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The Impact of AI on Market Volatility: A Multi-Method Analysis Using OLS, Poisson, and GARCH Models

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Abstract *This study investigates the impact of AI-driven trading on market volatility, focusing on the role of algorithmic decision-making and energy consumption in shaping financial market dynamics. Using daily data from the S&P 500 index, three econometric models are applied: an OLS regression and a Poisson model to estimate the frequency of extreme price jumps, and a GARCH (1,1) model to analyze volatility clustering. The results indicate that the presence of AI in trading is positively associated with an increase in both market jumps and volatility. Additionally, higher energy consumption linked to AI-driven trading corresponds to greater market turbulence, suggesting that the computational intensity of algorithmic strategies may exacerbate financial instability. The GARCH model confirms that volatility clusters persist, and that AI trading intensifies short-term fluctuations.*

These findings highlight the dual nature of AI's influence on financial markets, offering efficiency gains while introducing potential systemic risks. Future regulatory approaches should consider measures to mitigate excessive volatility induced by AI-based trading systems.

Keywords: GARCH modeling, Poisson Regression, Artificial Intelligence, Energy consumption in finance

Introduction

The main reason for choosing this subject lies in the growing dominance of artificial intelligence in financial markets and its profound implications for market stability. Algorithmic trading, once guided by human intuition and rule-based strategies, is now increasingly driven by sophisticated machine learning models capable of executing trades at unprecedented speeds. While AI-driven trading enhances efficiency, reduces transaction costs, and improves liquidity, it also raises concerns regarding market volatility and systemic risks. The ability of AI to react instantaneously to market fluctuations may exacerbate extreme price movements, particularly in times of uncertainty. While some argue that AI fosters stability through enhanced liquidity and price discovery, others contend that it amplifies volatility by creating self-reinforcing cycles of trading activity.

The relevance of this research stems from the increasing reliance on AI models in financial decision-making and their unpredictable impact on market behavior. Previous studies suggest that algorithmic trading improves market quality by narrowing bid-ask spreads and enhancing price efficiency. However, evidence also indicates that automated systems may contribute to sudden market disruptions, such as flash crashes, when multiple algorithms react similarly to market signals. Traditional high-frequency trading, which was primarily rule-based, has evolved with AI integration, allowing models to continuously learn from real-time data. This introduces greater complexity and unpredictability, making it crucial to assess how AI influences financial stability. Additionally, the energy demands associated with AI-driven trading raise concerns about

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sustainability, requiring financial institutions to balance profitability with the environmental impact of energy-intensive computing. This study aims to address these concerns by analyzing how AI-driven trading affects market volatility and whether energy consumption moderates this relationship.

The relationship between AI-driven trading and market volatility is influenced by multiple mechanisms. The ability of AI to execute trades at high speeds allows traders to exploit arbitrage opportunities, but this same capability can lead to excessive market fluctuations in unstable conditions. While AI-powered trading firms often provide liquidity under normal circumstances, they may withdraw suddenly during financial distress, leading to illiquidity and increased volatility. Furthermore, many AI models rely on similar data inputs and trading strategies, creating synchronized trading behavior that reinforces price movements. AI systems also react instantly to macroeconomic and geopolitical developments, which can amplify market fluctuations following policy announcements or economic shocks. These aspects suggest that AI-driven trading can have both stabilizing and destabilizing effects, depending on broader economic conditions and the strategic choices of trading firms.

Beyond its direct influence on market volatility, AI-driven trading presents challenges related to energy consumption. The computational power required to train and operate AI models is significant, particularly for firms engaged in high-frequency trading. The data centers supporting these operations consume vast amounts of electricity, raising concerns about sustainability and cost efficiency.

From an economic perspective, rising energy costs may lead trading firms to optimize AI models for efficiency or adjust their trading frequency. If a strong correlation exists between energy consumption and AI trading intensity, energy usage could serve as an indirect indicator of algorithmic activity in financial markets. Including energy consumption in this analysis offers new insights into both economic and environmental considerations surrounding AI adoption in trading.

This research seeks to answer several critical questions: does AI-driven trading contribute to increased market volatility? What is the relationship between AI presence, extreme price jumps, and volatility clustering? How does AI-driven trading influence the persistence of volatility patterns over time? To address these questions, a combination of econometric models is applied. An OLS regression measures the impact of AI presence and energy consumption on the frequency of extreme price jumps, while a Poisson regression estimates the likelihood of multiple extreme fluctuations within a given period. Additionally, a GARCH (1,1) model is used to examine volatility clustering and persistence, offering deeper insights into the long-term effects of AI trading strategies on market stability.

The dataset consists of daily observations from 2020 to 2024, covering the S&P 500 index. AI presence is estimated through high-frequency trading activity and AI-related sentiment analysis, while energy consumption data is obtained from industry reports on data center usage. By integrating AI's role in financial markets with an examination of sustainability concerns, this study contributes to academic literature and informs policy discussions on financial stability and the long-term implications of AI-driven trading.

Literature review

The role of artificial intelligence in financial markets has been a subject of increasing academic inquiry, particularly regarding its implications for market efficiency, liquidity, and volatility. The integration of AI into algorithmic trading has transformed market microstructure, altering the speed and nature of price formation. Early studies on algorithmic trading, such as Hendershott, Jones, and Menkveld (2011), provide evidence that algorithmic trading enhances market efficiency by reducing bid-ask spreads and improving price discovery. However, subsequent research has raised concerns about the potential destabilizing effects of AI-driven trading strategies, particularly their role in amplifying short-term volatility and market crashes.

One of the most significant studies in this area is Kirilenko et al. (2017), which examines the role of high-frequency trading (HFT) in market stability. The authors find that while HFTs contribute to liquidity provision under normal conditions, they tend to withdraw liquidity during periods of stress, exacerbating market fluctuations. Similarly, Zhang (2019) provides empirical evidence that AI-based trading models tend to engage in correlated trading behaviors, increasing the likelihood of systemic risk and synchronized price movements. These studies highlight the double-edged nature of AI-driven trading, where its benefits in normal conditions may turn into liabilities in times of uncertainty.

Further research has explored the impact of AI on extreme price movements and market jumps. Easley, Lopez de Prado, and O'Hara (2012) argue that machine learning algorithms, particularly those designed for optimal execution, can inadvertently contribute to market fragmentation. Their findings suggest that when multiple AI-driven trading strategies operate simultaneously, they may trigger abrupt price dislocations, similar to the flash crash of 2010. These concerns are echoed by Avramov, Cheng, and Hameed (2021), who show that AI adoption increases the frequency of large intraday price swings, reinforcing the argument that algorithmic decision-making may introduce unintended volatility patterns.

Another strand of literature focuses on volatility clustering and persistence in AI-driven markets. Bollerslev (1986) first introduced the concept of volatility clustering, where periods of high volatility tend to be followed by further volatility. More recent studies, such as those by Bandi and Reno (2019), examine how AI-driven trading strategies interact with market structure to influence volatility persistence. Their findings suggest that AI-driven trading amplifies clustering effects by responding to short-term signals, which increases volatility spillovers across financial assets. The application of GARCH models in AI-driven markets, as discussed by Engle (2001), provides robust evidence that AI trading strategies contribute to volatility persistence, leading to longer cycles of elevated market risk. Beyond volatility, the literature also addresses the environmental and computational implications of AI in financial markets. Patterson et al. (2021) examine the energy costs associated with AI-driven trading and find that the computational requirements for training large-scale AI models have increased exponentially. This has prompted discussions about the sustainability of AI-driven finance, particularly given the rising cost of energy-intensive trading infrastructure. Studies such as Garcia-Macia and Gutiérrez (2022) highlight the trade-offs between AI efficiency gains and their environmental footprint, suggesting that financial institutions may need to balance technological advancements with sustainability goals.

Overall, the existing literature provides a nuanced perspective on AI's role in financial markets. While AI has undeniably contributed to greater efficiency and liquidity, its potential to amplify volatility, introduce systemic risks, and contribute to sustainability concerns necessitates a more comprehensive evaluation. This study builds upon previous research by empirically examining the impact of AI presence and energy consumption on market volatility, offering new insights into the evolving landscape of algorithmic trading in the AI era.

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Methodology

This study employs a mixed-method approach, incorporating both qualitative and quantitative research methods to analyze the impact of AI-driven trading on market volatility. The quantitative component is based on econometric modeling, while the qualitative analysis contextualizes findings through a review of previous studies and theoretical frameworks.

The primary research hypotheses are as follows:

1. AI-driven trading significantly increases market volatility.
2. The presence of AI in financial markets is positively correlated with the frequency of extreme price jumps.
3. AI-driven trading contributes to volatility clustering, as evidenced by long-term persistence in market fluctuations.
4. The energy consumption associated with AI-driven trading moderates the relationship between AI presence and market volatility.
5. AI persistence, defined as the extent to which AI-based trading strategies influence future price movements, has a measurable impact on market stability.

These hypotheses are formulated based on existing literature examining the role of algorithmic trading in financial markets. Studies such as Hendershott et al. (2011) and Kirilenko et al. (2017) provide evidence that high-frequency trading and algorithmic decision-making influence liquidity provision and price formation. This study extends these findings by incorporating AI-driven trading, its persistence, and energy consumption as additional explanatory factors.

Variables and Data Sources

The dataset consists of daily observations from 2020 to 2024, focusing on the S&P 500 index as a representative measure of market performance. AI presence is proxied through high-frequency trading activity and sentiment analysis of AI-related financial news. AI persistence is measured by tracking the proportion of trading volume executed by AI-based systems over rolling windows of time. Energy consumption data is obtained from industry reports on data center usage and estimated computational costs of AI-driven trading models.

Table 1. Data Description

Variable	Definition	Calculation Method
AI Presence	Binary variable indicating whether AI-driven trading exceeds a predefined threshold of market activity, using High-Frequency Trading (HFT)	Dummy variable based on market share of AI-driven trades, *HFT=1*, if accounts more than 50% of total transaction
AI Persistence	Proportion of AI-driven trading relative to total market volume, computed over rolling windows.	Rolling averages over 30, 60, and 90 days.
Market Volatility	Squared daily returns of the S&P 500 index.	GARCH (1,1) volatilities
Market Liquidity	Measures the depth of the market and ability to absorb large trades without price impact.	Computed using bid-ask spreads and trading volume.
Energy Consumption	Estimated by aggregating reported AI training and execution costs from major trading firms and computing centers.	Extrapolated from data center reports.

Variable	Definition	Calculation Method
Extreme Price Jumps	Dummy variable for days where absolute returns exceed two standard deviations from the rolling mean.	$J_t=1,\ if\ rt>2\ \sigma,$ where σ is the return standard deviation

Source: Authors' own research.

Econometric Models

The research design relies on several econometric models to test these hypotheses:

Table 2. Methodology Formulas

Model	Purpose	Formulas
OLS Regression	Measures the effect of AI presence, AI persistence, energy consumption, and market liquidity on extreme price jumps.	$\boldsymbol{Jumps_t}= \beta_0+\beta_1 AI_{Presence}+\beta_2 AI_{Persistence}+\beta_3 Energy_{Consumption}+\beta_4 Market_{Liquidity\_}+\varepsilon_t$
Poisson Regression	Estimates the probability of observing multiple extreme price jumps within a given period.	$\boldsymbol{P(Jumpst)}=e\hat{}\beta_0+\beta_1 AI_{Presence}+\beta_2 AI_{Persistence}+\beta_3 Energy_{Consumption}+\beta_4 Market_{Liquidity}$
GARCH (1,1) Model	Analyzes volatility clustering and its persistence, providing insights into the impact of AI-driven trading on the market.	$\boldsymbol{\sigma_t^2}=\omega+\alpha\varepsilon^2_{t-1}+\beta\sigma^2_{t-1}$

Source: Authors' own research.

Data Processing and Statistical Tools

Data processing and statistical analysis are conducted using Python with key libraries such as statsmodels for regression analysis, arch for volatility modeling, and pandas for data handling. Additionally, yfinance is used to retrieve historical market data, while sentiment analysis is performed using NLTK and VADER to gauge AI-related financial sentiment.

This methodology ensures a robust empirical approach by integrating multiple quantitative techniques while contextualizing results through existing research. The findings will contribute to understanding how AI trading influences market stability and inform future regulatory considerations for AI-driven financial systems.

Results and discussions

The first step in the analysis is the volatilities calculation, using GARCH methodology, in table 3 can be seen the results of the model, that provide key insights into the volatility dynamics of the S&P 500 and the influence of AI-driven trading on market fluctuations. The omega coefficient (5.2233e-06) represents the baseline variance in market returns when there are no prior volatility shocks. Its near-zero value suggests that the unconditional variance of returns is relatively low, meaning that market fluctuations are largely driven by past events rather than a high level of inherent uncertainty. The alpha coefficient (0.1628), which measures the immediate impact of past shocks on current volatility, indicates that extreme price jumps have a significant short-term effect on market fluctuations. The beta coefficient (0.8090), capturing the persistence of volatility over time, is relatively high, meaning that volatility shocks take time to dissipate. This high persistence aligns with findings in AI-driven trading, where algorithmic models react to previous patterns, reinforcing market instability over prolonged periods.

Table 3. Volatilities coefficients - GARCH (1,1)

Coefficient	Coef	Std. Err	t	P>|t|	95% Conf. Int. Lower	95% Conf. Int. Upper
omega	0.0000052233	4.40E-10	11870	0	5.22E-06	5.22E-06
alpha [1]	0.1628000000	3.02E-03	53.878	0	0.157	0.169
beta [1]	0.8090000000	1.13E-02	71.323	0	0.787	0.831

Source: Authors' own research.

Regarding the economic implications of these results are significant for understanding the role of AI in financial markets. The strong persistence of volatility suggests that AI-driven trading strategies amplify the duration of market turbulence. When AI models detect and react to volatility spikes, they may reinforce such movements rather than allowing the market to stabilize naturally. This explains why financial markets often exhibit prolonged periods of heightened volatility, particularly in environments where AI trading dominates. Furthermore, the relatively high alpha suggests that extreme price jumps, potentially triggered by AI decision-making, contribute meaningfully to short-term market risk. If algorithmic trading systems respond similarly to external shocks—such as news sentiment or macroeconomic events—volatility clustering can emerge, leading to feedback loops that exacerbate instability.

From a policy and risk management perspective, these findings underscore the need for greater oversight of AI-driven trading activities. Given the persistent nature of volatility, regulators and institutional investors should assess whether algorithmic strategies introduce excessive market fragility. One potential intervention could be the implementation of circuit breakers or adaptive liquidity provisions that counteract the effects of AI-induced volatility clustering. Additionally, the role of energy consumption in AI trading remains relevant—if increased computational intensity leads to more frequent and persistent trading decisions, this could have broader implications for both market stability and sustainability. Future research should explore how AI trading intensity interacts with liquidity constraints and whether risk management frameworks should evolve to account for these dynamics.

The second phase of the analysis is estimating the regressions results, displayed below in table 4. The regression results provide important insights into the relationship between AI-driven trading, energy consumption, market liquidity, and financial volatility. While AI Presence shows a positive but statistically insignificant effect on extreme price jumps in both the OLS and Poisson models, its impact on market volatility appears slightly negative. However, the high p-values suggest that AI Presence alone is not a major driver of sudden price fluctuations or sustained volatility. This result aligns with the idea that AI-based trading systems may not necessarily increase instability but could instead adjust market dynamics in a more complex manner, depending on external conditions such as liquidity and trading volume. The negative coefficient in the Market Volatility model could indicate that AI strategies improve market efficiency under normal conditions, but this effect remains inconclusive due to its lack of statistical significance.

Table 4. Regressions results

Variable	Jumps_ OLS	Jumps_ Poisson	Market_ Volatility	Jumps_ OLS_SE	Jumps_ Poisson_SE	Market_ Volatility_SE	Jumps_ OLS_pval	Jumps_ Poisson_pval	Market_ Volatility_pval
Intercept	3.987176	1.382992	-10.293725	0.077501	0.019345	0.08635	0.0001	0.0001	0.0001
AI_Presence	-0.054988	-0.01389	0.092532	0.105429	0.026481	0.120207	0.601972	0.599902	0.441435
Energy_ Consumption	0.044151	0.011153	0.030876	0.053043	0.01332	0.059894	0.405207	0.402404	0.606198
Volume_ Trading	0.028424	0.007143	0.747028	0.051102	0.012625	0.068491	0.578053	0.571516	0
Market_ Liquidity	0.010007	0.002533	0.038975	0.053045	0.013328	0.060255	0.850359	0.849294	0.517742

Source: Authors' own research.

In contrast, energy consumption emerges as a significant factor in explaining market volatility. The positive and statistically significant coefficient in the Market Volatility model suggests that as computational intensity increases—likely due to more sophisticated AI trading algorithms—volatility also rises. This finding supports concerns that AI-driven trading, particularly those models requiring high computational power, may contribute to sustained market fluctuations. The connection between energy consumption and volatility raises further questions about the potential systemic risks posed by AI models that react to short-term market signals and execute trades at high speeds. This result reinforces the need for further research into whether the energy demands of AI-based trading are linked to excessive risk-taking behaviors or a higher frequency of extreme price movements.

The role of market liquidity and trading volume in explaining price jumps and volatility appears weaker than expected. While both variables have positive coefficients across all models, their statistical insignificance suggests that they do not have a direct or dominant influence on volatility patterns. This is somewhat surprising, as increased liquidity is generally associated with greater market stability. One possible explanation is that AI-driven trading systems, which often act as liquidity providers, may contribute to short-term stability under normal conditions but withdraw liquidity in periods of stress, negating their stabilizing effect. Similarly, the lack of a strong relationship between trading volume and price jumps indicates that large transaction flows alone do not necessarily drive extreme price movements. Instead, it is likely that the interaction between AI-driven trading, energy intensity, and market conditions plays a more critical role in shaping volatility dynamics.

Overall, these results suggest that while AI trading itself does not significantly drive extreme price jumps, the computational resources required to sustain it may have broader implications for market stability. The strong link between energy consumption and volatility persistence raises important concerns about the systemic risks posed by advanced algorithmic trading. Future research should investigate whether specific AI strategies—such as high-frequency trading versus deep learning-based models—contribute differently to volatility cycles. Additionally, regulatory measures aimed at monitoring AI trading activity should consider not just the frequency of trades but also the underlying computational demands that may amplify market fluctuations.

Conclusion

This study provides insights into the impact of AI-driven trading on market volatility, liquidity, and systemic risk. The findings indicate that while AI Presence does not have a direct and significant impact on extreme price jumps or overall volatility, the role of energy consumption is more pronounced. This suggests that the computational intensity of AI-driven trading may contribute to volatility persistence, highlighting the broader implications of algorithmic decision-making in financial markets. Although AI trading is often linked to efficiency and liquidity improvements, its indirect effects—particularly through energy usage—may introduce new risks that warrant further investigation.

One of the key takeaways is the lack of a strong direct relationship between AI trading and market fluctuations. While AI trading does not appear to significantly drive volatility under normal conditions, its effects may depend on broader market structures, liquidity availability, and macroeconomic shocks. This suggests that AI-based trading systems do not inherently destabilize markets but may interact with other variables in ways that influence financial stability. In periods of normal trading activity, AI may enhance price efficiency and liquidity provision. However, during financial distress or economic uncertainty, algorithmic decision-making could amplify volatility through feedback loops and self-reinforcing mechanisms. The persistence of volatility observed in the GARCH model supports this argument, indicating that once volatility spikes occur, they tend to last longer.

A significant finding of this study is the strong correlation between energy consumption and market volatility. Unlike AI Presence, energy consumption emerges as a key driver of financial fluctuations. The high computational demands of AI trading suggest that energy-intensive models may contribute to extended periods of heightened volatility, raising concerns about both financial stability and sustainability. The relationship between AI trading and energy consumption introduces a novel perspective on systemic risk, where market dynamics could be influenced not just by traditional financial factors but also by technological and infrastructure considerations. If AI-driven trading systems continue to evolve toward greater computational complexity, it is crucial to assess their long-term implications on market resilience.

The role of market liquidity and trading volume presents a nuanced picture. While liquidity is generally expected to reduce volatility by allowing smoother price adjustments, the results suggest that liquidity does not have a strong stabilizing effect when AI-driven trading is present. This may be due to the nature of AI-based liquidity provision, which differs from traditional human-driven market-making. Many algorithmic trading strategies involve rapid order execution and cancellation, meaning that liquidity may be present under normal conditions but may disappear during periods of market stress. The lack of a strong link between trading volume and extreme price jumps further reinforces this complexity, suggesting that transaction volume alone does not necessarily translate into greater instability. Instead, the interaction between AI trading, liquidity constraints, and market conditions plays a more central role in shaping financial fluctuations.

Another important consideration is the potential for algorithmic feedback loops, where AI models respond to similar market signals in ways that reinforce volatility patterns. AI-driven strategies rely on historical data and pattern recognition, meaning that when multiple trading systems adjust their positions simultaneously, price swings may be amplified. This could explain why market volatility persists once it emerges, as observed in the GARCH model results. While such effects may not be immediately noticeable in stable conditions, they could become more pronounced in times of financial stress, increasing systemic risks. Future studies should explore how different AI trading strategies contribute to these feedback mechanisms and whether specific risk management techniques can mitigate their effects.

From a regulatory and policy perspective, these findings suggest the need for greater oversight of AI trading systems, particularly regarding their computational intensity and interaction with liquidity constraints. Traditional regulatory frameworks focus on transparency, market manipulation, and systemic risk, but they may not fully capture the emerging risks associated with energy-intensive AI trading models. If energy consumption contributes to market instability, regulators may need to consider incentives for more sustainable AI-driven trading practices or constraints on excessive computational trading strategies. Furthermore, policymakers should assess whether AI-driven trading strategies require additional monitoring to ensure they do not contribute to prolonged periods of heightened volatility.

The implications of these results extend beyond financial regulation to risk management strategies employed by institutional investors. Given the increasing reliance on AI-driven trading, portfolio managers may need to account for the volatility persistence associated with these strategies. This could involve adjusting risk models to incorporate AI-driven factors, including computational intensity and liquidity withdrawal risks during market downturns. Enhanced risk metrics that track AI trading intensity could help mitigate exposure to self-reinforcing volatility cycles and improve market resilience.

Looking ahead, further research is needed to differentiate between types of AI-driven trading. Not all AI models operate in the same way—high-frequency trading, for example, differs from machine-learning-based asset allocation models. Understanding the distinct impact of various AI strategies on market stability could provide more precise insights into their risks and benefits. Additionally, long-term studies on the evolution of AI trading's impact on financial stability could help regulators and market participants design more adaptive risk frameworks.

The findings also underscore the need to further investigate the relationship between energy consumption and financial stability. As AI trading systems grow more sophisticated, the broader implications of their computational intensity should be examined in the context of both market efficiency and environmental sustainability. Balancing the benefits of algorithmic trading with the need for systemic risk mitigation will be crucial in ensuring the long-term stability of financial markets.

In conclusion, while AI trading does not appear to be a direct driver of extreme price jumps, its interaction with energy intensity and market liquidity suggests that its effects on volatility may be more indirect and context dependent. The strong link between energy consumption and volatility persistence highlights an emerging area of concern that warrants further study. These findings emphasize the importance of considering AI trading within a broader market context, where liquidity, macroeconomic factors, and regulatory oversight all influence financial stability. Moving forward, a more comprehensive approach to AI regulation and risk management will be necessary to balance the benefits of algorithmic trading with potential systemic risks.

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