond rapidly to fluctuations in market conditions. The development of low-latency trading platforms has been essential in facilitating these rapid transactions. The reduction of latency is particularly important in the context of high-frequency trading, where even a millisecond can determine whether a trade is profitable.

Another important aspect of technological infrastructure is market transparency. The widespread availability of financial data, coupled with advances in data analytics, has made it easier for investors to access and analyse market information. Real-time market data, such as stock prices, exchange rates, and commodity prices, is now available to traders around the world. Furthermore, the use of big data and machine learning has enhanced traders' ability to analyse market trends and predict future price movements. These innovations have led to more informed decision-making and more efficient markets.

While technological advancements have brought many benefits to global financial markets, they have also introduced new challenges. Cybersecurity has become a critical concern, as financial systems are increasingly vulnerable to attacks that could disrupt trading activities or compromise sensitive financial data. As financial markets become more interconnected, the risk of a global cyberattack increases, potentially leading to widespread instability.

Moreover, the rise of algorithmic and high-frequency trading has raised questions about market fairness and stability. These technologies can lead to flash crashes, where rapid price movements caused by automated trading algorithms can result in significant market disruptions. Regulators face the challenge of ensuring that technological innovations do not lead to market manipulation or unfair advantages for certain market participants.

The lack of regulatory oversight in some areas of financial technology (FinTech) has led to the emergence of regulatory arbitrage, where companies exploit regulatory gaps to avoid compliance with existing rules. For example, the rise of decentralized finance platforms and cryptocurrencies has created regulatory challenges, as many of these platforms operate outside traditional regulatory frameworks. As a result, governments and international regulatory bodies are working to develop new regulations to address the risks posed by emerging financial technologies.

The impact of technological infrastructure on financial trading can be modelled by considering the transaction cost and execution speed of a financial trade. The execution speed $Speed_j(t)$ is the time it takes to complete a trade in market j, and the transaction cost $C_j(t)$ is a function of latency, data processing, and other technological factors. The transaction cost model as:

$$C_j(t) = \alpha \cdot Latency_j(t) + \beta \cdot Complexity_j(t), \tag{3.8}$$

where:

- α and β are coefficients representing the sensitivity of transaction costs to latency and complexity,

- $\mathrm{Latency_j(t)}$ represents the time delay in executing a trade in market j,

- $\mathrm{Complexity_j(t)}$ represents the complexity of executing a trade, considering factors such as market depth and algorithmic trading strategies.

The impact of high-frequency trading on price discovery can be represented as:

$$\Delta P_j(t) = \gamma \cdot HFT_j(t) \cdot (E[I_j(t)] - P_j(t)), \tag{3.9}$$

where:

- $\Delta P_j(t)$ represents the change in asset price due to HFT,

- $HFT_j(t)$ represents the activity level of high-frequency trading in market j,

- $E[I_j(t)$ is the expected price based on available information,

- $P_j(t)$ is the current price in market j,

- γ is a scaling factor representing the sensitivity of price changes to HFT activity.

Numerous studies have shown how technological advances have shaped global financial markets. Research indicates that algorithmic trading and high-frequency trading have led to increased liquidity and more efficient price discovery in many markets [279]. However, these advancements have also raised concerns about market stability and the potential for flash crashes, where rapid price fluctuations occur due to automated trading [280]. Moreover, blockchain technology and cryptocurrencies have introduced new ways of conducting transactions without the need for intermediaries but have also presented regulatory challenges [281].

In addition, cybersecurity risks associated with financial technologies have turned out a major concern for regulators. As financial markets are becoming more dependent on technology, the potential for cyberattacks is increasing, necessitating stronger cybersecurity frameworks.

Finally, the last main condition is foreign exchange and currency market liquidity. The FX market is one of the largest and most liquid financial markets in the world, facilitating the exchange of currencies between international buyers and sellers. Currency markets play a critical role in global trade and investment, as they determine the relative value of national currencies, which in turn affects the pricing of goods, services, and assets across borders. The liquidity of foreign exchange markets is a key determinant of the efficiency and stability of global financial trading, as it allows market participants to enter and exit positions in currencies without significantly impacting prices. In the context of globalization, currency market liquidity is increasingly influenced by international trade flows, capital movements, and technological advancements.

Currency liquidity refers to the ease with which a currency can be bought or sold without causing a substantial movement in its price. Liquidity is vital in foreign exchange markets because it determines how efficiently prices are set and how quickly market participants can execute trades. The depth and breadth of the FX market contribute to its liquidity. Market depth refers to the amount of buy and sell orders available at each price level, while market breadth refers to the diversity of market participants, including governments, central banks, commercial banks, investment firms, hedge funds, and retail traders. The liquidity of a currency is influenced by a variety of factors, including:

1. Market size and volume: the larger the volume of trades in a currency, the higher its liquidity. The currencies of large economies such as the U.S. dollar, euro, and Japanese yen typically have greater liquidity due to the size of their economies and the volume of international trade and investment that involves these currencies.

2. Economic conditions: strong, stable economies tend to have more liquid currencies because they attract more international investment and trade. Economic factors such as inflation rates, interest rates, and political stability play a key role in determining currency liquidity.

3. Central bank policies: central banks, through their monetary policies, can influence currency liquidity by controlling money supply, interest rates, and foreign exchange reserves. Intervention in the FX market, through activities such as buying or selling currencies, can also affect liquidity levels and market stability.

4. Market participants: a high number of market participants, including institutions and retail traders, increase the depth and breadth of the market. The greater the participation, the easier it is to buy and sell currency positions.

The foreign exchange market is integral to the global financial system. Currency exchange rates, which are determined by the supply and demand of currencies in the FX market, have far-reaching implications for trade, investment, and economic growth. The ability to convert one currency into another facilitates international transactions, allowing businesses to import and export goods, invest across borders, and hedge against currency risk.

The importance of FX liquidity is highlighted during times of economic stress, where sudden shifts in exchange rates can lead to financial instability. For example, during the Asian financial crisis of 1997-1998, many countries in the region experienced sharp devaluations of their currencies due to a lack of liquidity and speculative attacks on their currencies. Similarly, the global financial crisis of 2008 saw large-scale interventions by central banks to stabilize currency markets and maintain liquidity in the face of a collapsing global banking system.

In a globalized financial environment, foreign exchange rates can have a direct impact on asset prices, interest rates, and the profitability of multinational corporations. For example, fluctuations in exchange rates can affect the value of foreign earnings for companies, the cost of imports and exports, and the performance of global investment portfolios.

The liquidity of the FX market also impacts the strategies employed by traders and investors. In liquid markets, traders can enter and exit positions quickly, making it easier to execute strategies based on short-term market movements. High liquidity helps reduce the bid-ask spread, which is the difference between the price at which a currency can be bought and the price at which it can be sold. A smaller bid-ask spread results in lower trading costs and improves market efficiency.

Hedging and speculation are two common strategies that depend on the liquidity of currency markets. Hedgers use currency derivatives, such as forwards, futures, and options, to protect themselves against unfavourable exchange rate movements. For example, a company that imports goods from another country may use currency derivatives to lock in exchange rates and mitigate the risk of currency fluctuations. Speculators, on the other hand, attempt to profit from short-term movements in exchange rates by buying and selling currencies based on predictions of market trends.

To understand the impact of liquidity on FX trading, we develop a liquidity-adjusted price model. Let $P_j(t)$ represent the price of currency j at time t, and let $l_j(t)$ represent the liquidity of currency j in the market. The price of a currency can be modelled as:

$$P_j(t) = \alpha \cdot E[I_j(t)] + \beta \cdot E[F_j(t)] \cdot l_j(t), \tag{3.10}$$

where:

- $E[\mathrm{I_j(t)}]$ is the expected information influencing the price of currency j,

- $\mathrm{E[F_j(t)]}$ is the expected global financial factors impacting currency j,

- $\mathrm{l_j(t)}$ is the liquidity of currency j at time t,

- α and β are scaling factors representing the sensitivity of the price to the respective factors.

The liquidity-adjusted price $P_j(t)$ reflects how market liquidity influences the ability of traders to respond to new information and financial factors, affecting the overall stability of the market.

Additionally, the transaction cost model for currency trading can be expressed as:

$$C_j(t) = \gamma \cdot \frac{1}{l_j(t)}, \tag{3.11}$$

where:

- $\mathrm{C_j(t)}$ is the transaction cost for trading currency j,

- $\mathrm{l_j(t)}$ is the liquidity of currency j,

- γ is a constant representing the relationship between liquidity and transaction costs.

As liquidity increases, transaction costs decrease, making it easier and more cost-effective for traders to execute transactions in the foreign exchange market.

Numerous studies have demonstrated the importance of FX market liquidity in global financial markets. The research shows that highly liquid currencies, such as the U.S. dollar and the euro, experience narrower bid-ask spreads and less price volatility, making them more attractive for investors and traders. On the other hand, less liquid currencies can be subject to sharp price movements, especially during periods of economic uncertainty or market stress [282].

The role of central banks in managing FX liquidity is well-documented, with studies showing that interventions by central banks to stabilize currency markets can restore confidence and prevent excessive volatility [283]. Additionally, the use of currency derivatives in hedging strategies is critical for managing currency risk in a globalized trading environment, as it allows firms and investors to lock in exchange rates and reduce exposure to unfavourable fluctuations.

Table 3.3 shows the 5 key conditions for the stability of global financial trading.

In summary, the globalization of financial markets has transformed the way financial trading occurs, creating new opportunities and challenges for participants across the globe. As markets become increasingly interconnected, financial trading relies on a complex interplay of conditions that must be met for markets to function efficiently and securely. In this context, the necessary conditions for financial trading to occur are multifaceted, requiring a combination of market efficiency, cross-border capital flows, regulatory frameworks, technological infrastructure, and currency market liquidity. Every of these conditions not only enhances market accessibility but also mitigates risks associated with volatility, instability, and information asymmetry.

Table 3.3

Key conditions for a stable financial trading environment under globalization

Key condition	Description	Impact on financial trading
Market efficiency and information availability	Prices reflect available information due to rapid global dissemination and reduced asymmetry	Ensures fair pricing, reduces arbitrage opportunities, and strengthens investor confidence.
Cross-border capital flows and risk sharing	Movement of funds across countries for investment and diversification; enables risk pooling	Improves capital allocation, portfolio diversification, and global economic growth
Regulatory framework and institutional support	Harmonized laws, oversight, and institutional backing ensure transparency, accountability, and investor protection	Minimizes systemic risks, attracts foreign investment, and fosters resilient global markets
Technological infrastructure and trading platforms	Advanced technological tools (e.g., algorithmic/HFT, blockchain, secure trading platforms) enable real-time global transactions	Enhances efficiency, liquidity, and transparency
Foreign exchange and currency market liquidity	Deep and liquid FX markets facilitate international transactions and currency risk management	Lowers transaction costs, stabilizes prices, supports trade/investment, and mitigates currency shocks

Source: author's own generalisation

One of the primary conditions for financial trading in a globalized environment is the efficiency of markets and the ability to process and react to information in real-time. The efficient market hypothesis asserts that all available information is reflected in asset prices, meaning that markets should react instantaneously to new data. The speed and accuracy with which information flows across borders influence the performance of markets globally. For instance, in an interconnected world, economic reports, financial statements, and geopolitical events can have immediate effects on global asset prices. Market efficiency is therefore contingent upon the free flow of information and the absence of barriers to access, which is increasingly facilitated by technological advancements in communications and data analytics.

Global financial markets are characterized by the free movement of capital across borders, which enables investors to diversify their portfolios, mitigate risks, and allocate resources efficiently. Capital mobility promotes economic growth by allowing funds to flow from capital-surplus countries to capital-deficit countries. Furthermore, risk-sharing mechanisms make it possible for investors to spread their exposure across different markets, reducing the impact of localized economic shocks. However, the rapid flow of capital also introduces risks, such as capital flight and volatility, which can destabilize markets if not managed properly. Thus, the ability to manage these flows and the risks associated with them is crucial for maintaining market stability in a globalized context.

A robust regulatory framework is essential to ensure that financial markets operate smoothly and transparently in a globalized environment. Without proper regulation, markets are prone to manipulation, excessive risk-taking, and systemic crises. International cooperation among regulatory bodies is necessary to harmonize rules and prevent regulatory arbitrage. Moreover, the institutional support provided by financial institutions and central banks enables the efficient functioning of markets by providing liquidity, stability, and risk management tools. The regulatory environment needs to adapt to emerging challenges, such as the rise of cryptocurrencies and decentralized finance, while ensuring the safety and integrity of financial transactions across borders.

Technological infrastructure is a critical enabler of global financial trading. Electronic trading platforms, algorithmic trading, and high-frequency trading have revolutionized how trades are executed and how information is processed. Low-latency networks, advanced data analytics, and blockchain technology are enhancing the efficiency, transparency, and security of global markets. These technological advancements allow investors to make faster and more informed decisions, improving market liquidity and reducing transaction costs. However, the rapid pace of technological change also raises concerns about market manipulation, cybersecurity risks, and the need for effective regulatory oversight to balance innovation with stability.

Finally, currency market liquidity is indispensable in a globalized financial system. The ability to trade currencies quickly and efficiently affects the broader economy by facilitating international trade, investment, and capital flows. Currency liquidity ensures that exchange rates remain relatively stable, providing businesses and investors with the confidence to engage in cross-border transactions. However, liquidity can be volatile, especially during periods of economic or geopolitical instability. Central banks and monetary authorities play an important role in stabilizing currency markets and ensuring liquidity through foreign exchange interventions and monetary policies. As globalization deepens, the interdependence of currency markets highlights the importance of maintaining liquidity to prevent disruptive fluctuations in exchange rates.

In conclusion, proposals for the formation of a stable financial trading environment were generalised. Their foundation is based on combining institutional, technological, and regulatory elements into a coherent system that supports resilience and transparency of market processes. The novelty of these proposals lies in their integrated character. Stability is approached not only through stricter regulation and supervision but also through the advancement of digital infrastructure, the encouragement of innovative yet secure trading technologies, and the harmonization of rules across jurisdictions. A significant feature is the emphasis on balancing efficiency with security, ensuring that the growth of financial trading is not achieved at the cost of systemic vulnerability. The significance of the proposed measures is their universality and adaptability. They can be implemented at both national and international levels, creating a foundation for sustainable market functioning, reducing the probability of crises, and strengthening confidence among investors and participants. By addressing institutional gaps, improving technological safeguards, and enhancing coordination of oversight, the proposals provide a roadmap toward a more reliable and stable environment for financial trading.

3.3. Recommendations for enhancing financial trading profitability

This section consolidates the previous chapters' insights on financial trading information basis hierarchies, strategy advancements, and efficiency into a dynamic modelling framework that connects profitability with global capital movements and stochastic market fluctuations. By embedding elements of regulatory adaptation and dynamic risk management discussed in the previous study, the model serves as a predictive tool for optimising returns across diverse economic conditions. Its interdisciplinary design bridges the mechanics of financial trading with broader macroeconomic theory, providing a strategic lens for assessing profitability amid ongoing market innovation and global interconnectedness. This integrated framework brings together the study's exploration of technological disruption, systemic stability, and adaptive financial strategies, forming a comprehensive foundation for guiding decision-making in complex trading environments.

This exploration aims to present a novel dynamic model that better reflects the new profit mechanisms within financial markets under globalization. The focus will be on understanding how the integration of advanced trading mechanisms (e.g., automated trading strategies, arbitrage, financial derivatives) interacts with global capital flows, interest rates, market liquidity, and economic growth. The model is structured as a system of differential equations capturing economic growth, capital accumulation, and asset price dynamics, with stochastic processes modelling volatility and shocks. By embedding algorithmic and high-frequency trading profit functions alongside traditional capital flow and productivity equations, the framework integrates financial technology innovations directly into macroeconomic analysis. This conceptual design provides a rigorous, interdisciplinary foundation, bridging financial economics, macroeconomics, AI, and computational finance, and addressing existing theoretical gaps in modelling of current global markets.

To develop a robust and comprehensive dynamic model for analysing financial trading mechanisms in the context of globalization, this study analyses the application background and main features of this dynamic model design and reviews key research and foundational works that explore financial trading, capital flows, macroeconomic modelling, and the impacts of globalization on economic growth (Annex C).

In the building of a dynamic model, especially one that seeks to analyse financial trading's new profit mechanisms in the context of globalization, it is crucial to identify and define key variables and parameters that drive the model's behaviour. These variables reflect the interactions between global markets, capital flows, financial trading mechanisms, and economic growth. Each parameter will be linked to the broader framework of macroeconomic theory, but must also incorporate the unique dynamics introduced by financial globalization. Then the study will outline the critical variables and parameters in the model, elaborating on their definitions, relationships, and roles within the dynamic system.

The first critical variable is Capital flow (C). Capital flow refers to the movement of money for investment, trade, or business production across borders. In the context of globalization, capital flows are no longer restricted to traditional investments in physical assets (e.g., factories, real estate) but also include foreign direct investments, portfolio investments, and financial transactions (e.g., bonds, equities, derivatives). Capital flows significantly influence the overall stability and growth of national economies, and they are impacted by the factors such as interest rates, currency exchange rates, and international economic policies.

Mathematically, capital flow C_t at any given time t is a function of several variables, which include investment decisions, risk assessments, and global economic conditions:

$$C_t = \int_{\Omega} \dot{C}\,(X_t, Y_t)dt, \tag{3.12}$$

where:

- X_t represents the set of global economic policies affecting capital flow at time t, such as monetary policy, trade agreements, and tax regulations,

- Y_t represents risk profiles or market volatility at time t, which could include global shocks or specific events (e.g., financial crises, geopolitical risks, etc.) that influence investors' decisions.

Capital flows play a central role in global market equilibrium by influencing interest rates, investment behaviour, and macroeconomic stability. In the model, C_t can also be influenced by shocks to market sentiment or changes in portfolio diversification strategies as international markets become increasingly interconnected.

The second critical variable is global interest rates (r). Interest rates are a primary driver of global investment decisions, and they reflect the cost of borrowing capital. The interest rate r_t is determined by a number of factors, including central bank policies, global liquidity, inflation expectations, and market risk. In the context of globalization, interest rates do not just reflect domestic conditions; rather, they are influenced by global forces, as capital moves freely across borders, seeking the highest return for the lowest risk.

Global interest rate (r) cannot be set by any single institution, and it reflects global equilibrium shaped by cross-border capital flows, international investors, and global liquidity. In practice, U.S. Treasury yields usually serve as the benchmark of global interest rates and the “risk-free rate” for the world. which can be influenced by factors such as liquidity, market participation, and trading algorithms Central bank policy rates, such as those set by the Federal Reserve or ECB, can influence cross-border capital flows and portfolio allocation as investors adjust their positions globally in search of optimal returns. These flows also directly affect U.S. Treasury yields, which serve as the global benchmark for borrowing costs. Together, this mechanism shapes global interest rates, transmitting financial conditions across world markets almost instantaneously. Here, the global interest rate r_t is defined as a function of market volatility (σ_t) and global economic conditions (ω_t):

$$r_t = f(\sigma_t, \omega_t), \tag{3.13}$$

where:

- σ_t represents the risk premium in the market at time t, accounting for the uncertainty in global asset prices (e.g., equity volatility, bond yields),

- ω_t represents global economic volatility or the presence of shocks in the world economy (e.g., financial crises, political instability).

As globalization allows financial markets to become more interconnected, the transmission mechanism of interest rate changes has become more instantaneous. When central banks in one region adjust interest rates, this has immediate effects on other economies due to capital flows that respond to differences in returns on investment. This dynamic creates a contagion effect in which financial disturbances can spread rapidly across the globe.

Then, the third critical variable is Profit from Financial Trading (π). A key focus of this model is the profit mechanisms arising from financial trading, which include profits generated from algorithmic trading, high-frequency trading, and arbitrage opportunities in different financial markets. As financial markets become more automated and interconnected, new sources of profits are emerging that were not traditionally captured in classical macroeconomic models.

The profit from financial trading π_t at any given time t depends on the volume of trading, the effectiveness of market strategies, and the costs associated with trading (e.g., transaction fees, market frictions):

$$\pi_t = \int_0^T (f(T_t, M_t, F_t))\, dt, \tag{3.14}$$

where:

- T_t is the trading volume at time t, which can be influenced by factors such as liquidity, market participation, and trading algorithms,

- M_t represents the set of macroeconomic factors influencing trading at time t, such as interest rates, exchange rates, and policy decisions,

- F_t represents financial factors, such as the cost of trading, transaction fees, and the presence of market frictions.

This function captures how profits from financial trading are generated in real time as traders react to market conditions. It accounts for the behaviour of automated trading algorithms that adjust dynamically to evolving market information, and it integrates market frictions that impact profitability.

The fourth critical variable is Market liquidity (L). Market liquidity refers to how easily assets can be bought or sold in the market without causing significant price fluctuations. A high degree of liquidity allows for faster price discovery and efficient trading, which is a critical factor in the globalization of financial markets. Global market liquidity affects the flow of capital, the speed of price adjustments, and the overall stability of the financial system.

The liquidity L_t at any time t is influenced by a range of factors, including macroeconomic variables and the speed of market adjustments to new information:

$$L_t = g(M_t, S_t), \tag{3.15}$$

where:

- M_t refers to macroeconomic factors such as fiscal policy, trade balances, and capital market regulations, which determine the depth and accessibility of markets,

- S_t refers to the speed of market adjustments to shocks, which captures how quickly markets respond to new information or external changes.

Global financial markets have become more liquid over time, but this liquidity is not always evenly distributed across markets or asset classes. In emerging markets, for example, liquidity may be lower, making it more difficult to execute trades without significant price changes. Understanding liquidity dynamics is important for assessing the risk and efficiency of global financial systems.

The last critical variable is the Economic growth rate (g). The economic growth rate is an essential macroeconomic variable that determines the overall expansion or contraction of the economy over time. Economic growth is typically driven by changes in the capital stock, technological progress, and labour force participation. In the context of globalization, the economic growth rate g_t also depends heavily on the flow of international capital and the adoption of new technologies in financial markets.

The growth rate g_t at time t is defined as the derivative of output Y_t with respect to time:

$$g_t = \frac{\partial Y}{\partial t} = \rho(M_t, F_t, C_t), \tag{3.16}$$

where:

- Y is the GDP or output of the economy, which is driven by capital accumulation, technological innovation, and labor productivity,

- ρ captures the sensitivity of economic growth to global capital flows, market liquidity, and trading mechanisms.

In a globalised world, the growth rate of an economy is increasingly influenced by external factors such as foreign investment, global interest rates, and international financial crises. As capital flows across borders and technology spreads rapidly, countries that are integrated into the global economy may experience higher growth rates, while those that are more isolated may struggle to keep pace.

These variables and parameters form the core framework for the dynamic model. By accounting for capital flows, global interest rates, profit from financial trading, market liquidity, and economic growth, the model allows us to better understand the complexities introduced by globalization and financial innovation. Each of these parameters is interconnected, reflecting the dynamic nature of financial markets and the broader economy. By analysing how these factors evolve and interact, it can derive a more accurate representation of the new profit mechanisms in the context of globalization.

To capture the complexity of financial trading mechanisms and their interaction with global economic variables, the model must integrate dynamic, nonlinear, and stochastic elements. Here is the outline of the structure of the model, which will be represented by a system of differential equations and stochastic processes. These equations will describe the evolution of critical macroeconomic variables over time and account for the interdependencies between them, particularly how financial trading mechanisms, such as high-frequency trading and algorithmic trading, influence capital accumulation, interest rates, market liquidity, and economic growth.

In any macroeconomic model, the evolution of capital is a central factor in determining economic growth. Capital accumulation represents the investment of resources into productive assets, which increase the economy's capacity to produce goods and services over time.

The capital stock K_t in this model is driven by investment and depreciation. The basic formulation for capital accumulation follows the classic Solow-type equation but is extended to incorporate global capital flows and financial trading mechanisms:

$$\frac{dK_t}{dt} = I_t - \delta K_t, \tag{3.17}$$

where:

- K_t is the total capital stock at time t,

- I_t is the investment rate at time t, which depends on interest rates, global capital flows, and financial market conditions,

- δ is the depreciation rate of capital, which represents the rate at which capital becomes obsolete or loses value over time (e.g., due to wear and tear or technological obsolescence).

The investment rate I_t is defined as a function of global market conditions, capital flows, and the return on investment in the global financial market:

$$I_t = \alpha_1(r_t - \delta) + \alpha_2(\frac{C_t}{L_t}), \tag{3.18}$$

where:

- r_t is the interest rate at time t, which captures the cost of capital and influences investment decisions,

- C_t is the capital flow at time t, which represents the net inflow or outflow of capital across borders due to globalization,

- L_t is the market liquidity at time t, which reflects the ease of buying and selling assets. More liquid markets allow for faster adjustments in investment,

- α_1 and α_2 are parameters that determine the sensitivity of investment to changes in interest rates and capital flows.

This formulation highlights the feedback loop between investment decisions and market conditions: as global capital flows increase or liquidity improves, the rate of investment I_t increases, thereby boosting capital accumulation K_t, which further impacts the economy's ability to produce output.

The growth of output, or GDP, is a key macroeconomic variable, and in this model, it is determined by the accumulation of capital and labour, along with the influence of global technological progress and financial trading.

Here we employ a Cobb-Douglas production function to model GDP growth, which is a widely used specification in macroeconomics:

$$Y_t = A_t K_t^{\beta} L_t^{1-\beta}, \tag{3.19}$$

where:

- Y_t is the output (GDP) at time t,

- A_t is total factor productivity (TFP) at time t, which reflects technological progress, market efficiency, and globalization's impact on productivity. It is a critical driver of long-term growth and can be influenced by the adoption of new financial technologies and trading mechanisms,

- K_t is the capital stock at time t, as defined earlier,

- L_t is the labour force at time t, which may also be influenced by globalization and migration trends,

- β is the capital share in output, typically between 0.3 and 0.4 for most economies.

The evolution of total factor productivity A_t depends on a combination of technological advancements, knowledge diffusion, and global financial integration. As financial trading mechanisms advance, they can indirectly contribute to economic growth by enhancing capital market efficiency, increasing liquidity, and lowering transaction costs. Thus, A_t is influenced by both technological progress in financial trading and broader globalization processes:

$$A_t = \rho_1(M_t, F_t) + \rho_2(C_t, L_t), \tag{3.20}$$

where:

- M_t represents the set of macroeconomic factors, such as fiscal policies, trade policies, and institutional changes,

- F_t captures the influence of financial market innovations, such as new trading strategies, algorithmic trading, and high-frequency trading,

- ρ_1 and ρ_2 are parameters that measure the responsiveness of TFP to these factors.

This model assumes that financial innovations (including the advent of algorithmic trading) lead to higher efficiency in capital markets, which indirectly boosts productivity and output. Capital mobility also enhances the speed with which new technologies are adopted globally, leading to higher A_t and sustained growth.

One of the core elements of this model is the global financial market, which determines asset prices, the availability of capital, and the conditions under which trading profits can be realised. In a globalised economy, financial markets are highly interconnected, with asset prices being determined not just by domestic conditions but also by global capital flows, interest rates, and trading strategies.

The asset price p_t at time t is a function of market liquidity L_t, global capital flows C_t, and trading volume T_t, influenced by the speed and volume of trades in global financial markets:

$$p_t = \frac{1}{1+r_t} \int_S T_t(M_t)\, dS, \tag{3.21}$$

where:

- p_t is the price of assets (e.g., stocks, bonds) in the global market at time t.

- r_t is the interest rate at time t, which is related to the cost of capital,

- S represents the set of market conditions, such as investor sentiment, volatility, and macroeconomic news (e.g., the Federal Reserve raised rates by 0.25%),

- T_t is the trading volume at time t, which reflects the degree of market participation.

The evolution of asset prices is also influenced by the speed of market adjustment, S, which determines how quickly markets react to new information, and by the overall level of market frictions (e.g., transaction costs). More liquid markets tend to experience faster price discovery, whereas markets with high transaction costs or slow adjustments may see delayed reactions to new economic data.

Given the complexity and unpredictability of financial markets, it is important to incorporate stochastic shocks into the model. These shocks represent sudden, unexpected changes in economic conditions, such as a financial crisis, geopolitical turmoil, or a market bubble burst, which can have widespread consequences for global markets.

The model uses a stochastic process to account for random fluctuations in key macroeconomic variables (such as interest rates, capital flows, and output):

$$dX_t = \mu_t dt + \sigma_t dW_t, \tag{3.22}$$

where:

- X_t represents the vector of key macroeconomic variables (e.g., capital stock, interest rates, and output).

- μ_t is the drift term, which represents the expected rate of change of the variable over time,

- σ_t is the volatility term, which measures the degree of uncertainty or randomness,

- W_t is a Wiener process (also called Brownian motion), which captures the randomness in the evolution of economic variables.

Stochastic shocks allow the model to simulate how markets behave under unexpected events, which is essential for capturing the real-world volatility of financial markets. These shocks are particularly important when considering the role of financial trading innovations, as they often exacerbate market volatility in the face of global crises.

The dynamic system outlined here integrates the evolution of key macroeconomic variables, such as capital accumulation, GDP growth, global financial markets, and stochastic shocks, into a comprehensive model that can simulate the effects of globalization and financial trading mechanisms. By accounting for investment dynamics, market liquidity, and stochastic volatility, the model provides a flexible framework to analyse how financial trading profits, capital flows, and global interconnectedness shape economic outcomes over time.

The global financial landscape has dramatically evolved with the advent of algorithmic trading, high-frequency trading, and new profit mechanisms that leverage global interconnectedness. These innovations have disrupted traditional methods of capital generation, where profits were primarily linked to long-term investments or returns on physical assets. Today, financial markets offer a diverse set of opportunities for profit generation, including the ability to capitalize on small price fluctuations, market inefficiencies, and real-time arbitrage opportunities.

Here we explore how these innovations have transformed profit mechanisms in financial markets and how they are incorporated into the dynamic model. The key areas of focus include the role of algorithmic trading, the impact of market frictions, and the challenges associated with high-frequency trading. By incorporating these elements into the model, it aims to capture the dynamic, nonlinear, and stochastic nature of global financial markets in the era of advanced trading technologies.

Algorithmic trading refers to the use of advanced mathematical models, computer algorithms, and real-time data to execute trades in financial markets. These algorithms can perform thousands of trades per second, reacting to market signals and exploiting price inefficiencies across multiple markets. This mechanism enables traders to capitalise on small price differentials that would be invisible to human traders, with profits derived from minute price changes aggregated over a large volume of transactions.

In the context of globalization, algorithmic trading allows firms to access a global pool of assets, arbitrage opportunities, and new types of financial instruments that were previously unavailable or impractical. These mechanisms operate across a wide range of asset classes, including equities, derivatives, commodities, and even cryptocurrencies.

The profits from algorithmic trading (π_t) are driven by trading volume (T_t), macroeconomic factors (M_t), and financial factors (F_t), as well as transaction costs and market frictions. The model for profit from algorithmic trading is:

$$\pi_t = \int_0^T (f(T_t, M_t, F_t))\, dt, \tag{3.23}$$

where:

- T_t is the trading volume at time t, reflecting the number of transactions executed by algorithms,

- M_t represents the macroeconomic factors that influence trading, such as interest rates, inflation, and exchange rates,

- F_t accounts for financial factors, such as asset prices, market volatility, and trading strategies,

- f is a function that reflects the trading strategy's effectiveness, which can vary depending on market conditions, asset types, and time horizons.

Algorithmic trading profits are highly sensitive to the speed of execution, market volatility, and liquidity. In periods of high market uncertainty, trading algorithms can adapt quickly to market shocks, allowing traders to profit from price discrepancies across different markets. The use of algorithms reduces the lag time between information acquisition and trade execution, which is essential in a globalized market where market-moving news can spread across borders instantly.

Algorithmic trading affects capital accumulation and economic growth indirectly by influencing asset prices, market liquidity, and the behaviour of global capital flows. For example:

- increased trading volume can lead to higher liquidity, which reduces the cost of capital and encourages more investment;

- the lowering of transaction costs through automation allows for more efficient resource allocation, which promotes faster capital accumulation and technological innovation;

- as algorithmic trading becomes more prevalent, financial markets tend to become more efficient, with asset prices reflecting available information more quickly.

This dynamic effect is captured in the model through its influence on investment (I_t), capital accumulation (K_t), and output (Y_t).

High-frequency trading is a subset of algorithmic trading that involves executing a large number of orders at extremely high speeds (often in milliseconds). HFT firms use powerful computer systems to analyse market data and execute trades at lightning speed, profiting from minuscule price changes or market inefficiencies that exist for only brief moments. Key features of HFT are:

- speed: the core advantage of HFT is speed – HFT systems are capable of processing millions of transactions per second, exploiting very small differences in asset prices that occur in milliseconds;

- liquidity provision: HFT firms often act as liquidity providers, facilitating transactions between buyers and sellers. This role helps stabilise the market but also allows traders to profit from bid-ask spreads;

- arbitrage: HFT algorithms are frequently used for arbitrage, exploiting small differences in prices of the same asset across different markets (e.g., discrepancies in exchange rates or commodity prices);

- market impact: while HFT can increase liquidity in some cases, it can also increase market volatility, especially during times of financial instability, when prices can fluctuate rapidly due to algorithmic reactions to external news.

The profit generated by HFT at time t can be modelled as a function of the trading volume, market volatility, and asset price fluctuations:

$$\pi_t^{HFT} = T_t \times (\frac{1}{1+\tau_t}) \times r_t, \tag{3.24}$$

where:

- π_t^{HFT} represents the profit from high-frequency trading at time t,

- T_t is the trading volume generated by HFT strategies,

- τ_t is the transaction cost associated with executing each trade, which can vary depending on liquidity and market conditions,

- r_t is the rate of return on trades executed, which is affected by market volatility and trading strategy.

The success of HFT strategies depends on the liquidity of the market and the speed of the algorithm. More liquid markets allow HFT firms to execute more trades without significantly affecting prices, which increases profitability.

In any financial market, frictions and transaction costs play a significant role in shaping trading behaviour and profitability. Market frictions refer to the factors that prevent markets from operating perfectly, such as transaction fees, taxes, slippage, and information asymmetry. Key frictions are:

- transaction costs: these include brokerage fees, exchange fees, and other costs associated with executing trades. In the context of algorithmic trading and HFT, these costs can add up significantly, reducing overall profitability;

- slippage: this occurs when an order is executed at a different price than the expected one, usually due to low liquidity or fast price changes;

- market liquidity: the degree of liquidity in a market can create friction when executing large trades. In illiquid markets, large trades can have a substantial impact on asset prices;

- information asymmetry: financial markets are rarely perfectly transparent. Market participants may have unequal access to information, which can create inefficiencies and give certain traders an advantage.

The impact of market frictions on profitability is incorporated by modifying the profit function to account for transaction costs and liquidity constraints:

$$\pi_t^{friction} = T_t \times (1 - \tau_t) \times f(L_t, S_t), \tag{3.25}$$

where:

- τ_t represents the transaction cost at time t,

- L_t is the market liquidity at time t, which determines the speed and efficiency of executing trades,

- S_t represents the speed of market adjustment to shocks, which affects how quickly the market responds to new information.

The interaction between global capital flows, financial innovation, and market frictions creates a highly complex and dynamic financial environment. Global integration allows financial markets to operate in a way that was previously impossible, with real-time capital flows and instant access to a wide variety of trading strategies.

The model integrates these innovations by considering the dynamic feedback loops between global capital flows, market liquidity, and financial trading mechanisms. For example, as algorithmic trading becomes more prevalent and capital flows increase across borders, the dynamics of market liquidity and transaction costs are altered, which in turn impacts the profits generated by these strategies.

Finally, the new profit mechanisms generated by algorithmic trading and HFT contribute to capital accumulation and economic growth by increasing the efficiency of financial markets. As these trading mechanisms reduce transaction costs, increase market liquidity, and provide more accurate price signals, they help channel capital more efficiently into productive investments, leading to higher economic growth.

The effect of these innovations on capital accumulation and output growth is captured through the investment dynamics (I_t), as the increased efficiency of capital markets leads to higher investment rates and ultimately higher capital stock and output.

The innovative profit mechanisms introduced by algorithmic trading and high-frequency trading are transforming the structure of global financial markets. Incorporating these mechanisms into the model can help capture the dynamic, nonlinear interactions between market liquidity, trading strategies, capital flows, and economic growth. The model also accounts for the impact of market frictions and transaction costs, which are critical in determining the profitability of these new trading strategies.

In a globalised financial world, these innovations are reshaping how capital is allocated and how profits are generated, providing insights into how financial trading mechanisms influence the broader economy.

To better understand the dynamics of the global financial system and the impact of innovative trading mechanisms, it is necessary to simulate the model and analyse its behaviour under various scenarios. The dynamic model proposed in this study incorporates several key variables, such as capital accumulation, output growth, global financial market behaviour, and profit mechanisms from financial trading. Since the interactions between these variables are complex, non-linear, and affected by stochastic shocks, simulation provides an invaluable tool to capture the evolving dynamics of the system over time.

Then the study will outline the approach to simulating the model's behaviour, focusing on key dynamics such as capital accumulation, interest rates, financial trading profits, and economic growth. There are also several simulation scenarios that highlight the model's performance under different conditions, including the introduction of shocks, changes in market liquidity, and shifts in global capital flows.

Given the complexity of the model, it is useful to employ numerical methods to solve the system of differential equations and stochastic processes. These methods are necessary due to the nonlinearity of the equations and the inclusion of random shocks, which preclude an analytical solution. Key numerical methods include:

1. Euler's Method: a simple and commonly used method for numerically solving ordinary differential equations (ODEs). Euler's method approximates the solution by taking small time steps and iteratively updating the state of the system. This is suitable for simulating the evolution of variables like capital stock (K_t), output (Y_t), and interest rates (r_t). The updated formula for Euler's method is:

$$x_{t+1} = x_t + h \cdot f(x_t, t), \tag{3.26}$$

where x_t represents the state of the system (e.g., K_t, Y_t, or r_t) at time t, h is the time step, and $f(x_t, t)$ is the rate of change of x_t.

2. Runge-Kutta Method: this method is more accurate than Euler's method and is often used for solving nonlinear ODEs. It approximates the solution by considering intermediate steps and providing a better estimate of the system's state at each time point.

The fourth-order Runge-Kutta method (RK4) is particularly effective for this model, as it provides a good balance between accuracy and computational efficiency.

The RK4 updated formula is as follows:

$$x_{t+1} = x_t + \frac{h}{6}(k_1 + 2k_2 + 2k_3 + k_4), \tag{3.27}$$

where:

- $k_1 = f(x_t, t)$,

- $k_2 = f(x_t + \frac{h}{2}, t + \frac{h}{2})$,

- $k_3 = f(x_t + \frac{h}{2}, t + \frac{h}{2})$,

- $k_4 = f(x_t + h, t + h)$.

This method ensures better accuracy in capturing nonlinear interactions between variables such as capital accumulation, investment, and financial profits.

3. Monte Carlo simulations: in addition to deterministic methods, Monte Carlo simulations can be used to model the impact of stochastic shocks. These simulations are especially useful for capturing random fluctuations in key variables such as interest rates, asset prices, and market liquidity. By running multiple simulations with different random seeds, it can generate a distribution of possible outcomes, providing insights into the probability distributions of key macroeconomic variables.

Table 3.4 provides a comprehensive overview of the key functional components of the dynamic model for enhancing the profitability of financial trading.

The dynamic model for enhancing the profitability of financial trading summarises each component's mathematical formulation, its economic interpretation, practical application in modelling or policy analysis, and its theoretical significance. Together, these elements illustrate how capital flows, interest rates, investment dynamics, productivity, and modern trading mechanisms like algorithmic and high-frequency trading interact within a stochastic, interconnected global financial system. The framework supports advanced simulations and policy evaluations under both normal conditions and crisis scenarios.

Then fig 3.1. shows the linkages in the whole dynamic model for enhancing the profitability of financial trading.

Table 3.4

Key functional components of the dynamic model for enhancing the profitability of financial trading

Component	Formula	Explanation	Application	Significance
1	2	3	4	5
Capital flow (C)	$C = f(\Phi\_t, \sigma\_t)$	Movement of money across borders for investments or trades, influenced by global policies and risk profiles	Determines market equilibrium and investment patterns in globalized economies	Core to understanding how capital mobility affects economic stability and growth
Interest rate (r)	$r = f(\rho\_t, \varepsilon\_t)$	Interest cost of capital, shaped by global risk premium and economic volatility	Affects investment decisions and is transmitted quickly across economies due to globalization	Central to the model's feedback mechanism in capital allocation and investment
Profit from financial trading (π)	$\pi = f(\Omega\_t, \psi\_t, \theta\_t)$	Profit arising from HFT, arbitrage, and algorithmic strategies depending on trade volume and frictions	Key to modelling modern trading profitability and strategy performance	Reflects the shift from traditional investment-based profits to strategy-driven trading
Market liquidity (L)	$L = f(\mu\_t, \delta\_t)$	Ease of buying/selling assets, influenced by macro policies and market shock absorption speed	Determines how information is priced and how smoothly markets operate	Affects asset pricing, capital flow responsiveness, and trading conditions
Economic growth rate (g)	$g = dY/dt$	Rate of GDP growth, dependent on capital stock, TFP, and labour productivity	Measures the economy's performance in response to capital accumulation	Ultimate output metric capturing model's long-term macroeconomic impacts
Capital accumulation (K)	$dK/dt = I\_t - \delta K$	Change in capital stock over time as a function of investment and depreciation	Determines productive capacity and future output potential	Bridge between short-term trading effects and long-term economic growth

Continuation of the table 3.4

1	2	3	4	5
Investment rate (I)	I = f(r_t, C_t, L_t)	Function of interest rate, capital flow, and liquidity that drives capital growth	Influences accumulation of capital and hence production	Shows link between global conditions and domestic economic expansion
Output (Y)	Y = A_t K_t^α L_t^(1-α)	Cobb-Douglas production linking output to capital and labour	Used to assess how globalization and tech influence productive output	Integrates tech, capital, and labour into the GDP function
TFP (A)	A = f(χ_t, ξ_t)	Total Factor Productivity driven by macro factors and financial innovations	Captures efficiency and innovation effects in the production process	Accounts for gains from financial integration and tech-driven productivity
Asset price (P)	P = f(r_t, ξ_t, Ω_t)	Price of assets based on interest rate, macro factors, and trade volume	Represents valuation in global financial markets	Links trading behaviour to capital markets and wealth effects
Stochastic shocks	dX = μdt + σdW	Random changes in macro variables using Brownian motion	Simulates uncertainty in financial markets	Essential for modelling real-world volatility and systemic risk
Algorithmic trading profit (π_AT)	π_AT = f(Ω_t, ψ_t, θ_t, τ_t)	Profits from algorithmic trading, driven by trading volume, macro and financial factors, and strategy effectiveness	Captures real-time trading gains from algorithmic strategies across multiple asset classes	Highlights efficiency, automation, and reaction speed as core profitability drivers in global finance
High-frequency trading profit (π_HFT)	π_HFT = f(Ω_t, τ_t, r_t)	Profits from executing massive trade volumes at millisecond speeds, leveraging micro price discrepancies	Quantifies ultra-fast trades that capitalize on temporary inefficiencies and bid-ask spreads	Essential to understanding modern liquidity provision and flash profit opportunities

Source: author's own generalisation

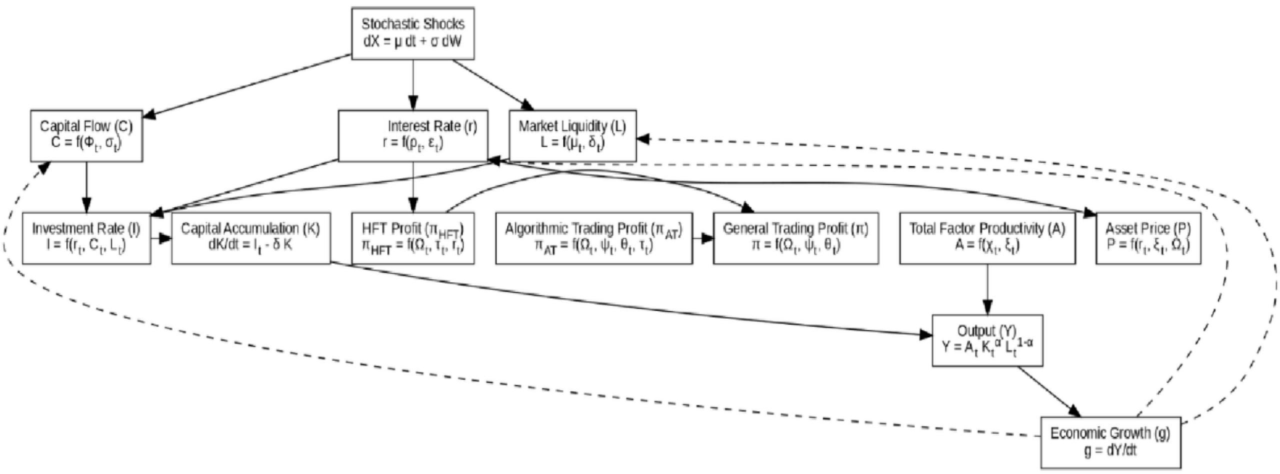

Fig. 3.1. Dynamic model for enhancing the profitability of financial trading

Source: author's own proposal

To understand the behaviour of the model under various conditions, several simulation scenarios can be run. These scenarios will explore how the model responds to changes in market conditions, global financial shocks, and the introduction of new financial trading mechanisms, thus further showing the future applications and research directions of this model (Annex D).

In addition to the simulation scenarios, we also perform a sensitivity analysis to assess how the model responds to changes in key parameters, such as:

- interest rates (r_t): how sensitive is the economy to changes in the global cost of capital?

- market liquidity (L_t): what impact does liquidity have on trading profits and economic growth?

- global capital flows (C_t): how do changes in the level of capital mobility affect investment and output?

This analysis will help identify which parameters are the most important in determining economic outcomes and how financial trading mechanisms interact with other macroeconomic factors.

To visualize the results of the simulations, function graphs for key variables are shown. These graphs demonstrate the evolution of the system over time under different scenarios, providing a clear picture of how the economy responds to changes in market conditions (Annex E).

The proposed dynamic model can be operationalized in real-world trading and policy environments through the following technology-integrated approach:

Step 1. Data acquisition and preprocessing:

1. Collect real-time and historical structured data (capital flows, trading volumes, bid-ask spreads, interest rates, GDP) from global financial databases.

2. Use LLMs to process unstructured textual data, such as financial news, regulatory statements, and analyst reports, extracting sentiment indicators and event classifications as quantitative model inputs.

Step 2. Machine Learning-based parameter calibration:

1. Apply supervised ML algorithms (e.g. Random Forests, Gradient Boosting Machines) to estimate model parameters by training on historical input-output relationships (e.g. liquidity effects on profitability, interest rate sensitivity of investment).

2. Perform cross-validation and out-of-sample testing to ensure model generalizability across market conditions.

Step 3. Deep learning for nonlinear dynamic pattern recognition:

1. Utilize deep neural networks and Long Short-Term Memory based models to capture nonlinear temporal dependencies, such as volatility clustering and liquidity-profits relationships.

2. Incorporate these models within the dynamic system to enhance predictive accuracy for key variables (e.g. liquidity-adjusted trading profits, capital accumulation).

Step 4. Algorithmic trading strategy integration: embed algorithmic trading and HFT strategies into the model's profit functions, using ML/DL outputs as predictive features for signal generation. For example:

- LSTM-based volatility forecasts adjust HFT position sizes dynamically.

- LLM-derived global macroeconomic sentiment shifts modify cross-market arbitrage strategy triggers.

Step 5. Design the real-time implementation pipeline with the proposed dynamic model: develop an end-to-end system incorporating, for example:

- LLM APIs (e.g. GPT-based models) for continuous unstructured data analysis.

- ML/DL modules for parameter updating and market state classification.

- Algorithmic trading engines (Python Zipline, proprietary C++ systems) for automatic strategy execution and risk control.

Step 6. Strategic and policy applications:

- Financial institutions: optimize portfolio leverage, asset allocations, and trading strategy design using real-time model outputs integrating ML, DL, and LLM insights.

- Algorithmic trading desks: continuously update strategy triggers and risk thresholds based on integrated predictive models.

- Policymakers and regulators: simulate systemic impacts of capital controls, transaction taxes, and regulatory changes using scenario analyses within the enhanced dynamic model.

This integrated approach transforms the dynamic model into a powerful, adaptive, and operationally actionable tool, enabling traders, strategists, and policymakers to navigate complex global markets with advanced technological precision and foresight. The model incorporates several key innovations that are increasingly becoming central to the global economy:

1. Integration of global financial dynamics: the model reflects the interconnectedness of financial markets, highlighting the growing influence of global capital flows, interest rates, and financial trading mechanisms (such as high-frequency trading and algorithmic trading). By focusing on the interaction between market liquidity, capital accumulation, and financial innovations, the model emphasizes how global financial integration shapes macroeconomic outcomes such as economic growth and stability.

2. Financial trading mechanisms as a profit source: the introduction of financial trading profits (through algorithmic trading, HFT, and arbitrage) into the model provides a more nuanced understanding of how profits are generated in modern financial markets. This contrasts with traditional models that focus primarily on

investment returns and capital accumulation. The model identifies new sources of market inefficiencies and how financial market innovations can impact global economic dynamics, such as asset price fluctuations, liquidity crises, and systemic risk.

3. Policy insights: policymakers can use this model to understand how changes in financial regulation, market liquidity, or interest rates affect economic stability. The integration of stochastic shocks allows for the exploration of policy effectiveness during financial crises or periods of market volatility, helping policymakers make informed decisions on issues like capital flow controls, monetary policy, and regulation of financial markets.

4. A holistic framework: unlike traditional models that often treat financial markets as external factors to the macroeconomy, this model treats financial markets as endogenous variables, showing how they are shaped by and, in turn, shape global economic outcomes. This provides a more accurate reflection of real-world dynamics where financial markets are inherently volatile, subject to global shocks, and influenced by technological advancements.

The significance of this model lies in its ability to provide a realistic, integrated, and comprehensive framework for analysing the complex interactions between financial markets and macroeconomic variables in the context of globalization. The key aspects of its significance include:

1. Capturing the complexity of modern financial systems: financial systems today are shaped by rapid technological advancements and global connectivity, factors that traditional models failed to capture. By including financial innovations, market frictions, and global capital flows, the model provides a much-needed update to existing macroeconomic models, making it highly relevant in the context of the modern, interconnected financial world.

2. Addressing globalization’s economic impact: globalization has fundamentally changed the way how financial markets operate. This model provides a means to better understand the economic effects of global capital flows, cross-border investments, and the global integration of financial markets. It is especially valuable in

examining how financial integration affects national economies in terms of growth, stability, and risk exposure.

3. Contribution to financial market theory: by integrating algorithmic trading and high-frequency trading into the macroeconomic framework, the model contributes to financial market theory, offering insights into how these trading strategies impact on market liquidity, price discovery, and economic growth.

4. Relevance to contemporary economic crises: the model's ability to simulate financial shocks and their impact on global markets makes it highly significant in understanding financial crises. Given the increasing frequency of global financial disruptions (e.g., the 2008 financial crisis, the COVID-19 market disruptions), this model offers an important tool for crisis management and policy response analysis.

The assessment model embedded in the proposed dynamic model incorporates several innovative elements:

- liquidity-adjusted profit functions: unlike traditional models assuming frictionless execution, this model incorporates nonlinear transaction cost adjustments based on liquidity metrics, reflecting real-world market frictions;

- adaptive sensitivity parameters: parameters measuring the elasticity of profits with respect to market volatility, trading volume, and liquidity are endogenously calibrated, enabling dynamic risk-adjusted performance assessments;

- stochastic volatility integration: by embedding Brownian motion processes in the profitability and liquidity equations, the model captures the impact of real-time market uncertainty on financial trading outcomes;

- LLM-based unstructured data integration: incorporates insights from Large Language Models to quantify qualitative market information (e.g., news sentiment) as model inputs;

- cross-variable endogenous feedback loops: trading profits influence capital accumulation and market liquidity, which in turn affect future trading conditions, forming realistic systemic interactions.

These novel elements collectively provide a more accurate, adaptive, and operationally meaningful assessment of financial trading profitability, enhancing strategic decision-making under complex and uncertain market conditions.

In conclusion, a dynamic model for enhancing the profitability of financial trading was developed. This model integrates strategic, analytical, and technological components into a single system, enabling traders to adapt to changing market conditions in real time. The main feature of the model is its dynamic nature, which allows trading strategies to be continuously adjusted according to fluctuations in risk, liquidity, and market volatility. By combining classical profitability metrics with advanced predictive analytics and digital technologies, the model provides a balance between maximising returns and maintaining controlled exposure to risks. The novelty of the model lies in its ability to simulate various trading scenarios and to generate adaptive recommendations that enhance decision-making. Unlike static approaches, this model evolves with the market environment, offering a flexible and forward-looking tool for sustainable profit growth. The significance of the proposed model is its practical applicability. It can be used by professional traders, institutions, and regulators to evaluate the efficiency of trading strategies, optimise portfolio performance, and strengthen competitiveness in global markets. In addition, its adaptability makes it suitable for both developed and emerging financial systems.

CONCLUSIONS TO CHAPTER III

The comprehensive risk management framework for financial trading was designed. It integrates classical tools and modern quantitative methods into a consistent system, ensuring that different categories of risks are assessed not separately but in their interconnection. The distinguishing feature of this conceptual scheme is the inclusion of technological and informational factors, which reflect the realities of algorithmic and digitalized markets. The significance of this framework is its capacity to strengthen the resilience of trading practices and to provide both regulators and market participants with a universal instrument for risk control.

The proposals for building a stable financial trading environment were generalised. They combine regulatory, institutional, and technological measures into a comprehensive set of directions aimed at preventing instability. Emphasis was placed on balancing innovation with security, ensuring that market growth is aligned with systemic safety. The novelty of these proposals lies in their integrative nature, which enables harmonization across jurisdictions and the promotion of sustainable functioning of global markets. Their practical value is demonstrated in offering a roadmap for long-term stability and investor confidence.

The dynamic model was introduced to enhance financial trading profitability. This model adapts trading decisions to market fluctuations, integrates predictive analytics, and ensures that profit growth is achieved under controlled risk. The unique strength of the model is its ability to simulate different scenarios and provide flexible recommendations that evolve together with market changes. Its value lies in practical applicability, offering traders and institutions a tool for enhancing performance and competitiveness in diverse financial systems.

In conclusion, the tasks were fully realized through the formulation of a risk management framework, the generalisation of proposals for a stable environment, and the introduction of a dynamic model to enhance the profitability of financial trading. The novelty of these results lies in their multidimensional character: risk, stability, and profitability are addressed within one coherent system, ensuring both theoretical significance and practical usability in modern financial trading.

CONCLUSIONS

The theoretical and practical aspects were enhanced, and the recommendations for the further development of financial trading under globalization were provided in the dissertation in order to increase the efficiency, stability, and inclusivity of developed and emerging financial markets.

The definition of financial trading was improved: financial trading is an immediate or specifically pre-set process performed by financial trading participants based on the features of one or more financial assets and market information with the purpose of direct or indirect financial benefit. The roles of systemic and investment participants were also highlighted, and a comprehensive classification of financial trading combining hierarchical and faceted methods was developed, reflecting the diversity of trading forms. Financial trading risks, including market, credit, liquidity, operational, and systemic risks, were systematically outlined. The value of these results lies in a clear and unified conceptual foundation that reduces misunderstandings, supports accurate risk evaluation, and enhances regulatory clarity.

The financial trading strategies were characterized and evaluated, demonstrating their progression from traditional analytical approaches to modern algorithmic and artificial intelligence-driven methods. Their comparative strengths, weaknesses, and adaptability to global volatility were outlined. The Four-quadrant of financial trading strategies was proposed, categorizing the strategies by their technological intensity and strategic complexity, which distinguishes autonomous intelligent trading, intelligent-assisted trading, traditional trading, and mechanical trading. It equips traders and institutions with structured guidance on strategy selection in varying market conditions, while also assisting regulators in anticipating systemic consequences.

The five-level hierarchy of information basis for financial trading efficiency was proposed, starting with foundational trading data, moving through aggregated indicators and macroeconomic statistics, and extending to systemic and contextual factors such as regulation, geopolitics, and technological progress. It makes it possible to better understand how different types of information interact in shaping decisions. It also helps to show that efficiency and transparency in financial trading are inseparable from the quality, integrity, and availability of data.

The institutional and legal provisions regulating financial trading were generalized, demonstrating their significant influence on stability and market trust. The six stages of financial trading functioning were described, focusing on the post-2010 regulatory landscape with such features as responsible investing impact, new technologies implementation, decentralized finance development to ensure market stability, investor protection, and fair practices in a globalized context.

The tendencies of global financial trading were examined, highlighting the transformative impact of digitalization, the interdependence of financial markets, and the introduction of new financial instruments. A “lag cycle” pattern explanation was identified, showing that financial trading cycles in emerging financial markets typically trail those of developed markets, which explains how risks and opportunities are transmitted across borders. It enables policymakers and practitioners to anticipate challenges, manage risks, and harness opportunities associated with globalization.

The dynamic model for assessing financial trading efficiency was developed. The model integrates price dynamics, liquidity, transaction costs, and information flows into a single efficiency index, thereby allowing for quantitative measurement of financial trading efficiency under real-world conditions. The significance of this contribution lies in providing a more comprehensive tool for measuring efficiency, because it enables a balanced evaluation of how trading mechanisms serve not only immediate profit goals but also long-term economic development.

The financial trading risk management framework under globalization was designed. It brings together methods for identifying, quantifying, and mitigating risks across all major categories, including market, credit, liquidity, operational, and systemic risks. The framework incorporates advanced quantitative models such as VaR, GARCH, copula approaches, Monte Carlo simulations, and network models, enhanced with artificial intelligence for real-time monitoring and predictive insights, structured into a five-step implementation process. This framework is valuable because of its adaptability to rapidly changing conditions in globalized and technology-driven markets, offering institutions practical guidance for reducing vulnerabilities.

The recommendations for a stable financial trading environment under globalization were generalised, focusing on transparency, institutional cooperation, and resistance to external shocks. The five conditions for systemic stability were identified: 1) market efficiency and information availability, 2) cross-border capital flows and risk sharing, 3) regulatory framework and institutional support, 4) technological infrastructure and trading platforms, 5) foreign exchange and currency market liquidity. This approach provides policymakers and regulators with actionable measures for building market stability that is sustainable over time.

The dynamic model for enhancing financial trading profitability was constructed. This model is adapted to changing global market conditions, combining analytical tools, risk-adjusted strategies, and technological solutions to maximize returns while maintaining a systemic balance. The dynamic model offers traders, institutions, and regulators a practical mechanism that aligns profit objectives with resilience and inclusivity. The novelty of the contribution is in presenting profitability not as a static measure of gains, but as a dynamic construct shaped by evolving technologies, market interdependencies, and regulatory environments.

The results of the dissertation form a comprehensive scientific and practical contribution to the theory and practice of financial trading. The value of the research lies in uniting conceptual clarification, methodological development, and applied recommendations into a single coherent framework that addresses both academic and practical needs. The above mentioned results will stimulate further development of financial trading under globalization, ensuring its adaptability to technological, institutional, and market transformations.

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ANNEXES

Annex A

List of references for systematic literature review

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Annex B

The cycle of financial markets under globalization

Historically, financial markets have been shaped by long-term cycles, such as the Kondratiev waves, which span 40-50 years and are driven by technological innovation and major shifts in economic paradigms [220, p.8-25]. These cycles have been increasingly influenced by globalization, as technological advancements and capital flows transcend national borders.

The Kondratiev cycle, or “long wave” is a key concept in understanding how globalization has influenced financial markets. This cycle is divided into two phases: expansion and contraction. The expansion phase is characterized by technological innovation, increased productivity, and economic growth, while the contraction phase sees economic slowdowns, financial crises, and market corrections.

Since the early 1980s, the global economy has been in the expansion phase of the current Kondratiev cycle, driven by the rise of information technology, the internet, and telecommunications [220, p. 26-40]. However, as the cycle approaches its downturn, signs of contraction are becoming evident, with global economic growth slowing and financial markets experiencing increased volatility.

In addition to Kondratiev cycles, financial markets are also influenced by mid-term Juglar cycles and short-term Kitchin cycles. Juglar cycles, lasting about 7-11 years, are driven by fluctuations in business investments and are closely linked to the phases of economic recovery and recession. Kitchin cycles, on the other hand, last about 3-5 years and are driven by inventory adjustments and short-term fluctuations in demand [221, p.10-20].

Globalization has synchronized these cycles across economies, leading to simultaneous economic expansions and contractions in different regions. This synchronization amplifies the effects of economic downturns, as seen during the global financial crisis of 2008, when a downturn in the U.S. housing market triggered a worldwide recession.

Technological innovation plays a crucial role in driving financial market cycles under globalization. The current Kondratiev wave, often referred to as the “fifth technological revolution” has been characterized by the digital revolution dominated by advancements in computing, telecommunications, and the internet. As this wave reaches maturity, the world is on the cusp of the sixth Kondratiev wave, driven by emerging technologies such as artificial intelligence, biotechnology, and renewable energy.

The transition between these technological waves often leads to financial market turbulence as old industries decline and new ones emerge. This can be seen in the cryptocurrency market, which represents a new frontier in the financial landscape [222]. Cryptocurrencies, driven by blockchain technology, are an example of how technological innovation can create new markets and disrupt traditional financial systems.

As an important example, the cryptocurrency market, although relatively young, exhibits clear cyclical behaviour influenced by global financial trends. As a speculative and highly volatile market, cryptocurrencies like Bitcoin and Ethereum have experienced boom-and-bust cycles that mirror the broader Kondratiev and Juglar cycles.

The Accumulation Phase: during the accumulation phase, cryptocurrency prices stabilize after a market correction or crash. This phase is characterized by low volatility and gradual accumulation of assets by savvy investors, often referred to as “whales”. As globalization facilitates capital flows, this phase can attract international investors seeking to capitalize on future growth [61; 223, p.110-120].

The Growth Phase: the growth phase sees rapid price increases as market optimism returns and new investors enter the market. This phase is often driven by technological advancements, regulatory developments, and increasing adoption of cryptocurrencies as a legitimate asset class. Globalization amplifies this phase by enabling global participation in cryptocurrency markets, further driving up prices [61; 223, p. 120-130].

The Distribution Phase: in the distribution phase, early investors begin to take profits as prices reach new highs. This phase often coincides with increasing market speculation and media hype, drawing in less experienced investors. The global nature of cryptocurrency markets means that price movements in one region can quickly spread to others, leading to widespread market activity [61; 223, p. 130-140].

The Correction Phase: finally, the correction phase occurs when market enthusiasm wanes, leading to a significant drop in prices. This phase is often exacerbated by panic selling, regulatory crackdowns, or negative news. The interconnectedness of global markets means that corrections in cryptocurrency prices can have broader implications for financial markets, especially as more institutional investors become involved [61; 223, p. 140-150].

As the world continues to globalize, financial market cycles will likely become even more interconnected. The next Kondratiev wave, driven by innovations in AI, biotechnology, and renewable energy, will shape the future of global financial markets. These technological advancements will create new opportunities and challenges, leading to the emergence of new industries and the decline of others.

The cryptocurrency market, as part of this broader financial landscape, will continue to evolve, influenced by these global cycles. As digital currencies become more integrated into the global financial system, their cyclical behaviour will play a crucial role in shaping the future of financial markets under globalization.

Since 1970, globalization was primarily concentrated in developed Western countries, such as the United States, Canada, Western Europe, Japan, and Australia. These countries had stronger international trade connections, were more integrated into the global economy, and had higher levels of technology and information exchange. Developing Regions, much of Africa, Asia, and South America, had significantly lower levels of globalization. Many countries in these regions were either underdeveloped or in the early stages of industrialization, with limited participation in global trade and economic networks. By 2021, globalization had expanded significantly, reaching almost every part of the world. The maps show that many more countries, especially in Asia, Africa, and South America, have become more integrated into the global economy. Emerging economies like China, India, and Brazil show much deeper levels of globalization, reflecting their substantial integration into global trade, investment, and technology networks. While most regions of the world have seen increased levels of globalization, some countries, particularly in Sub-Saharan Africa, still lag behind, though they are more integrated compared to 1970. The main differences are reflected in:

- Broader Participation: the most noticeable difference between 1970 and 2021 is the broader participation in globalization. Many countries that were relatively isolated in 1970 are now more connected to the global economy.
- Depth of Integration: the depth of integration into global networks has increased across the world, with countries engaging more in international trade, investment, technology exchange, and information flows.

Annex C

Background, features and literature reviews on profitability models of financial trading under globalization

The modern financial landscape has undergone substantial transformations, primarily driven by the forces of globalization, technological advancements, and the increasing sophistication of financial trading mechanisms. Over the past few decades, globalization has facilitated unprecedented capital flows across borders, leading to interconnectedness in financial markets, supply chains, and economic policy. This interconnectedness has introduced new dynamics that shape macroeconomic outcomes in ways that traditional models may fail to capture.

In this context, financial trading mechanisms, including high-frequency trading, algorithmic trading, and derivatives markets, have evolved from niche market strategies to dominant forces that influence financial markets worldwide. These developments challenge established macroeconomic models, particularly those that have historically focused on static equilibrium assumptions, and demand a more dynamic and nuanced approach.

One of the key elements of globalization has been the liberalisation of capital flows, which has resulted in capital moving more freely across borders. Financial markets are no longer segmented, and capital no longer stays within national borders or within specific regional markets. As a result, investments, loans, and savings are increasingly sourced from global markets, with significant impacts on interest rates, capital accumulation, and economic growth at both the regional and global levels.

This phenomenon has led to new profit mechanisms in financial markets that reflect the global nature of these transactions. For instance, high-frequency trading, which uses powerful algorithms to execute trades within milliseconds, and algorithmic trading have emerged as major sources of profitability, even in markets that appear to be efficient. These innovations allow traders to take advantage of minuscule price differences across markets (e.g., arbitrage), but their implications for market stability and long-term economic growth are still poorly understood. This section will argue that these new profit mechanisms, enabled by globalization, are profoundly altering the nature of financial trading.

Traditional macroeconomic models were built upon assumptions of closed economies, stable interest rates, and relatively predictable financial behaviour. Models such as the IS-LM framework, Solow growth model, and AD-AS model focus on understanding the broad interrelationships between output, inflation, and unemployment, assuming that national economies are more or less self-contained. However, with globalization, national economies have become increasingly linked, with capital markets, goods markets, and labour markets becoming more integrated. As capital flows freely across borders and financial assets can be traded globally, the relationships between these variables must be reconsidered.

The introduction of dynamic elements, such as stochastic shocks, varying interest rates, and rapid portfolio adjustments, into macroeconomic models reflects the new realities of financial globalization. Additionally, market liquidity, which refers to the ability to buy or sell assets without significant price changes, is no longer just a passive factor but a critical variable that affects how global markets function and how quickly new information is priced into markets. This suggests that financial markets are now more dynamic and less predictable.

Moreover, globalization introduces asymmetries in the financial system: different economies are affected by global financial markets in distinct ways due to differences in access to capital, policy flexibility, and exposure to external shocks. For instance, emerging economies may be more vulnerable to sudden capital outflows or speculative attacks, whereas developed economies may benefit from greater market liquidity and capital inflows.

Additionally, market frictions, such as transaction costs, capital market imperfections, and information asymmetries, complicate traditional models, as they often assume perfect competition and instantaneous adjustment to new information. These assumptions no longer hold in a globalised, highly connected financial world where prices can be highly volatile and arbitrage opportunities arise in real time.

The dynamic model proposed in this study is designed to capture the interdependent, nonlinear, and stochastic dynamics of global financial markets, integrating modern trading mechanisms such as algorithmic trading, high-frequency trading, and advanced AI-based strategies within a macroeconomic framework. Its core purposes are:

- structural integration: bridging capital accumulation, interest rates set by central banks, market liquidity, and financial trading profitability into a unified endogenous system;

- dynamic adaptability: reflecting how policy shifts, technological innovations, and market shocks propagate through financial trading strategies to affect macroeconomic outcomes;

- strategic and technological applicability: enabling policymakers, financial institutions, and academic researchers to simulate, assess, and optimize economic and trading decisions in globalized environments.

The advent of algorithmic trading and HFT has also revolutionized how profits are generated in financial markets. These mechanisms involve using advanced mathematical models to process large amounts of data and execute trades at speeds far beyond human capability. The profits in these new trading mechanisms are also usually influenced by:

- market liquidity: high liquidity allows to perform more transactions, but it also requires advanced techniques to navigate price fluctuations;

- interest rates: interest rates set by central banks affect returns on investments and trading strategies, with significant implications for profit generation;

- market frictions: transaction costs, taxes, and market inefficiencies all influence the profitability of these mechanisms.

Financial trading profits are no longer purely tied to long-term investments or risk-bearing capital. Instead, profits arise from complex trading strategies that take advantage of market microstructure inefficiencies, leveraging the global flow of capital and the instantaneous nature of price changes. This creates a fundamentally different profit generation model than what has been traditionally discussed in macroeconomics, which often relies on long-term equilibria and ignores the role of high-frequency, algorithmic, or arbitrage-based profit mechanisms.

The new model thus seeks to examine how these trading mechanisms contribute to global financial stability, economic growth, and volatility, and how different regions or economies interact with these mechanisms in the context of globalization. Researchers can delve into the mathematical elements and dynamic system representations of these processes, along with empirical and simulation-based evidence to test the model's robustness.

The following literature review aims to contextualize the proposed model within the broader academic framework and highlight the theoretical foundations and empirical evidence that inform the model's design.

The impact of financial markets and trading mechanisms on the broader economy has been a central focus of macroeconomic research for decades. Traditional models like the IS-LM, Solow growth model, and AD-AS curve often overlook the complexities introduced by global capital flows, market liquidity, and financial innovations. However, in recent years, scholars have increasingly incorporated these factors into macroeconomic frameworks to better understand the evolving nature of global markets.

Feldstein, M. (2000), in his work "Aspects of Global Economic Integration: Outlook for the Future", explores the integration of global financial markets and its effects on national economies. Feldstein argues that global capital flows can accelerate economic growth by providing access to cheaper capital, but they also pose risks, such as increased volatility and the potential for financial crises. His work highlights the importance of integrating capital flows into macroeconomic models to better understand global economic dynamics [284].

Lucas, R. E. (1990) in "Why Doesn't Capital Flow from Rich to Poor Countries?" offers a foundational analysis of the role of capital flows in economic growth. While the model developed by Lucas does not incorporate global trading mechanisms or financial innovations, it sets the stage for later work on understanding the interaction between capital mobility and economic growth. Lucas highlights that factors like country-specific risks and institutions can mediate the effects of capital inflows on growth [285].

Stiglitz, J. E. (2000), in “The Contributions of the Economics of Information to the Analysis of Markets with Imperfect Information”, investigates the role of information asymmetry and market frictions in financial markets. His work shows how financial markets are often inefficient and prone to volatility, especially in the presence of market frictions such as transaction costs, asymmetric information, and liquidity constraints. Stiglitz’s findings have direct implications for the model, as they suggest that global financial markets are influenced by more than just supply and demand dynamics [286].

Almgren, R., & Chriss, N. (2001), in their paper “Optimal Execution of Portfolio Transactions”, develop a model for optimal trading strategies using algorithmic trading. They examine the impact of transaction costs and market liquidity on trading decisions. This research is essential for understanding how financial trading strategies, particularly algorithmic trading, affect market efficiency and overall economic outcomes. The concepts outlined by Almgren and Chriss serve as the foundation for the profit mechanisms in the model [287].

Menkveld, A. J. (2013), in his paper “High-Frequency Trading and the New-Market Makers”, discusses the role of HFT in modern financial markets. He emphasizes how HFT firms provide liquidity and facilitate price discovery, but also contribute to market instability during periods of high volatility. Menkveld’s research underscores the dual role of HFT as both a market stabilizer and a source of risk, aligning with the arguments made in the model about the complex role of financial trading innovations [288].

The interaction between globalization and capital flows has been widely studied in the context of both financial market integration and macroeconomic outcomes. Globalization, defined as the increasing interdependence of national economies, has created new opportunities for capital flow, especially in the form of portfolio investments and foreign direct investments.

Obstfeld, M., & Taylor, A. M. (2004), in their book “Global Capital Markets:

Integration, Crisis, and Growth", explore how the increasing integration of global capital markets affects national economies. They argue that global financial integration leads to more efficient capital allocation, but also exposes economies to global financial crises and shocks. This insight informs the model, which emphasizes the need to account for global market frictions and the impact of cross-border capital flows on economic growth and financial stability [289, p.180-220].

Bekaert, G., Harvey, C. R., & Lundblad, C. (2005), in "Does Financial Liberalization Spur Growth?", examine the relationship between financial liberalization (the relaxation of capital controls) and economic growth. Their findings suggest that capital account liberalization leads to higher economic growth, particularly in emerging markets. However, they also note that this relationship is conditional on the strength of financial institutions and market infrastructure. This work reinforces the importance of incorporating financial trading mechanisms into the model to understand the role of global capital flows and market frictions in economic outcomes [290].

The incorporation of stochastic shocks into macroeconomic models allows for the analysis of unexpected events that disrupt the normal functioning of financial markets. Financial markets are inherently uncertain, and shocks such as financial crises, political upheavals, or natural disasters can have profound impacts on economic variables like capital accumulation, investment rates, and interest rates.

Reinhart, C. M., & Rogoff, K. S. (2009), in "This Time Is Different: Eight Centuries of Financial Folly", provide an in-depth historical analysis of financial crises and their impact on global economies. They argue that financial markets are prone to bubbles, panics, and excessive risk-taking, and that the effects of crises are felt globally due to the interconnectedness of financial systems. This research directly informs the model's approach to incorporating stochastic shocks and understanding the mechanisms by which global financial crises can affect national economies [291, p.200-250].

Gertler, M., & Kiyotaki, N. (2010), in "Financial Intermediation and Credit Policy in Business Cycle Analysis", examine how financial frictions and credit market shocks impact business cycles. Their work highlights the importance of credit markets and liquidity in transmitting financial shocks to the broader economy, which is a crucial element in the design of the dynamic macroeconomic model [292].

The concept of market liquidity has gained significant attention in recent years due to its role in determining the efficiency of financial markets. Liquidity affects the ease with which assets can be traded without causing large price changes, and it plays a critical role in the profitability of financial trading mechanisms. Liquidity and Market Efficiency:

Kyle, A. S. (1985), in “Continuous Auctions and Insider Trading”, develops a theoretical model that connects market liquidity to the presence of informed traders and market makers. Kyle’s model has been instrumental in understanding how liquidity affects asset prices and trading behaviour, particularly in the context of market efficiency [293].

Amihud, Y., & Mendelson, H. (1986), in “Asset Pricing and the Bid-Ask Spread”, study the relationship between market liquidity and asset pricing. They argue that illiquidity (or high transaction costs) increases the bid-ask spread, which reduces market efficiency. This work is crucial in understanding how financial market frictions impact trading strategies and, consequently, global capital flows [294].

The literature reviewed provides a strong theoretical and empirical foundation for the development of the dynamic model. It underscores the importance of global capital flows, market liquidity, and financial trading mechanisms in shaping economic outcomes. Incorporating these elements into a comprehensive dynamic framework makes it possible to analyze the effects of financial innovations, market frictions, and stochastic shocks on the global economy.

The research findings on algorithmic trading, high-frequency trading, globalization, and financial shocks are pivotal in informing the design of the model. The existing literature suggests that while global financial integration offers significant growth opportunities, it also introduces new risks and complexities that need to be captured in a more dynamic and flexible model.

Annex D

The scenario applications of the dynamic model

Scenario 1. Impact of a global financial shock. This scenario introduces a stochastic shock to the model that affects global capital flows, interest rates, and financial trading profits. This shock could represent an event such as a global recession, a banking crisis, or a sudden political disruption. The shock will cause a temporary decline in market liquidity (L_t) and a rise in volatility (σ_t), which will, in turn, influence trading strategies and capital accumulation. To simulate the effect of the shock on key variables:

- Capital Stock (k_t): as capital flows decline, investment decreases, leading to a reduction in the capital stock and a slowdown in economic growth;

- Interest rates (r_t): a financial shock typically leads to a rise in interest rates as investors demand higher returns to compensate for increased risk;

- Market liquidity (L_t): liquidity is likely to contract as investors become more cautious, which can exacerbate the impact of the shock on asset prices and profits from financial trading.

This scenario will allow us to examine how the model responds to global economic disruptions and how financial trading mechanisms can either mitigate or amplify the effects of such shocks.

Scenario 2. Increasing market liquidity. This scenario assumes a permanent increase in global market liquidity due to improvements in financial infrastructure, such as the adoption of new technologies for faster trading or the relaxation of capital controls. An increase in liquidity (L_t) can make it easier to execute trades, reducing transaction costs and improving the speed of capital allocation.

The simulation will investigate the effects of higher liquidity on:

- financial trading profits (π_t) with lower transaction costs and faster execution, algorithmic traders and HFT firms will see higher profits;

- capital accumulation (K_t): as liquidity improves, it becomes easier for firms to raise capital and make investments, leading to an increase in capital stock and economic growth;

- interest rates (r_t): the effect on interest rates will depend on the relative magnitude of changes in liquidity and investment demand. Higher liquidity could reduce interest rates by making capital more available, but it may also increase demand for riskier assets, which could drive up returns.

This scenario will allow us to explore the implications of improving financial markets and how market liquidity influences the broader economy, particularly in the context of financial trading innovations.

Scenario 3. Increased capital flows and financial integration. This scenario simulates the effects of increased capital flows due to further global financial integration. This might occur as a result of trade liberalization, the reduction of capital controls, or the growth of emerging markets. As capital flows across borders more freely, the model will track how this influx of capital impacts:

- Capital stock (K_t): higher capital flows will increase investment in domestic and foreign markets, leading to higher capital accumulation and output growth;

- Interest rates (r_t): increased capital flows may lead to lower interest rates in some economies, as the supply of capital increases relative to demand. However, in markets that are less integrated, the influx of capital could cause asset price inflation and increased financial instability;

- Global financial markets: the increased integration of financial markets will also likely lead to more sophisticated trading strategies (including algorithmic and high-frequency trading) and changes in the risk-return profiles of various asset classes.

This scenario allows us to assess the effects of financial globalization on global economic stability and growth. It will also shed light on how capital flows influence the dynamics of financial trading profits and market behaviour.

Given its complexity and depth, this model holds several academic applications in a variety of fields, particularly within macroeconomics, finance, and global economics. Below are potential avenues for future academic research and applications:

1) Macroeconomic policy evaluation: central banks and financial regulators can use this model to test various monetary and fiscal policies under different market conditions. For example, simulations could help assess the impacts of interest rate changes, capital controls, and quantitative easing on financial market stability and economic growth. Future research could focus on policy optimization based on the model's simulations, providing empirical data for policy recommendations that balance economic growth and market stability.

2) Financial stability and risk assessment: this model's ability to simulate the interaction between financial market innovations and traditional economic variables makes it ideal for studying financial stability. Research could explore how factors such as algorithmic trading and HFT contribute to market volatility or asset price bubbles, which are central to financial stability analyses. The model could be extended to evaluate systemic risk and financial contagion across borders in the case of financial crises or shocks (e.g., global recessions, market crashes).

3) Empirical testing of financial market theories: future academic studies could focus on empirically testing the model using real-world data to evaluate its predictions about capital flows, investment patterns, and financial trading profits. This would involve using data from financial markets to calibrate the model's parameters and compare its results with observed economic behaviour. The inclusion of stochastic shocks in the model can be tested against historical data on financial crises and their aftermaths, contributing to the growing body of literature on financial market dynamics and business cycle theory.

4) Globalization and its impact on developing economies: the model can be used to assess the effects of financial globalization on emerging markets. It could

explore how capital inflows and financial innovations affect the growth and volatility of developing economies, particularly in terms of market liquidity and capital accumulation. This is highly relevant to development economics, as researchers can study the role of global capital markets in improving or exacerbating economic outcomes in emerging economies.

5) Evolution of financial markets and trading mechanisms: future work can also involve expanding the model to incorporate more complex financial instruments, such as derivatives, cryptocurrencies, and blockchain technology. These elements are becoming increasingly influential in financial markets and their interactions with macroeconomic variables.

The model can also be used to study the evolution of trading technologies, investigating the role of AI, machine learning, and automated decision-making in reshaping global financial systems.

Despite its numerous advantages, the model also has certain limitations that should be considered in future research and application. These shortcomings highlight areas where the model can be expanded or refined:

1. Simplifications in market behaviour: while the model incorporates many important factors, it still simplifies the complexities of real-world financial markets. For instance, it assumes that capital flows and interest rates are primarily driven by market liquidity and macroeconomic factors, but it does not fully account for behavioural finance aspects, such as investor psychology, herding behaviour, or market sentiment, which are critical in understanding market booms and crashes.

2. Lack of micro-level detail: the model currently focuses on macro-level aggregates, such as capital accumulation and global trading profits. While this is useful for understanding broader economic trends, it may lack the granularity needed to analyse the behaviour of individual market participants, including firms, institutional investors, or retail traders. Incorporating a microeconomic foundation or agent-based modelling approach could improve the model's ability to simulate individual decision-making and market dynamics.

3. Limited representation of financial instruments: the model primarily focuses on traditional financial markets and trading strategies. As financial markets evolve, newer instruments like derivatives, cryptocurrencies, and complex financial products are playing an increasingly important role in global capital flows and market dynamics. Expanding the model to include these instruments could make it more comprehensive and reflective of modern market behaviour.

4. Assumption of rational market behaviour: the model assumes that market participants (including traders and investors) act rationally, aiming to maximise profits through arbitrage or algorithmic strategies. However, real-world financial markets often experience irrational behaviours, such as speculation, bubbles, and overreaction to market news. Incorporating behavioural economics and market psychology into the model could provide a more accurate representation of financial market dynamics.

5. Data requirements and calibration: the model's complexity requires extensive real-world data to calibrate its parameters accurately. Collecting such data can be challenging, especially for emerging markets where data availability is limited. Further, the calibration of the model to real-world scenarios will require robust statistical methods and high-frequency trading data, which are often difficult to obtain.

Annex E

Results of the model simulations over time under different scenarios

These graphs will show the evolution of the system over time under different scenarios, providing a clear picture of how the economy responds to changes in market conditions. The key graphs include:

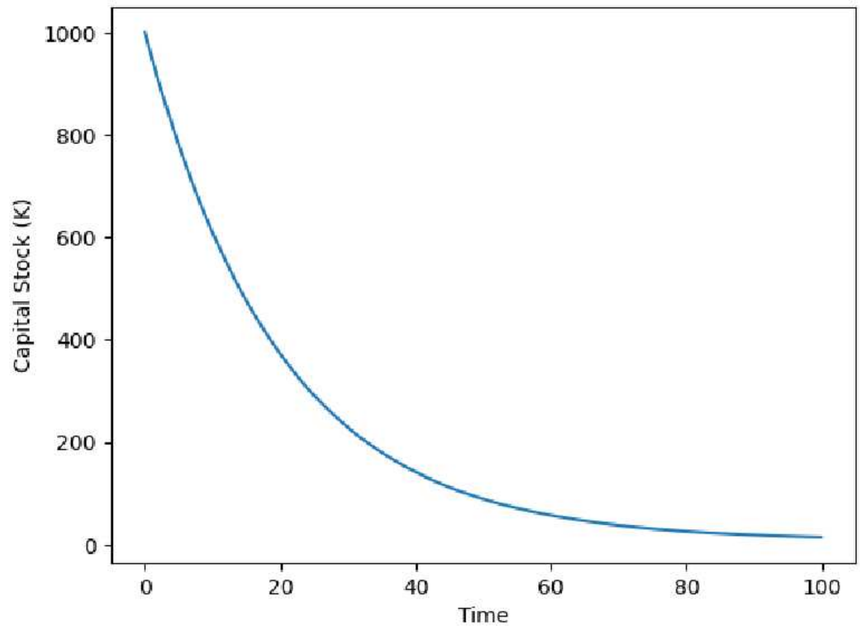

Fig. E.1. Capital accumulation over time (Euler's Method)
Source: author's own calculation

Figure E.1 shows how the capital stock K_t evolves over time using Euler's method. The capital stock grows steadily due to investment I_t, which depends on interest rates r, capital flows C and market liquidity L. Depreciation δ reduces the net accumulation of capital over time. This is the baseline scenario without any shocks or changes in market conditions.

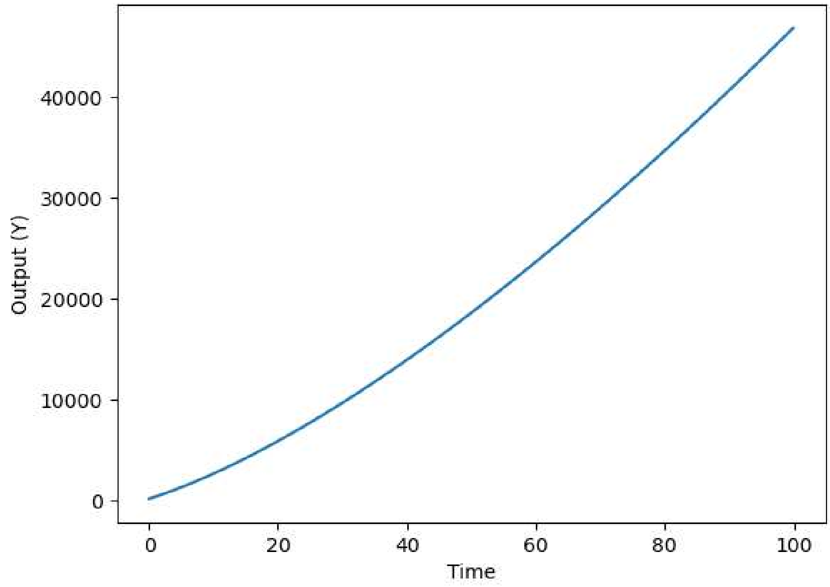

Fig. E.2. Output growth over time (Runge-Kutta Method)

Source: author's own calculation

Figure E.2 shows the growth of output Y_t over time using the Runge-Kutta method. Output is calculated using a Cobb-Douglas production function: $Y_t = A_t K_t^{\beta} L_t^{1-\beta}$. As capital stock K_t grows, output Y_t also increases, reflecting the positive relationship between capital accumulation and economic growth. The Runge-Kutta method provides a more accurate approximation of output growth dynamics compared to Euler's method.

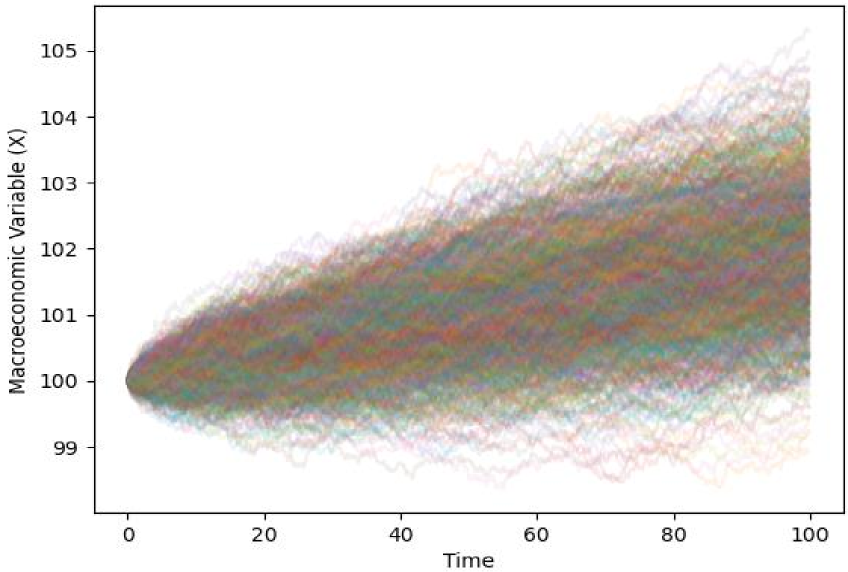

Fig. E.3. Monte Carlo simulation of stochastic shocks

Source: author's own calculation

Figure E.3 shows the impact of stochastic shocks on a macroeconomic variable X_t (e.g., capital stock, output, or interest rates) using Monte Carlo simulations. Each line represents a different simulation path, reflecting the randomness and uncertainty in financial markets. The graph demonstrates how stochastic shocks can lead to significant variability in macroeconomic variables over time.

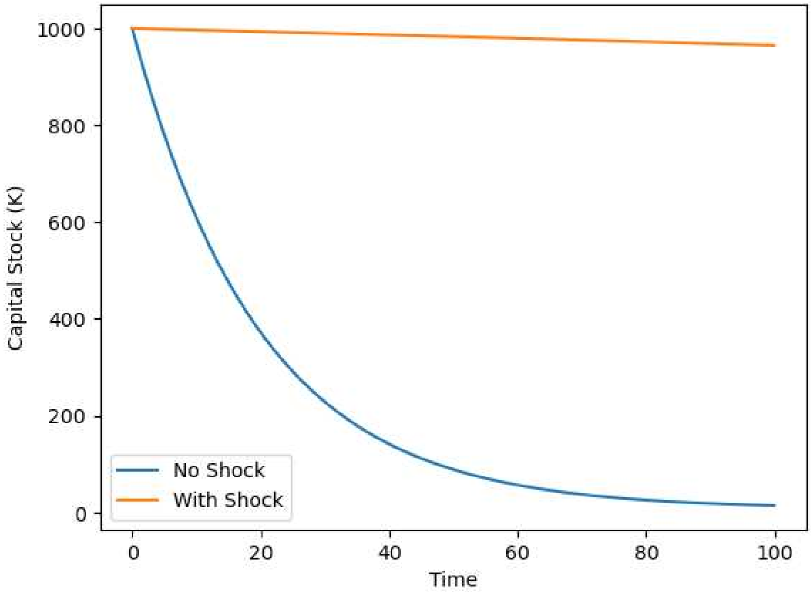

Fig. E.4. Impact of a global financial shock on capital accumulation

Source: author's own calculation

Figure E.4 compares the capital stock K_t with and without a global financial shock. The shock occurs at time $t = 50$ and reduces capital flows C by 10%, simulating a sudden drop in investment due to a financial crisis. After the shock, the capital stock grows at a slower rate, reflecting the negative impact of reduced capital flows on investment and capital accumulation.

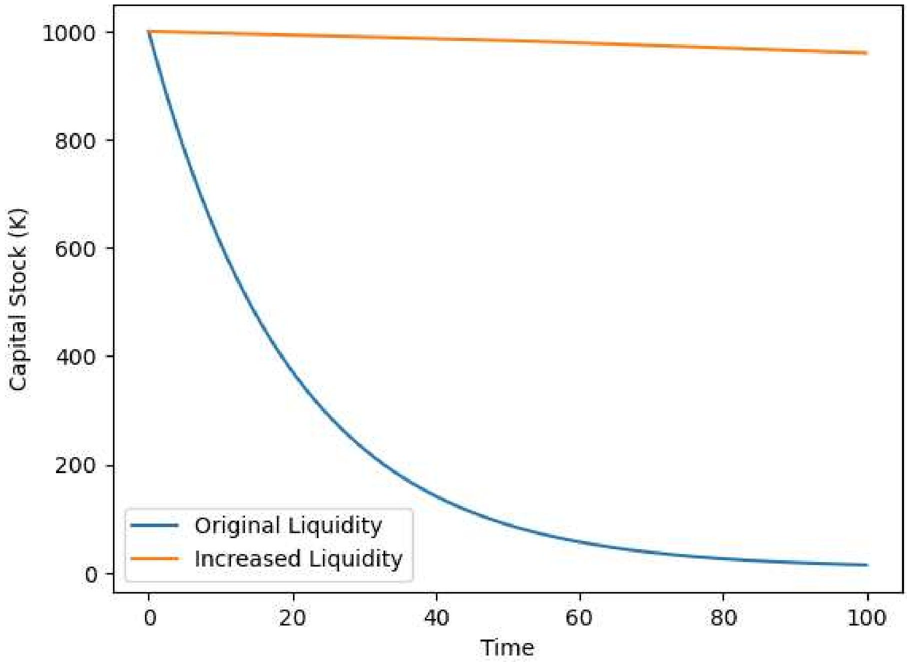

Fig. E.5. Impact of increased market liquidity on capital accumulation

Source: author’s own calculation

Figure E.5 shows the effect of increased market liquidity L on capital accumulation. At time $t = 50$, market liquidity increases by 50%, making it easier to buy and sell assets without significant price changes. The increased liquidity leads to higher investment I_t, resulting in faster capital accumulation.

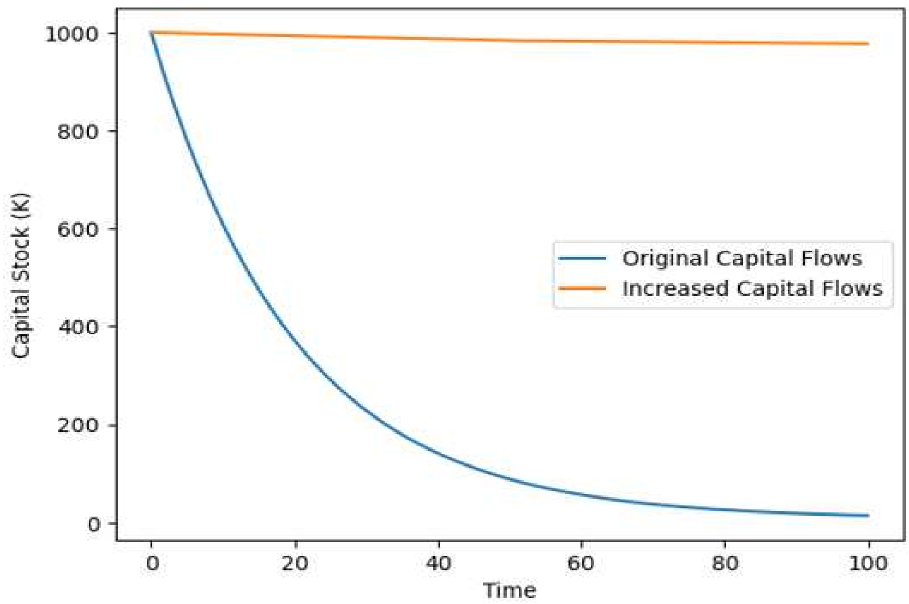

Fig. E.6. Impact of increased capital flows on capital accumulation

Source: author's own calculation

Figure E.6 illustrates the effect of increased capital flows C on capital accumulation. At time $t = 50$, capital flows increase by 50%, simulating greater financial integration or liberalization of capital controls. The increased capital flows lead to higher investment I_t, resulting in faster capital accumulation.

Simulation is a powerful tool for understanding the behaviour of complex systems. By applying it to the dynamic model, it can gain valuable insights into the interactions between global financial markets, capital flows, and financial trading mechanisms. The simulations help us evaluate the effects of global financial shocks, liquidity changes, and financial integration on macroeconomic variables such as capital accumulation, interest rates, and economic growth. These insights can inform policy decisions and provide a deeper understanding of how financial trading innovations impact global economies.

Annex F

Letters of implementation

МІНІСТЕРСТВО
ОСВІТИ І НАУКИ
УКРАЇНИ

КИЇВСЬКИЙ
НАЦІОНАЛЬНИЙ УНІВЕРСИТЕТ
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11.04.2025 № 013/178

На № ______

ДОВІДКА

про впровадження результатів дисертаційної роботи на здобуття наукового ступеня доктора філософії зі спеціальності «Фінанси, банківська справа та страхування» аспіранта третього року навчання ОНП «Фінанси, банківська справа та страхування» Київського національного університету імені Тараса Шевченка Хоу Пен'юе

Основні положення та результати дисертації щодо розвитку фінансового трейдингу в умовах глобалізації, підготовленої на здобуття наукового ступеня доктора філософії зі спеціальності «Фінанси, банківська справа та страхування» аспірантом третього року навчання ОНП «Фінанси, банківська справа та страхування» Хоу Пен'юе, були впроваджені в навчальний процес на кафедрі страхування, банківської справи та ризик-менеджменту економічного факультету Київського національного університету імені Тараса Шевченка при викладанні дисциплін «Ринок фінансових послуг» і «Фінансова інформація та прийняття стратегічних рішень» («Financial information and strategic decision making»), а саме:

— удосконалено визначення і класифікацію фінансового трейдингу, а також систематизовано технології та інституційно-правове забезпечення у сфері фінансового трейдингу, що було враховано при підготовці другого видання підручника з дисципліни «Ринок фінансових послуг», яка читається студентам II курсу спеціальності 072 «Фінанси, банківська справа, страхування та фондовий ринок» ОП «Фінансовий бізнес» в 2024/2025 навчальному році;

— структуровано за п'ятьма рівнями інформаційне забезпечення для здійснення фінансового трейдингу, що використовується при проведенні лекцій з курсу «Фінансова інформація та прийняття стратегічних рішень», який читається студентам II курсу магістратури спеціальності 072 «Фінанси, банківська справа, страхування та фондовий ринок» ОП «Фінансові інститути та ризик-менеджмент» економічного факультету в 2024/2025 навчальному році.

Застосування матеріалів дисертації Хоу П. у викладанні зазначених курсів сприятиме кращому засвоєнню студентами матеріалу та підвищенню якості підготовки фахівців для фінансової сфери

Проректорка з наукової роботи **Ганна ТОЛСТАНОВА**

Україна * Київський національний університет імені Тараса Шевченка * Ідентифікаційний код 02070944

ТОВАРИСТВО З ОБМЕЖЕНОЮ ВІДПОВІДАЛЬНІСТЮ
«ФІНАНСОВА КОМПАНІЯ «ФІНЕКСПРЕС»
03067, місто Київ, вул. Гарматна, будинок 4, поверх 6, офіс 3,4,5

14.04.2025 № 14/04-2025-6

ДОВІДКА
про впровадження результатів дисертаційної роботи аспіранта третього року навчання ОНП «Фінанси, банківська справа та страхування» Київського національного університету імені Тараса Шевченка Хоу Пен'юе, підготовленої на здобуття наукового ступеня доктора філософії зі спеціальності «Фінанси, банківська справа та страхування»

Основні положення та результати дисертації, що присвячена розвитку фінансового трейдингу в умовах глобалізації, та яка підготовлена аспірантом третього року навчання ОНП «Фінанси, банківська справа та страхування» Хоу Пен'юе на здобуття наукового ступеня доктора філософії зі спеціальності «Фінанси, банківська справа та страхування», були впроваджені в діяльності ТОВ «Фінансова компанія «Фінекспрес» (далі – Компанія), зокрема щодо використання гібридного фреймворку з управління ризиками.

Даний підхід дозволить покращити виявлення ризиків у реальному часі, оскільки на відміну від статичних моделей динамічно адаптується до ринкових потрясінь, допомагає кількісно визначити невизначеність, зумовлену ентропією даних та усуває прогалини в традиційних підходах. Це сприятиме модернізації управління ризиками в напрямі його перетворення на проактивний процес, в тому числі, при впровадженні системи внутрішнього контролю в Компанії.

Директор ТОВ «Фінансова компанія «Фінекспрес» **Оксана ГУБІНА**

УКРАЇНА м. Київ ТОВАРИСТВО З ОБМЕЖЕНОЮ ВІДПОВІДАЛЬНІСТЮ "ФІНАНСОВА КОМПАНІЯ "ФІНЕКСПРЕС" ідентифікаційний код 39706018

Annex G

LIST OF PUBLICATIONS OF THE AUTHOR:

Articles in scientific professional journals:

1. Sholoiko, A., & Hou, P. (2023). Conceptualization of financial trading. *Bulletin of Taras Shevchenko National University of Kyiv. Economics*, (2)222, 150-156. https://doi.org/10.17721/1728-2667.2023/223-2/19 (personal contribution of the author: definition creation of the financial trading; categorization of the financial trading participants; development of the financial trading classification on the basis of a combination of hierarchical and faceted methods).

2. Шолойко, А. С., & Хоу, П. А. (2025). Циклічність фінансового трейдингу в умовах глобалізації [Cyclicality of financial trading under globalization]. *Інвестиції: практика та досвід*, (7), 77-81. https://doi.org/10.32702/2306-6814.2025.7.77 (personal contribution of the author: characteristic of financial trading cycles for the developed and emerging financial markets under globalization).

3. Шолойко, А. С., & Хоу, П. А. (2025). Розвиток регулювання фінансового трейдингу в умовах глобалізації [Development of financial trading regulation under globalization]. *Підприємництво і торгівля*, (44), 80-87. https://doi.org/10.32782/2522-1256-2025-44-10 (personal contribution of the author: generalisation of stages of financial trading regulation under globalization and description of the modern stage).

4. Sholoiko, A. S., and Hou, P. (2025). Financial Trading Technological Advancements: Systematic Review. *Scientific Innovations*, 21(3), 16-28. https://doi.org/10.15407/scine21.03.016 (personal contribution of the author: categorization of financial trading technologies based on machine technology and trading strategies).

Approbation publications:

5. Hou, P. (2023). Characteristics of financial trading participants. *Shevchenkivska Vesna 2023: Problems and prospects of Ukraine's post-war economic recovery:* Proceedings of the international conference (Vol. 21, p. 153). Interservis.

https://econom.knu.ua/wp-content/uploads/2023/04/Збірник-Шевченківська-весна.docx.pdf

6. Hou, P. (2023). Comprehensive financial trading classification. *World trends and prospects of development of the financial system of Ukraine:* Proceedings of the international conference (Vol. 16, pp. 185–186). Taras Shevchenko National University of Kyiv. https://econom.knu.ua/wp-content/uploads/2023/07/%D0%9C%D0%B0%D1%82%D0%B5%D1%80%D1%96%D0%B0%D0%BB%D0%B8-%D0%BA%D0%BE%D0%BD%D1%84%D0%B5%D1%80%D0%B5%D0%BD%D1%86%D1%96%D1%97-_-%D0%B7%D0%BC%D1%96%D1%81%D1%82.pdf

7. Hou, P. (2024). Emergence and future regulations of large language models in financial investment. *Economics. Finance. Business. Management:* Proceedings of the international forum 3.0 (pp. 61–62). Taras Shevchenko National University of Kyiv. http://surl.li/tvjpk

8. Hou, P. (2024). The tendencies of financial trading facing risks under globalization: national cases. *Financial business: Stability, inclusiveness and social responsibility:* Proceedings of the international conference December readings (Vol. 15, pp. 186 – 187).

9. Hou, P. (2024). Trends in financial trading under globalization. *The 1st Modern Finance Conference: Book of abstracts*. (p. 2). MFI.