The Effects of Artificial Intelligence on Market Data

August 27, 2025 | Report from a Jordan & Jordan Summer Intern

My assignment did not start well. In my first interview, one of the participants exclaimed, “so you want to take my job?” It wasn’t because I was the latest hire, but rather because I was analyzing which market data functions might be replaced by AI. I understood Jordan & Jordan had a track record of leveraging technology to more effectively serve the financial industry, but AI feels different, and J&J employees and their clients were raising a good question.

I looked to answer the question after reviewing a recent study, *Expertise*, by David Autor and Neil Thompson where they discuss whether or not the automation of tasks augments or diminishes the value of the remaining labor. David Autor is the Daniel (1972) and Gail Rubinfeld Professor in the MIT Department of Economics, and Neil Thompson is an Innovation Scholar at MIT's Computer Science and Artificial Intelligence Lab and the Initiative on the Digital Economy. They challenge the view that automation is always bad for labor. Their study looked at the job market from a broad perspective, and then closely looked at two specific jobs: Accounting Clerks and Stock and Inventory Clerks.

I attempted to apply their methodology to market data jobs by segmenting the market data roles and then determining those mostly affected by AI, –“ when job tasks are automated, does this augment or diminish the value of labor in the tasks that remain?” ([1]).

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[1] Autor, David, and Neil Thompson. *Expertise*, Massachusetts Institute of Technology , 20 June 2025, economics.mit.edu/sites/default/files/2025-06/Autor-Thompson-Expertise-22050620.pdf.

LLM and generative models have become a staple of our daily lives, and as the models learn market data which jobs will benefit and which won't? The extent to which a task requires expertise will define the magnitude to which it can be replaced. If non-automatable tasks don't require expertise, then wages will fall, and, if non-automatable tasks require expertise, then wages will rise, and employment will fall. The complexity lies within the classification of expertise or not, and the entirety of the scale in between. To solve this, one must look at two key trends:

1. Is there a barrier to entry? Does the task require extensive training? This would mean that it would be more difficult to train the model up to speed, likely making the replacement process inefficient.
2. Is the task hierarchical? Experts can do inexpert work, but not vice versa. This system though, is not as clear cut in practice. Within each job, each task must be explored to effectively conclude the susceptibility to being automated.

We surveyed approximately 20 market data professionals to segment and quantify the market data tasks, and then adapted the Autor–Thompson expertise framework, which treats each function as having a complexity score ϕ between 0 and 1. A value of 0 corresponds to a generic administrative task while a value of 1 corresponds to the most complex market data leadership role, requiring mastery of all departmental functions. The 25-question survey also explores automation improvements to date, the current environment and future expectations.

To connect this to automation risk, we use the studies "capital share" equation:

$$\alpha(\phi) = \frac{\min\{\phi,\, I\}}{\theta(1-\phi)+\phi}$$

Here:

- ϕ = task's expertise level (from 0 to 1)
- I = automation frontier (tasks with $\phi \le I$ can be automated)
- θ = proportion of generic tasks bundled into the role

As I increases, more tasks fall below the automation frontier, raising the share of work done by AI ($\alpha(\phi)$) and changing the expertise profile of the remaining human work.

The results suggest that people will not be replaced by their current job description, rather, specific functions within those roles may be assumed by AI. A good example is vendor management. Many of the administrative tasks such as onboarding and contract renewals can be replaced by AI, but the interaction between the vendor and customer will still require personal interaction and negotiation on large contracts.

The analysis showed that AI will be taking away tasks of many people but work in that area will still be required. The result may be reduced staffing, but those who remain will have broader knowledge and will receive higher wages. Eventually, this will also create a shift in the way tasks are packaged within jobs. These individual functions will be broken down and categorized by task rather than under one job title. The thought process being AI aids in specific tasks where it is efficient and does so broadly for many people in different roles across an industry.

Firms vary in their levels of automation, and roles and workflow differ across organizations. The following is an attempt to organize and rank the tasks based on survey results and insight from market data professionals. The rankings were fed into the capital share equation above and are ranked as most likely to more easily supplemented by AI from top of each table.

Business Relationship and Advisory

- Meeting notes, summary, follow-ups
- Responses on basic inquiries
- Automation needs versus current alternatives
- Responding to end-user about contractual usage rights (application, location, entity)
- Self Help Chat front end
- Advisory dialogue on strategy, business needs and alternatives
- Market Data Management to ensure data needs met-most effective quality, cost, risk

Sourcing

- Automated dialogue on request
- Contract agreement, little or no dialogue on small and medium agreements
- Automated renewal or cancelation
- Solution alternatives
- Catalog for external services
- Big contracts, people negotiation

Vendor & Exchange Relationship

- Initial dialogue on needs

- Easier onboarding at certain exchanges/vendors
- Reports/tools to assist with audit management
- Business requirements converted into exchange or vendor offering
- Completing requests for certain vendors with simpler contracts
- Interpret current agreements/contracts
- Audit findings negotiation
- Legal and senior management signoff

Inventory & Administration

- Inventory tracking
- Moves, adds, changes
- Identifying duplicate services
- Automated updates to third-party inventory systems via uploads
- Turning users off and on
- Reconciling with invoices & usage
- Inventory system updates for market data management and reporting automated via vendor feeds

Invoice & Financial Analysis

- First-pass invoice reconciliation
- Allocation charge backs to users
- Invoice ingestion and matching
- Reconciling with invoices & usage, agreements

Reporting and Application Management

- Vendor/exchange reporting processes
- Declarations to vendors and exchanges
- Entitling or removing a user from an application
- Usage monitoring
- Automated licenses true up with end users/app owners
- Automated application assessment

When grouped, the distribution revealed a clear split: administrative and transactional tasks clustered around 0.2–0.3, while strategic advisory and relationship-driven functions clustered near 0.8–0.9. The average across all tasks was about 0.46, highlighting how much of the market data workflow falls in the "mid-expertise" range—precisely the area where automation can be most effective and helpful.

Using this information and plugging it into the capital share equation we were able to find three different situations:

- A **low-expertise task** like meeting notes ($\phi = 0.1$) is already below any reasonable frontier (say, $I=0.3$), meaning nearly all of its value can be automated. At this level, the task is already far below the automation frontier. Even when I is relatively low, most of its value can be automated because it requires minimal training and is repetitive. These tasks represent the "low-hanging fruit" of automation—cheap to replace and unlikely to retain value in human hands.
- A **mid-expertise task** like contract agreement on smaller deals ($\phi = 0.3$–0.4) becomes automatable once the frontier rises slightly; moving I from 0.3 to 0.5 raises its automation share from about 30% to nearly 50%. This lies just at the edge of the frontier. When $I=0.3$, only a small fraction is automated, but as the frontier expands to $I=0.5$, automation potential jumps significantly. This illustrates the "fragile middle"—tasks that seem secure until AI capabilities advance slightly, after which they become heavily exposed.
- A **high-expertise task** such as advisory dialogue on strategy ($\phi = 0.9$) remains largely insulated—its automation share stays close to zero regardless of small shifts in I. Even with a frontier shift, the automation share stays close to zero. These tasks are insulated because they rely on judgment, tacit knowledge, and relational skills. In fact, as lower-level work is automated away, the relative importance (and pay) of such high-expertise human tasks tends to rise.

This analysis shows that AI will reduce tasks of various roles but work in that area will still be required. Therefore, there will be fewer people but those who remain must demonstrate broader knowledge.

In summary, to my new friend who challenged me on Day 1, there are opportunities, and you and others will adapt to the challenge and provide services where smart humans are required. Embrace it and best wishes for a key role in managing market data with your AI assistant.