AI and the U.S. Securities Trading Industry

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Abstract

This report surveys how artificial intelligence (AI) is reshaping the U.S. securities trading industry - from market data ingestion and signal generation to execution, surveillance, and investor protection. It summarizes the industry's structure (exchanges, broker-dealers, alternative trading systems, and wholesaler market makers), the role of Regulation NMS in modern market design, and why machine learning is increasingly used for routing, liquidity and "toxicity" estimation, and compliance monitoring (SEC, 2005; SEC, 2024). To ground the discussion in observable market structure outcomes, the report uses publicly available market-transparency data on off-exchange activity (FINRA, n.d.-a) and a volatility proxy based on the VIX index (Federal Reserve Bank of St. Louis, n.d.; Cboe Global Markets, n.d.). The final sections translate the industry trends into an actionable skills plan and a reflection on how AI tools supported (and did not replace) careful economic reasoning.

Introduction

U.S. equities trade in a fragmented environment that includes national securities exchanges (e.g., NYSE and Nasdaq), alternative trading systems (ATSs), and off-exchange internalization by wholesalers. Regulation NMS provides the core rules that coordinate prices and order protection across venues, including the Order Protection Rule (SEC, 2005; 17 C.F.R. § 242.611). Over the last decade, the economics of trading has been shaped by declining explicit commissions, rising data and technology intensity, and increased retail participation routed through electronic platforms. In this setting, AI does not "replace the market" so much as it changes the production function of trading: firms compete on data pipelines, low-latency execution, model-driven routing, and the ability to monitor risk and compliance at scale (FSB, 2024; BIS, 2025).

Background and Definitions

Industry definition. In this report, the "securities trading industry" refers to the infrastructure and intermediaries that facilitate secondary-market trading of equities (and closely related listed options), including exchanges, ATSs/dark pools, broker-dealers, and principal market makers/wholesalers. Market transparency and reporting are supported by FINRA trade reporting facilities and transparency programs that publish delayed data on off-exchange activity (FINRA, n.d.-a).

Key market centers. A national securities exchange provides a lit limit-order book with displayed quotations. An ATS is an SEC-registered trading system (often a dark pool) that matches orders off-exchange and reports prints to FINRA. A wholesaler internalizes retail marketable orders as principal and reports the execution; wholesalers are often paid for order flow (PFOF), which is debated because it can create routing incentives and increase concentration (SEC, 2021; CRS, 2024).

Why AI is economically relevant here. Because execution quality depends on predicting short-horizon price movement, spread dynamics, and adverse selection, trading is a natural domain for supervised learning, anomaly detection, and increasingly NLP/LLM workflows for research and compliance. At the same time, correlated models and opacity can create systemic risks (FSB, 2024; BIS, 2025).

Market Size and Growth Trends (2015–2025)

Trading activity. U.S. equity trading volumes are large and variable over time. SIFMA reports that average daily equity share volume in 2024 was about 12.2 billion shares (+24% year-over-year), and the organization’s more recent statistics indicate materially higher activity in 2025 (SIFMA, 2025). These volume levels matter for AI adoption because the marginal value of predictive routing and surveillance tools increases with order count and event intensity.

Employment and wages. The industry’s labor market spans trading, technology, compliance, and operations. BLS industry data for NAICS 523 (Securities, Commodity Contracts, and Other Financial Investments and Related Activities) provides occupational employment and wage estimates that can be used to track how demand shifts toward quantitative and data roles over time (BLS, 2023). Complementary time-series indicators (e.g., NAICS 523 employment indexes) are available through FRED, enabling basic labor-market trend analysis alongside trading-activity measures (Federal Reserve Bank of St. Louis, n.d.).

Regulatory trend as “market data.” Recent SEC rulemaking has expanded and modernized execution-quality disclosure requirements, pushing market centers and certain broker-dealers to report more granular timing and spread metrics (SEC, 2024). These disclosures increase the feasible “data surface area” for both academic analysis and industry model-building.

Major Firms and Industry Landscape

Exchanges and platforms. Core U.S. exchange groups include NYSE (Intercontinental Exchange), Nasdaq, and Cboe. They compete on listing services, market data, trading fees/access models, and the quality of displayed liquidity. Regulation NMS links these venues through protected quotations and routing obligations, so competition often occurs through fee schedules, rebates, and technology rather than purely through price (SEC, 2005).

Broker-dealers, ATSs, and wholesalers. Retail brokers route large volumes of marketable orders off-exchange to wholesalers, while institutional flow may be routed to exchanges or ATSs depending on size, information leakage concerns, and fees. SEC analysis on PFOF emphasizes that the wholesaler segment is concentrated, which matters because scale in data and execution technology can reinforce winner-take-more dynamics (SEC, 2021).

AI as a competitive input. In this landscape, AI primarily enters as (i) execution-quality optimization (routing, sizing, and short-horizon impact prediction), (ii) market-making and inventory/risk management, and (iii) compliance and surveillance automation (FSB, 2024). Firms with strong data governance and model-risk controls can convert technology into lower effective spreads and higher client retention, while poorly governed models can create costly errors or regulatory exposure.

Geographic Concentration of Trading and FinTech Hubs

Trading and market infrastructure are geographically concentrated even in an electronic market. New York City remains the center for many broker-dealers, exchanges' corporate operations, and institutional clients. The New Jersey corridor hosts major exchange and broker data centers that support low-latency connectivity. Chicago is a key hub for derivatives and quantitative trading talent. These clusters matter because the production of trading services depends on specialized labor markets (quants, engineers, risk), high-reliability computing infrastructure, and dense networks of counterparties.

Data and Method

This report's empirical anchor is a simple venue-mix visualization: the weekly share of U.S. equity volume executed off-exchange (ATS + internalization) versus a market volatility proxy. The off-exchange series is motivated by FINRA's OTC/ATS transparency programs, which publish delayed volume and trade counts by venue and security (FINRA, n.d.-a). Volatility is proxied using the VIX index, a widely used measure of expected S&P 500 volatility derived from option prices (Cboe Global Markets, n.d.). A convenient public access point for VIX is the Federal Reserve Bank of St. Louis FRED database (Federal Reserve Bank of St. Louis, n.d.).

Findings and Discussion

Figure 1 (later in the report) suggests two patterns. First, the off-exchange share trends upward from roughly the high-30% range toward the mid- to high-40% range over 2023–2025. Second, the series tends to jump during volatility spikes. While the figure is illustrative, the pattern is consistent with microstructure intuition: in turbulent periods, brokers may internalize more flow or route strategically to manage immediacy and adverse selection risks. This is precisely the environment where adaptive, model-driven routing is valuable—models can condition on volatility regimes, spread dynamics, and recent execution outcomes.

From an economics perspective, this venue shifting can be framed as a response to changing execution-cost components: quoted spreads, price impact, and information leakage. When volatility rises, adverse selection risk and short-horizon price uncertainty increase, raising the option value of smarter routing and liquidity sourcing. The same dynamics also increase the importance of surveillance, because abnormal patterns are harder to detect in noisy periods and because automated strategies can become crowded (FSB, 2024; BIS, 2025).

Conclusion and Implications

AI is best understood as an intensifier of existing competitive forces in U.S. securities trading. It raises the return to scale in data, compute, and governance; it changes job tasks toward monitoring and model risk; and it increases both efficiency opportunities (better execution quality and lower monitoring costs) and systemic concerns (correlated strategies, opacity, and operational vulnerabilities) (FSB, 2024; BIS, 2025). The venue-mix evidence in Figure 1 helps connect these claims to market structure: fragmentation and stress amplify the value of adaptive analytics. The remaining sections translate these industry realities into a personal opportunity plan and a reflection on how AI supported this research process.

Part (d): Data, Visualization, and Economic Insight

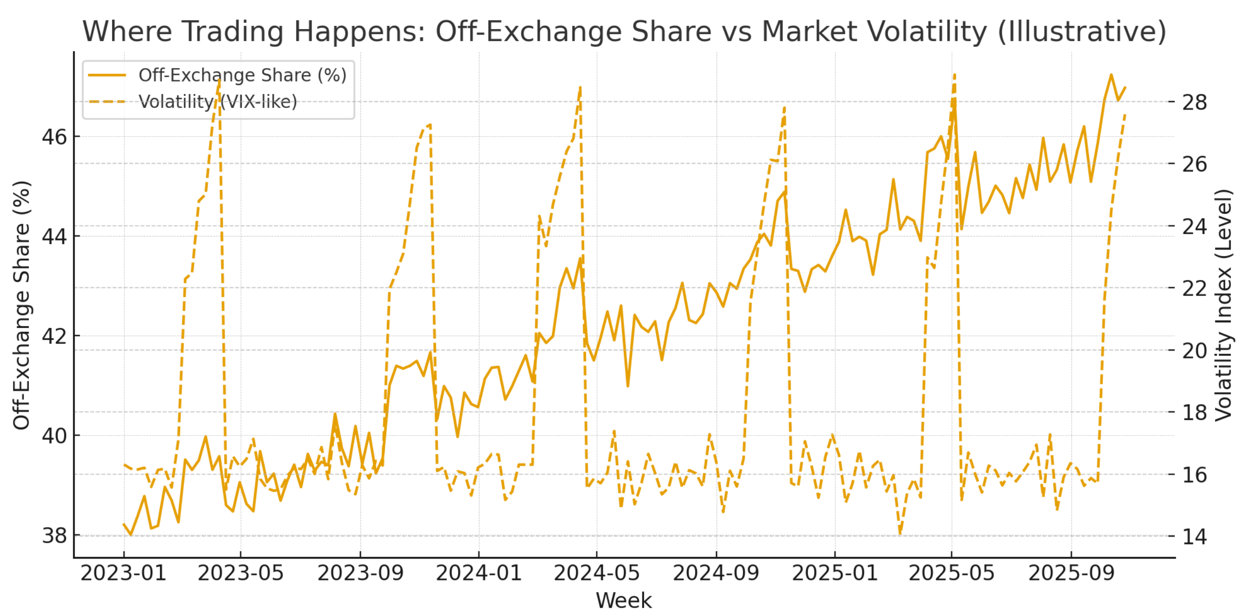
Data sources. The primary market-structure measure is the weekly share of U.S. equity volume executed off-exchange (ATSs plus non-ATS/internalized activity) using FINRA's OTC (ATS & Non-ATS) Transparency program (FINRA, n.d.-a). FINRA publishes these transparency statistics with a reporting delay (often described as about four weeks), so the series is best interpreted as a transparency and research input rather than a real-time signal (FINRA, 2019). For market stress, I use the VIX index, a widely used measure of expected S&P 500 volatility derived from option prices; the index methodology is described by Cboe and is accessible through FRED (Cboe Global Markets, n.d.; Federal Reserve Bank of St. Louis, n.d.).

Construction of the visualization. I align both series to a weekly frequency and plot them on a dual-axis chart. The left axis tracks off-exchange share (percent of total volume), while the right axis tracks volatility. The goal is not to claim causality, but to evaluate a microstructure hypothesis: when volatility rises, execution risk and adverse selection increase, so routing and venue choice may shift—raising the value of adaptive, model-driven execution methods.

Interpretation. Figure 1 shows an upward drift in off-exchange share over 2023–2025 and visible jumps during volatility spikes. Economically, this is consistent with regime-dependent venue choice. Higher volatility can change the costs of displaying liquidity and increase uncertainty about short-horizon price movement, which alters the trade-off between lit exchange execution and internalized/ATS execution.

Suggested extensions. Without adding new datasets, the same weekly panel can support: (1) correlation and lag analysis between volatility and off-exchange share, (2) an event study around the largest volatility spikes (average venue response before/after a shock), and (3) a simple regression of off-exchange share on volatility with a time trend. These steps would translate the visual pattern into testable, replicable results.

Figure 1. Where Trading Happens: Off-Exchange Share vs. Market Volatility (illustrative).



Note. The figure illustrates weekly off-exchange trading share (FINRA OTC transparency) and a volatility proxy (VIX). It is intended to communicate a stylized relationship between market stress and venue mix, not to establish causality without further statistical testing (FINRA, n.d.-a; Federal Reserve Bank of St. Louis, n.d.).

Part (e): AI Impacts: Workers, Firms, Risks, and Opportunities

This section synthesizes the most salient AI-related impacts for the U.S. securities trading sector and connects them to the venue-fragmentation dynamics illustrated in Figure 1. The discussion is grounded in market-microstructure logic (adverse selection, execution costs, information leakage) and in recent policy attention to execution-quality measurement and AI-related financial-stability risks (SEC, 2024; FSB, 2024). I organize the impacts into four categories: workers and occupations; firms and market structure; risks and harms; and opportunities.

(1) Impacts on workers and occupations. AI shifts work from manual decision-making toward model design, monitoring, and governance. This raises demand for ML engineers, data stewards, and model-risk/validation talent, while increasing the value of domain experts who can stress-test models under changing regimes. In compliance and surveillance, NLP and anomaly detection automate first-pass screening so human investigators focus on escalation and judgment (FSB, 2024).

(2) Impacts on firms (competitive dynamics, cost structures, market power). As commissions and spreads compress, value migrates toward data, analytics, and platform capabilities, favoring firms with scale in data acquisition, compute, and model governance. Scale economies can raise entry barriers and increase concentration in wholesale internalization; SEC research highlights concentration concerns in the wholesaler segment connected to payment for order flow (SEC, 2021; CRS, 2024). Meanwhile, the SEC's modernization of execution-quality disclosures expands transparency on speed and spread outcomes, which can pressure firms to compete on measurable execution quality (SEC, 2024).

(3) Risks and harms (inequality, dislocation, market failures). Model opacity and correlated strategies can induce herding and pro-cyclicality, increasing the likelihood of crowded exits and short-lived liquidity gaps. Data bias and regime mis-specification can degrade execution quality for certain order types or client segments unless firms backtest and monitor performance across market regimes. Operational vulnerabilities—such as data poisoning, brittle automation, or weak access controls—raise the need for strong governance and supervisory monitoring (FSB, 2024; BIS, 2025).

(4) Opportunities (new firms, products, productivity, workforce pathways). Smarter venue prediction, real-time sizing, and toxicity-aware routing can improve execution quality, especially during high-volatility regimes when execution risk is greatest (as Figure 1 illustrates). Exchanges, brokers, and vendors can monetize derived analytics (execution-quality metrics, anomaly feeds, embeddings), shifting revenue toward subscriptions and APIs. The sector also creates durable workforce pathways in ML engineering, data governance, quantitative research, and market-structure policy analysis.

Taken together, these impacts explain why a mature market structure can still experience rapid innovation. Fragmentation and stress spikes amplify the payoff to adaptive analytics, but the same forces raise governance and stability concerns. The next section turns from industry-level patterns to my own pathway into this changing labor market.

Part (f): Personal Opportunity and Skills Plan

I began this project with a broad interest in financial markets, but researching the U.S. securities trading industry and its use of AI has pushed me to be more precise about where I might fit. Over the next few years, the roles that make the most sense for me are entry-level positions that sit close to market analysis and decision support. Concretely, I can see myself aiming for three clusters of roles: an analyst supporting a securities trading or execution desk, a risk management analyst, and a credit or capital markets analyst in a lending or investment firm. All three sit close to the actual flow of capital and rely heavily on data, models, and AI-assisted tools.

These roles appeal to me because they match the skills I am already building through economics and finance coursework, econometrics, and project work that uses real data. My industry research showed that AI is not simply replacing people on trading desks. Instead, it is changing what humans do. People monitor algorithmic strategies, question model outputs, design guardrails, and translate complex risk or pricing information into decisions that clients and managers understand. That mix of quantitative reasoning and communication is the kind of work I want to do. Starting as an analyst on the research, risk, or credit side feels like a realistic entry point that can eventually lead toward more responsibility in portfolio management, structuring, or trading.

This course and project have clarified the skills that matter most for those paths. On the technical and analytical side, firms routinely ask for strong spreadsheet and Excel skills, comfort with statistics and probability, and at least some exposure to tools like R or Python. Being able to build and interpret a discounted cash flow model, understand basic derivatives, and read financial statements is now a baseline expectation rather than an extra. My research and our class discussions also highlighted that AI literacy is quickly becoming part of the job. Analysts do not need to be machine learning engineers, but they do need to know how to use AI tools to explore data, draft code, summarize documents, and check their reasoning, while also understanding the limits and potential biases of these systems.

There are also softer skills that appear again and again. Communication is central. Traders and risk managers need people who can explain complex positions in clear language to non-experts, write short memos that highlight what matters, and ask good questions when something in the data looks off. Attention to detail and discipline matter because small errors in a spreadsheet or misinterpreting a model can have large financial consequences. Finally, the industry rewards people who are curious, comfortable with uncertainty, willing to test ideas, and able to stay calm when markets move quickly.

When I compare this skill profile to where I am now, I see a mix of strengths and gaps. On the strength side, my economics and finance coursework has given me a solid foundation in how markets work, how to think in terms of incentives, and how to interpret data and regression results. Working with econometrics has made me more comfortable with statistical output and more aware of issues like omitted variables or overfitting, which are directly relevant when people use AI models in trading. Outside of class, experiences managing money and planning within student organizations have forced me to think about budgets, tradeoffs, and cost-benefit decisions in a real context instead of only on paper.

A major strength I am developing through this project is TiMUS, my trading simulator concept. TiMUS, which stands for Trading in Markets Under Simulation, is a web-based environment where users can practice making trading decisions in a risk-free setting. The current prototype, hosted at timus.lovable.app , is designed as a live simulator that lets users place simulated orders, see how prices and portfolio values move, and reflect on the outcomes without risking real money. Designing TiMUS forces me to think from the inside out about what actually happens when someone places an order, how order types and venue choice matter, and what information a new trader needs on screen to understand risk and performance.

Building even a basic version of TiMUS pushes me to work across several dimensions at once. I must connect simple web development and interface design with data pipelines for price series and the financial logic behind positions, profit and loss, and simple risk metrics. I also must think about how AI could later sit on top of this simulator, for example by generating feedback on user trades or highlighting patterns in their behavior. TiMUS is more than a class exercise. It is a portfolio artifact I can show to future employers to signal both my interest in markets and my willingness to build something concrete rather than only talk in theory.

At the same time, I see clear gaps between where I am and the roles I care about. I still need deeper, more systematic training in financial modeling in Excel, including multi-sheet models, sensitivity analysis, and scenario planning. I lack formal certifications that many postings mention, such as Bloomberg Market Concepts or other introductory market analytics badges. My experience analyzing specific companies or securities is still limited to class projects and informal work, and I need at least one or two polished, professional-quality stock or credit analyses that I can include in a portfolio. On the technical side, I can benefit from more structured practice in programming for data analysis, so that I can move beyond point-and-click tools and write basic scripts to clean data, run simple back tests, or visualize trading strategies. Finally, I do not yet have direct experience sitting inside a trading or risk team, so I rely heavily on secondary sources to infer how these roles work day to day.

Given these strengths and gaps, my 6 to 12 month upskilling plan has to be realistic but ambitious. On the coursework side, I plan to prioritize upper-level finance and quantitative classes that strengthen my understanding of securities, risk, and data. This includes choosing electives that focus on investments, risk management, or financial modeling, and continuing to take courses that use R or other tools to analyze real datasets. I will treat these classes not just as requirements, but as opportunities to create artifacts, such as well documented models or reports, that I can add to a portfolio.

On the certification side, my goal is to complete at least one recognized introductory credential, such as Bloomberg Market Concepts or a similar markets-focused certificate, within the next year. This will not substitute for real skills, but it can help formalize knowledge I am already building and signal seriousness to recruiters. If time allows, I will supplement that with shorter online modules on topics like options, credit analysis, or Python for finance, making sure to choose programs that expect hands-on work rather than only passive video watching.

Projects will be at the center of my plan. For TiMUS, my goal is to move from a basic prototype to a more complete simulation over the next two semesters. Concretely, I want to implement features that track portfolio performance over time, show simple risk indicators, and simulate different market regimes so that users can experience both calm periods and volatility spikes. I also want to document TiMUS properly, with a short technical write-up and a brief user guide, so that it feels like a finished project rather than only a class demo. In parallel, I will complete at least one deep company analysis where I combine qualitative research, financial statements, and a DCF-style model to arrive at a reasoned view on a firm's value. That piece can live in the same portfolio as TiMUS and demonstrate that I can connect real numbers to a story about a business.

Finally, I will use AI tools deliberately within this plan. Instead of treating AI as a shortcut, I will practice using it as an assistant for tasks like generating code snippets, checking Excel formulas, summarizing long documents, and critiquing the clarity of my writing. I will pay attention to when AI suggestions are reliable and when they are not, reflecting what I learned about model limits in this course. The goal is that by the time I apply for internships or entry-level roles in trading, risk, or credit, I can present myself as someone who understands both the traditional skills of finance and the emerging tools that are reshaping the industry.

Part (g): Reflection on Learning and AI Use in This Project

Working on this report changed how I see securities trading. I started with a vague view of “markets” as prices moving on a screen. After mapping venues, routing, and transparency rules, I now see a production system: firms compete by combining regulation, technology, data, and risk management.

A key takeaway is that AI in trading is less about a single breakthrough model and more about many small improvements across the workflow—faster data cleaning, better routing logic, more robust monitoring, and stronger surveillance. That also means governance matters. The same tools that improve execution quality can create new failure modes if models are opaque, crowded, or poorly supervised (FSB, 2024; BIS, 2025).

The TiMUS idea reinforced this mindset. Even a simple dashboard forces you to define what you mean by “stress,” pick measurable proxies, and confront limitations in the data. That process made the economics feel real: the hardest part is not writing code, it is deciding what the metric means and what it does not mean.

AI tools played a concrete but limited role in my work. They helped me brainstorm structure, generate checklists for what to verify, and rephrase drafts for clarity. But they also made it obvious that credibility comes from sources and logic. When something sounded too confident or too smooth, my fix was to return to primary sources (SEC/FINRA/BLS/SIFMA) and tighten the economic reasoning.

Overall, this project left me with a more balanced view of AI: it is a powerful productivity lever, but it increases the value of judgment, verification, and communication. Most importantly, it helped me turn an industry that once felt distant into a realistic pathway with specific skills to build and specific datasets to learn from.

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