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The Impact of Emerging E-Commerce Platforms on Amazon's Stock Price Performance

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Abstract: Objective: This study analyzes how emerging e-commerce competitors—Temu, eBay, and Etsy—influenced Amazon's stock returns and volatility between 2018 and 2024. **Approach:** Using covariance analysis and GARCH-type models, the findings reveal that Amazon's returns were significantly affected by market shocks and competitive pressures, with clear evidence of volatility clustering and asymmetric effects. While eBay and Etsy moved largely in tandem with Amazon, Temu's returns displayed an inverse relationship, suggesting its rapid market expansion occurred partly at Amazon's expense. **Results:** These results support the study's objective by demonstrating that rising competition from new entrants materially altered investor sentiment and short-term stock performance in the global e-commerce space. The study also contributes to the intersection of the Efficient Market Hypothesis (EMH) and Behavioral Finance. It shows that investor reactions to competitive developments were not always rational, with herding behaviour and sentiment-driven responses amplifying short-term volatility. Amazon's heightened sensitivity to firm-specific shocks, relative to broader market trends, underscores its exposure to competitive and innovation-driven risks in a fast-evolving digital landscape. **Value:** From a practical standpoint, the research highlights the importance for investors to monitor behavioural signals and market narratives, which can influence valuation and risk beyond traditional fundamentals. For e-commerce firms, the results underscore the need for continuous innovation, strategic differentiation, and adaptive pricing to retain market share. While limited by a focused sample and geographic scope, this study lays groundwork for future research

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incorporating broader datasets, cross-country analysis, and sentiment indices to better understand the interplay of competition and investor psychology in digital markets.

Keywords: Behavioural finance; Volatility; GARCH

JEL Classification: G2; G4

1. Introduction

Over the last decade the electronic commerce sector popularly known as e-commerce has experienced remarkable transformation, propelled by technological advancements and shifting consumer behaviour (Shahbaz, 2024). This transformation has significantly reshaped the global business environment, reducing the reliance in traditional retail models by offering flexibility, adaptability and convenience (Simakov, 2020) According to Hao (2019) in particular countries like China have witnessed dramatic rise in online shopping, fuelled by the widespread use of computers and the internet. The world at large has evolved to online participation such as online banking that we use daily. The convenience of 24/7 access, lower operating costs, and minimal inventory pressures have made online platforms attractive to both consumer and merchant. As a result, e-commerce ushered in a new era of digital commerce by removing the barriers to traditional business operations and opening up new business prospects (Hao & Choi, 2019).

E-commerce has a rich history, from primitive electronic data transactions in the 1960s and the first online retail transactions in 1994, to the modern popularity of e-commerce giants such as Amazon with a revenue of 280.5 billion USD (Agyeman et al., 2022). In 2024 Ahmar and Shahbaz conducted a comparative analysis of the innovative strategies employed by three prominent e-commerce companies: Amazon, Alibaba, and eBay. Through a comprehensive examination of their business models, technological advancements, customer engagement strategies, and market expansion efforts, where their focus was providing insights into the key factors driving success in the highly competitive e-commerce landscape (Moodley et al., 2025). For consumers, the convenience of accessing products over the Internet anytime and anywhere, often at lower prices, gives online shopping high advantages. On the other hand, merchants benefit from the ability to sell products without the need to physically stock them, which significantly reduces operational costs, inventory pressures, and many of the risks typically associated with traditional business models (Hao & Choi, 2019).

However, the landscape is shifting as new platforms such as Alibaba, ASOS, Boohoo Group and Temu enter and become popular in the industry and course disruption in the market dynamic. Major e-commerce companies like Amazon who are known for their well-built wide range consumer confidence through technological innovation, it provides secure payment gateways and robust logistics systems which help overcome consumers initial scepticism (Ahmar & Shahbaz, 2024). Amazon faces intense competition which could lead to fragmentation of the e-commerce industry and threatens its performance knowing this allows us to reflect upon the problem.

The increasing popularity of emerging e-commerce platforms such Alibaba, ASOS, Boohoo Group and Temu due to the COVID-19 pandemic has introduced notable disruptions in the global e-commerce landscape posing a growing challenge to the market dominance of established giants like Amazon (Moodley, 2025b). While Amazon has long maintained a strong brand reputation and global customer base (Ahmar & Shahbaz, 2024). Its stock price has experienced notable volatility in recent years, raising questions about the impact of new e-commerce entrants on investor sentiment and market performance.

Previous studies have explored various dimensions of the e-commerce sector, including the innovative strategies employed by major players, their operational efficiencies, and the surge in revenue during the COVID-19 pandemic (Agyeman et al., 2022; den Ouden, 2021; Hao & Choi, 2024). Other scholars examined the entrepreneurial evolution of e-commerce platforms, focusing on their adaptability and competitiveness (Simakov, 2020). However, there remains a gap in literature regarding the direct impact of emerging platforms on the stock performance of established giants. Fewer studies have investigated how consumers immigrate towards new online platforms, influenced by behavioural factors such as herding behavior, may be affecting the volatility and performance of stocks like Amazon's.

This study aims to address this gap by exploring the shift in consumer preference from dominate platforms like Amazon to new entrants like Aliababa, ASOS, Boohoo Group and Temu. It will examine how these shifts, driven by low pricing, convenience, fast shipping and aggressive discount strategies, are reflected in stock price movement, volatility and whether the Efficient Market Hypothesis still holds in these emerging e-commerce contexts. By analysing the e-commerce industry in comparison to the market, this paper seeks to understand the extent to which emerging e-commerce platforms influence the financial health and investor confidence in industry giants, with knowing this we can investigate our goals/objectives.

The primary objective of this research study is to analyse the impact of new e-commerce entrants on the stock price volatility of industry giant Amazon, and factors that lead to the shift on consumer behaviour.

To facilitate the achievement of the primary objective, the empirical portion of the study consists of the following objectives: To analyse the effect of emerging e-commerce competitors on the stock returns of Amazon using the covariance analysis. To investigate the extent to which the presence of new e-commerce competitors influences Amazon's stock price volatility. To analyse the volatility of Amazon's stock price index in relation to the market.

2. Literature Review

2.1. Theoretical Justification

The rapid growth of e-commerce has significantly transformed consumer behaviour and market dynamics, necessitating a deeper understanding of its impact on firm performance and investor responses. This study addresses the need to explore the interplay between consumer impulsivity, investor psychology, and the strategic challenges faced by e-commerce companies within an evolving competitive landscape. The literature review begins by examining foundational theories such as the Efficient Market Hypothesis and Behavioural Finance, and which provide theoretical justification for understanding market efficiency and investor behaviour in digital markets. Following this, an empirical review highlights key findings on consumer impulse buying, social media influence, stock market reactions, and the effects of international expansion on e-commerce firms. Together, these perspectives frame the complex environment in which e-commerce firms operate and outline the basis for this study's investigation.

2.1.1. Efficient Market Hypothesis

The most well-known theory that is the backbone of financial theories is the Efficient Market Hypothesis theory (EMH) developed by Fama (1970). The Efficient Market Hypothesis (EMH) theory states that financial markets, especially stock markets, are efficient and that prices reflect all available information. Fama (1970) argues prices adjust rapidly to the arrival of new information either public or private information, and that it is impossible to "beat the market" and achieve above average returns in the market. The EMH theory is divided into three forms, the Weak form, Semi-Strong form and the Strong for each based on the type of information reflected in prices. The weak form asserts that prices reflect all information historical prices and volume information, and that the use of technical analysis strategies cannot be used to yield abnormal returns. The Semi-strong form claims that current stock prices reflect not only historical information but all publicly available information about the companies' securities. Lastly the Strong from suggests that stock price reflects all available information both public and private known by any market participant about the company.

The Efficient Market Hypothesis further points out that new information regarding securities enter the market randomly an independently through the "Random Walk theory", and that investors respond quickly and rationally to the arrival of this new information leading to unbiased price adjustment. The EMH assumes that investors act rationally and that they make decisions of investing based on available information, and that investors possesses/share homogenous expectation leading to the same valuation and actions. The Efficient Market Hypothesis proposes that the arrival and popularity of new e-commerce establishments/companies is quickly and accurately reflected in the Amazon's stock price. All publicly available information regarding the competitors of Amazon, including earnings reports, market trends, news about new entrants or innovations, and regulatory developments, is immediately reflected in stock prices.

Thus, fundamental and technical analysis cannot consistently generate excess returns. According to the EMH the stock price movement of Amazon is a fair representation of the collective knowledge of investors and the ever-evolving e-commerce landscape including risk and growth prospects. Additionally the EMH suggests that investors act rationally and independently but in reality we know that investors are irrational beings and that investor behaviour is driven by cognitive biases, emotions and social influence especially during periods of market disruption (Mehwish &Tariq, 2015).The Efficient Market Hypothesis provides foundation for market and investors reactions to new information such as the launch and growth of competing e-commerce companies. EMH also assists in assessing market efficiency in e-commerce sector.

The EMH theory has faced substantial criticism over the past decades theoretically and empirically, leading to the emergence of other theories such as Behavioural finance that explain the behaviour of investors and factors that influence them such as overreactions, biases and herding mentality.

2.1.2. Behavioural Finance

Behavioural finance theories emerged at the start of the 21st century as an alternative framework for understanding the financial market through the lens of psychology and sociology. Unlike traditional economics financial theories that assume rationality among investors, behavioural finance acknowledges that irrationality, cognitive biases and emotion reaction frequently drive market and investor behaviour (Mehwish & Tariq, 2025). Behavioural finance is composed of key areas and theories which can be used to explain cognitive biases and heuristics, these include but are not limited to herding behaviour and impulse behaviour.

2.1.2.1. Herding Behaviour

Herding Behaviour, a critical concept in behavioural finance, was extensively developed and formalised by scholars such as Banerjee (1992), Bikhchandani et al. (1992), Shiller (2000), Lee et al. (2015) and Zhang et al. (2018). Herding Behaviour theory contests that individuals tend to mimic the actions of a larger group or follow the majority even when such behaviour may not be justified by personal analysis (Ding & Li, 2018). Herd bias is triggered by psychological tendencies such as the desire to conform, fear of missing out (FOMO), or believing that others may have superior knowledge. Herding behaviour among investors can be driven by irrational motives, which can lead to market stress by pushing asset prices away from their fundamental value, creating asset bubbles and driving up market volatility (Blasco et al., 2012).

The theory states that when investors are faced with ambiguous or incomplete information, they may rationally infer that the crowd is better informed, leading them to disregard their own information and join the majority. Herding is an obvious intent by investors to ignore their personal analysis and copy the actions of our investors, leading them to trade the same securities in the same direction. Unlike traditional finance theories which assume investors are rational and markets are efficient, the herding theory suggests that collective psychological biases can result in systemic, predictable deviations from market efficiency (Moodley, 2025a). Herding behaviour explains how investors might react to new and popular e-commerce platforms and collectively act the same challenging the dominance of Amazon. Investors may perceive consumer migration towards these new platforms like Alibaba, Temu, ASOS as signal of declining competitiveness of Amazon even before fundamentals fully reflect the shift. Investors might also herd towards these other platforms simply because of the influence of other investors and the increasing traffic of attention that they receive. Instead of individually assessing each new company's competitive threat, investors may follow prevailing market sentiment or the actions of institutional investors, amplifying Amazon's stock price movements beyond what traditional fundamental analysis would predict.

While EMH posits that stock prices fully reflect all available information and investors are rational, herding behaviour highlights how psychological and social factors can cause systematic deviations from this rationality and market efficiency. Consumers can also be influenced by other consumers, leading them to engage more with these new companies neglecting establishes like Amazon because the products are offered elsewhere at a much lower cost.

2.2. Empirical Literature

The recent evolution of e-commerce has dramatically accelerated spontaneous and emotionally driven purchases, which often bypass deliberate and rational decision-making processes. In the context of e-commerce, such impulsive behaviour is further amplified by factors like website design, ease of access, and digital marketing cues especially social media (Lashari, 2025). Building on this, Verhagen and Dolen (2011) extended on this conceptualisation by applying Cognitive Emotion Theory (CET) to online settings, illustrating how online store features such as merchandise attractiveness, website enjoyment, and communication style help shape consumer emotions and trigger unplanned, impulsive purchases. Their empirical findings confirmed that these online store beliefs mediate through emotional responses like excitement or inspiration, ultimately leading to impulse buying. This is particularly relevant for hedonic products such as fashion and beauty items, where emotional engagement is high (Corbishley et al., 2022).

In a similar study Corbishley et al. (2022) investigates whether consumer personal involvement with the COVID-19 pandemic led to hedonic or utilitarian buying motives, and how these buying motives might have encouraged impulse or planned buying behaviour in a developed country (Germany) and developing country (South Africa). The authors found that respondents with high levels of involvement with COVID-19 also show high levels of hedonic motivation, whereas utilitarian motivation appeared less important and not linked to a greater involvement with COVID-19.Futhermore the study found that high levels of hedonic motivation is associated with impulsive buying and that there is no significance difference between the buying behaviour of consumers in a developing country and a developed country.

While the consumer side of impulse buying is well documented, its spillover effects on financial markets lacks attention. Increases in the popularity of other e-commerce companies might lead to observable shifts in investor sentiment and behaviour (Kumar, 2024). Scholars like Singh (2025) examine the role of social media sentiment as a predictor for stock returns by employing the ARIMA, GARCH and machine learning algorithms including LSTM and XGBoost to analyse the correlation between sentiment and stock returns. Findings reveal that social media sentiment significantly correlates with stock market returns beyond traditional financial indicators argue that investors are not immune to psychological biases and that they can be influenced by consumer sentiment and media narratives. For example, during periods of high consumer spending or viral sales events, like black Friday consumer irrational behaviour may be triggered which leads investors to overvalue e-commerce firms and increase speculative trading in associated stocks in the short-term (Ganesh, 2022). This relationship between consumer impulses and investor psychology becomes very significant, especially when analysing stock performance of dominant players like Amazon. Investor expectations often reflect perceived consumer behaviour. When platforms adopt new marketing strategies such as flash sales that encourage impulsive buying, investor confidence might increase possibly driving share prices above their fundamental values. This indicates that consumer impulsivity and investor sentiment support one another leading to short-term volatility in the stock market.

Extending beyond individual buyer or investor psychology, recent work has focused attention on group driven dynamics such as herding behaviour, especially in markets driven by news about consumer trends and disruptive marketing techniques. Kenneth et al. (2023) differentiates genuine herding active imitation from false herding resulting from related public information, determining that false herding is more common among worldwide investors. This is particularly prominent in e-commerce, where information, memes, or influencer promotions trigger joint investor response. Singh (2025) further argues that the speed and contagion of social media trends (think Temu, Shein, Alibaba) enable viral marketing to induce herding, amplifying both consumer excitement and investor momentum. This can lead to a surge in related stocks or a shift away from established players like Amazon without fundamental justification. Such sentiment-driven shifts are amplified by social media platforms, where rapid dissemination of opinions and shopping trends fuels speculative behaviour (Singh, 2025). Furthermore, Yoon and Oh (2022), examining the Korean stock market, reveal that retail investors' herding is significantly influenced by abnormal information creation activity (AICA) on social media, whereas institutional and foreign investors approach this information distinctly, often reducing their herding tendencies. Notably, negative bullish sentiment increases herding across all investor classes, while the rise of retail participation post-COVID-19 further intensifies these patterns in e-commerce stocks, potentially pushing investor flows away from established giants like Amazon.

E-commerce rapid growth has been driven by its implementation or engagement in cross-border sales programs, which have allowed not only foreign individuals to access their products but also foreign companies (Zahra et al., 2000).When people travel for either business, work, school, or even leisure, they are introduced to various cross-border goods and brands that are locally unavailable or expensive in their domestic areas, encouraging them to use transboundary e-commerce to purchase those goods (Agyeman et al., 2022). Acheampong (2022) adds that nations capitalizing on e-commerce see outsized gains in the global digital economy, whereas those that fall behind risk being sidelined.

Furthermore, researchers like Barua et al. (2001) examine the factors that drive e-business excellence and find that achieving excellence in e-business operations leads to improved financial performance. This research addresses the question of which operational factors drive firms to achieve excellence in e-business and generate financial returns. The results indicate that firms with a high score on operational measures of e-business achieve higher revenue, gross profit, return on assets and return on investment. The impact of competitive entry and international expansion on stock markets are curial to understand as they might affect the dynamics of e-commerce firms like Amazon. Competitive entry interjects new market pressures that can affect incumbent firms' market share, pricing power, and ultimately stock price volatility. Zhu and Kraemer (2005) established that the business value of e-commerce is contingent upon both technological readiness and local market structures, which moderate the competitive pressures experienced by e-commerce companies.

Expanding to international markets allows e-commerce firms to diversify their revenue streams (Ouden, 2021). However, it also brings uncertainty that may increase short-term stock volatility due to perceived risks and challenges in adaptation. Simakov (2020) highlights how the role of e-commerce platforms is breaking down international trade barriers, allowing firms to reach broader markets effectively but it requires strategic adaptation. This internationalization influences stock market responses not only through profit potential but also by changing investor expectations regarding firm resilience and growth in the context of global competition. Simakov (2020) discovers that venturing into global markets can promote diversification yet brings adaptation difficulties and investor uncertainty, frequently increasing short-term stock volatility. Modern examples such as Shein's disruptiveness affecting firms like ASOS, or Temu influencing Alibaba's and Amazon's investor sentiment underscore both the short-term overreaction and the longer-term need for innovation among incumbents.

In support of this, Agyeman et al. (2021) utilized a case study approach to analyse firms like Amazon, JD.com, Alibaba, and Sunning.com, emphasizing their revenue growth during the COVID-19 pandemic and the rising adoption of offline-to-online business models. Their research indicated a significant movement of trading towards digital platforms, forecasting that e-commerce would represent 22% of total global transactions by 2023, with a projected 95% prevalence by 2040. Complementing this, Wanghao Li (2024) examined the effects of the COVID-19 pandemic on Alibaba's stock price, assessing changes in its market behaviour during and following the outbreak through ARIMA models. These studies together demonstrate how e-commerce expansion is driven by the pandemic and changes in consumer behaviour intensify competitive dynamics and influence changing stock market reactions in the industry.

2.3. Research Gap

It is evident from the theoretical underpinnings reviewed that while the Efficient Market Hypothesis (EMH) assumes that stock prices, including those of dominant firms like Amazon, fully and rationally reflect all available information, this view has been substantially challenged by Behavioural Finance. Behavioural Finance emphasizes the role of investor irrationality, cognitive biases, emotions, and herding behaviour, especially during periods of market disruption and intense competition. These behavioural factors are particularly relevant in the rapidly evolving e-commerce sector, where consumer impulses and investor sentiment can drive stock price volatility beyond what traditional financial models might predict.

Empirically, the literature has largely focused on developed markets, with limited research exploring the dynamics within emerging e-commerce environments and their effects on incumbent firms such as Amazon. A significant research gap exists regarding how the entry and growing popularity of new e-commerce platforms impact Amazon's market dominance and stock price performance. This gap includes understanding the role of investor sentiment and herding behaviour towards these new entrants, which may influence perceptual shifts and valuation changes in platform markets. This study seeks to fill this gap by analysing how emerging e-commerce competitors affect Amazon's stock price through the lens of Behavioural Finance and investor sentiment. By doing so, it contributes to a better understanding of how market competition shapes firm valuations and investor perceptions in digital platform markets. The insights gained can help investors make more informed decisions by recognizing how behavioural responses to competitive dynamics influence stock performance in the e-commerce sector.

3. Methodology

3.1. Design, Data Collection and Sample Description

The main aim of the study was to analyse the effect of emerging and evolving e-commerce competitors on Amazon's stock price returns and the extent to which these competitors' presence influences Amazon's stock price volatility. By doing so, the study adopted a quantitative research design, with a sample period consisting of daily data from the period July 2018 to December 2024. The sample period accounts for historical financial markets events such as the 2019-2022 COVID-19 pandemic. The selection of the data frequency and sample period was dictated by the availability of data, specifically the one independent variable, Temu's returns. The choice of the sample period and data frequency followed that of previous literature, Li (2024) and Singh et al. (2024). The dependent variable is Amazon's stock price returns, and the independent variable consist of Amazon's competitors which are eBay Inc, Etsy Inc, and Temu. The data were collected from the IRESS database and EViews was the preferred econometric analysis program.

The selection on the dependent variable and independent variables was motivated by the objective of the study to analyse the impact of other e-commerce on the performance of Amazon's. Table 1 shows each of the included variables and a description of each and the database from which they were sourced. In addition to the above-mentioned variables, as by table 1, two control variables were included. The inflation rate is the rate at which the average level of prices for goods and services increase, resulting a decline in the purchasing power (Vipond, 2021). The inflation rate is selected to control for the macroeconomic effect of changing price level, which can impact Amazon's stock returns independently and its competitor's performance (Chiang & Chen, 2023). This ensures that the estimated impact of competitors on Amazon's returns is not biased by inflation-driven market fluctuations. Another control variable includes Money supply (M2), there are several categories in which money supply is separated including M1, M2 and M3 (Mofokeng & Moodley, 2025). However, a wide money supply M2 is used as a control variable because it reflects total amount of money available in the economy, which influences interest rates, inflation, and overall economic activity (Vo & Mai, 2023). By controlling for M2, the study accounts for the macroeconomic liquidity conditions that can affect investment decisions and stock returns. Nasdaq100 index is employed as the market proxy to compare and analyze Amazon's stock returns volatility. Since Amazon is one of the largest and most influential technology companies globally, it is a key constituent of the Nasdaq 100, which comprises the 100 largest non-financial companies listed on the Nasdaq Stock Market. This index effectively represents the overall performance and volatility of the leading technology sector companies.

There is no widely accepted, dedicated market proxy specifically for e-commerce companies. Therefore, the Nasdaq 100 serves as the best available proxy due to its broad coverage of the tech sector, which includes major internet and e-commerce firms alongside Amazon. Using the Nasdaq 100 as a market benchmark allows for meaningful comparison of Amazon's stock volatility relative to the broader market context in which it operates. The dependent and independent data was obtained from IRESS and Sant Louis Federal Reserve. Table 1 provides a summary of the variables used in the study.

Table 1. Summary of Variables

Variables	Description	Database
AMZN	Amazon's stock returns, which was founded in 1994 in the United States and is listed by NASDAQ.AMZN is the dependent variable.	IRESS
TEMU	PDD Holdings stock price returns which, is a parent company of TEMU since TEMU on its own is not listed. PDD is also listed by NASDAQ.	IRESS
EBAY	Ebay Inc stock price returns	IRESS
ETSY	Etsy Inc stock price returns	IRESS
M2	Money supply (M2) control variable 1.	Sant Louis Federal Reserve
INF	Inflation rate of the United States which is measured using the Consumer Price Index (CPI). control variable 2.	Sant Louis Federal Reserve
Nas100	It is the market proxy for e-commerce market.	IRESS

Authors' own construction (2025)

3.2. Model Specification

The study will conduct a covariance analysis, to measure how the returns of Amazon and its competitors move together over time. By examining covariance, the study can capture the direction and strength of the relationship between Amazon's returns and those of its rivals, offering insight into whether competitors' stock returns are positively or negatively associated with Amazon's.

A Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is used to assess the volatility of Amazon's stock return in response to the rise and the popularity of emerging e-commerce companies. The GARCH model is widely used in the finance to analyse the time-vary volatility by identifying patterns in periods of high and low volatility which reflects the nature of market behaviour (Asteriou & Hall, 2021).

The mean equation for all GARCH type models used in this study remains consistent and is specified as follows:

$$\sigma_t^2 = w + B_i \sigma_t^2 + a_i \varepsilon_{t-1} \qquad (1)$$

Where σ_t^2 is the conditional variance (volatility) of the return at time t. w is the constant term that represents the long-term average variance level. B_i represents the GRACH coefficient, that measures the effect of the past term variance on current variance. a_i is the arch effect while ε_t indicates the past squared residuals.

The study further explores the Exponential GARCH(EGARCH) and GJR GARCH to test for asymmetric volatility effects. The EGARCH allows us to determine whether the effect of the volatility shock is asymmetrical, which means that negative and positive shock have different effect on volatility (Nelson, 1991). The variance equation for EGARCH model allows for the exponential effect which enables the model to capture asymmetries without imposing non-negativity on parameters.

$$ln(\sigma_t^2) = w + a_i \left(\frac{\lfloor \varepsilon_{t-1} \rfloor}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right) + \gamma i \, \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + B_i \ln\left(\, \sigma_{t-1}^2\right) \qquad (2)$$

Where, γi captures the asymmetric effect (leverage effect). If $\gamma i < 0$, negative shocks increase volatility more than positive ones. The ln form ensures that $\sigma_t^2 > 0$ automatically (no non-negativity constraints).

Lastly the study estimates the GJR GARCH model that accounts for the leverage effect by introducing the dummy variable to differentiate between the effect of positive and negative shocks with the aim to measure whether bad news has a disproportional impact of volatility (Glosten et al., 1993).The model will be used to examine the rapid market expansion, whether it will result in heightened volatility doe Amazon's stock compared to positive development.

$$\sigma_t^2 = w + a_i\epsilon_{t-1}^2 + \gamma i\, I_{t-1}\epsilon_{t-1}^2 + B_i\, \sigma_{t-1}^2 \quad (3)$$

Where, I_{t-1} = 1if $\epsilon_{t-1}^2 < 0$ (bad news), and 0 otherwise. γi measures the asymmetry — the additional impact of negative shocks and $\gamma i > 0$, negative shocks have a stronger effect on volatility (leverage effect).

4. Empirical Results

4.1. Preliminary Tests

4.1.1. Graphical Representation

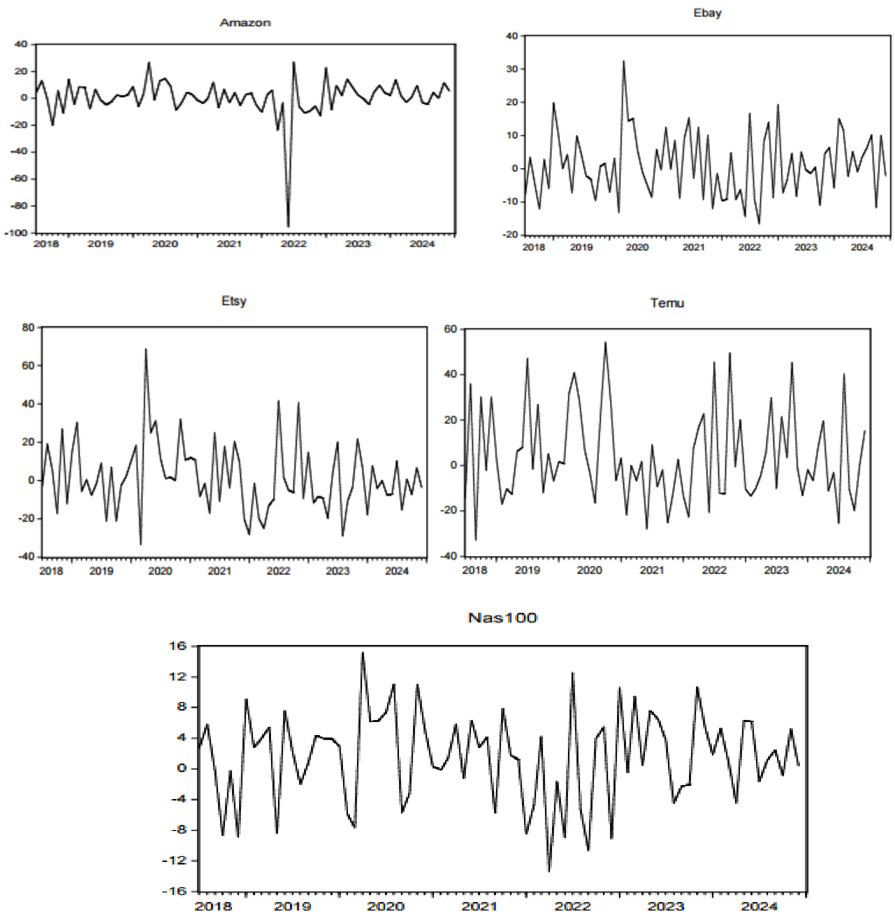

Figure 1. Returns of e-commerce companies and the market proxy

Source: The authors' own estimation (2025)

Figure 1 presents the graphical representation of Amazon and its chosen competitors and Nasdaq 100 which serves as the market proxy for amazon since there is no widely used market proxy for tech companies. The graphs show evidence that the returns of these e-commerce companies' variance are not constant overtime in fact it shows an autoregressive pattern, thus resulting in volatility clustering for all the companies. The visual graphs demonstrate that certain periods appear to be more volatile than others, hence the volatility of returns during these periods. The significant events that coincide with the volatile periods is the COVID-19 pandemic in 2020. The visual graphs also confirm the stationarity of the variables. Temu is the most volatile company which the highest change in return of 54% and the lowest change of 33%.

4.1.2. Descriptive Statistics

Table 2 provides the descriptive statistics, unit root test, and the ARCH tests for the various e-commerce companies, market proxy and macroeconomic variables. In part A, Amazon's mean return is lower than that of some competitors eBay, Etsy, and significantly lower than that of Temu, reflecting the competitive pressures in the e-commerce market. This suggests that emerging e-commerce companies, and other platforms are gaining popularity and capturing growth opportunities, consequently impacting Amazon's returns. The findings are supported by Ologunebi (2024) who emphasized how shifts in consumer behaviour and competitive dynamics in e-commerce influence firm performance and sales outcome.

Amazon's minimum return is notably extreme, and the high kurtosis indicate exposure to downside risk and sharp negative shocks, which can be linked to industry disruptions, regulatory changes, and competitive threats from agile newcomers offering differentiated pricing and product strategies (such as Temu's aggressive pricing). The negative skewness of Amazon suggests that investors are more likely to face substantial negative returns rather than positive spikes. This reflects market sensitivity to adverse competitive events or operational challenges. Similar market behavior is detailed by Berman (2020), who studied e-commerce platforms' performance and found volatility and downside risk driven by market sentiment and rapid changes in consumer preferences.

Table 2. Descriptive statistics, unit root test, and the ARCH tests result

Part A: Descriptive Statistics							
	AMAZON	**EBAY**	**ETSY**	**TEMU**	**INF**	**M2**	**NAS100**
Mean	0.507408	1.208461	1.848552	4.051636	0.315063	0.548184	1.591980
Median	1.648491	0.696518	-0.069381	0.715368	0.310989	0.364918	2.295343
Maximum	27.05960	32.50166	68.75650	54.26762	1.373608	6.327452	15.19178
Minimum	-95.58230	-16.58736	-33.50631	-32.86421	-0.668694	-1.455309	-13.36854
Std. Dev.	11.15520	7.508250	14.38013	16.37111	0.338529	1.005743	4.756247
Skewness	-3.670757	0.591943	0.773266	0.672120	0.335888	3.150616	-0.373916
Kurtosis	26.91832	3.663058	4.519846	2.861735	3.472249	16.09479	2.822454
Jarque-Bera	61189.94	179.9806	459.5906	178.5010	65.91313	20642.75	57.74832
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1190.378	2835.049	4336.703	9505.137	739.1372	1286.040	3734.785
Sum Sq.	292412.2	135622.6	492935.0	667002.1	501.6156	3077.001	58994.03
Sum Sq. Dev.	291808.2	132196.6	484918.4	628490.7	268.7410	2372.013	53048.33
Observations	2346	2346	2346	2346	2346	2346	2346
Part B: Unit root and stationarity tests							
ADF	-9.528378 ***	-9.426075 ***	-8.971669 ***	-8.985077 ***	-6.085688 ***	-5.124413 ***	-9.429321 ***
PP	-5.428590 ***	-5.519059 ***	-5.232888 ***	-5.341379 ***	-3.761984 ***	-2.975304 ***	-5.566577 ***
Order of integration	I (0)	I (0)	I (0)	I (0)	I (0)	I (0)	I (0)
Part C: Variance Inflation Factor							
VIF		2.268	2.029	1.125361	1.277453	1.416334	1.997071
Part D: Heteroskedasticity ARCH test							
ARCH LM	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***

*Notes: 1 *** indicate a statistical significance level of 1%, and 5%*

Source: Authors' own estimation (2025)

In contrast, Temu's mean return is the highest among the e-commerce platforms in your dataset, significantly above Amazon, eBay, and Etsy. This suggests that Temu has been experiencing strong positive stock price performance, likely driven by investor optimism about its rapid growth and market penetration in the highly competitive e-commerce sector. This aligns with market analyses noting Temu's aggressive pricing and expansion strategies as key drivers for its valuation gains in the market. The standard deviation for Temu is also the highest among all e-commerce companies listed, indicating that while Temu has strong growth potential reflected in its higher mean return, it also experiences high volatility and risk. This elevated volatility can be explained by Temu being a newer entrant, exposed to uncertainties such as market acceptance, operational scaling, regulatory changes, and competitive reactions from established players like Amazon.

Part B of Table 2 presents the unit root and stationarity tests. The for the ADF test, the t-statistics value is more negative than the associated critical values and all the variables are significant at the 1% significance level. The null hypothesis that the variables contain unit root is rejected, concluding that the variables are stationary (accepting the alternative hypothesis). The findings are further supported by the PP test statistics, as the study rejects the null hypothesis that the variables contain unit roots at all significant levels. The t-statistics of the PP test are also more negative than the associated critical values. The findings for the ADF and PP tests suggest that the variables are integrated at order 0.

Having found the variables to be stationary, the next step entails determining if the variables have ARCH effects. This condition must be met to estimate the GARCH models. Part C in Table 2 provides the ARCH LM test. The null hypothesis that the variables don't contain ARCH effects (the variables are homoscedastic) is rejected at a 1% significance level. Given these test results, the study will use GARCH models to estimate the extent to which the presence of new e-commerce competitors influences Amazon's stock price volatility and the volatility of Amazon's stock price index in relation to the market.

4.2. Empirical Model Results

4.2.1. Univariate GARCH Model Selection

Table 3 provides Amazon's univariate GARCH model specification and the market's univariate GARCH model specification. This study uses Schwarz's information criteria (SIC) to determine the best-fitted model for the univariate specification as the number of observations exceed 130. Moreover, this study considers the normal, Student's T, and generalized error distribution (GED) estimation techniques. For the influence of other e-commerce companies on Amazon the suggest GARCH model is the GARCH (1,1) model for the univariate model specification. For Amazon's volatility in relation the market, the suggested model is also the GARCH (1,1) model.

Table 3. Univariate GARCH model specification

GARCH				**GJR GARCH**			**EGARCH**		
	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED
Amazon	-0.8485	**-1.3452**	-1.0509	-0.8016	-1.0808	-0.9861	-0.7636	-1.1156	0.9594

Nas100	-1.4213	**-1.7169**	-1.4504	-1.4333	-1.21444	-1.3893	-1.2247	-1.4617	-1.3152

Note: Table indicates the superior model specifications based on SIC. 2

Source: Authors' own estimation (2025)

4.2.2. Univariate GARCH Model Results

Table 4 shows the univariate GARCH estimation based on the model specification. The mean equation is provided in Panel A, and the variance equation is presented in Panel B. In the mean equation the intercept (μ) provides the average return of Amazon when the returns of Amazon's competitors are zero. The returns Φ and ʒ are positive and significant, indicating that positive movements in these returns are associated with positive changes in Amazon's returns. The Ᵽ is also significant however, it is negative suggesting an inverse relationship between Temu's returns and Amazon's returns. These findings further confirms that analysis made from the descriptive stats that Temu returns may come at Amazon's expense, consistent with the competitive threat Temu poses as a disruptive e-commerce entrant.

α and β represent the AR and MA term respectively, both terms are positive and highly significant indicating that past values and errors influence current returns of Amazon however In Panel B, the variance equation intercept (ϕ) is greater than one but is insignificant, this implies that the volatility on Amazons returns are not explained by the interpret but by past shocks (ARCH term) and past variance (GARCH term).

Table 4 also presents the variance equations the univariate GARCH model that explains the volatility of Amazon's returns in relation to the market, where Amazon's returns are regressed against the market proxy (Nasdaq 100), and vice versa where Nasdaq 100 returns are regressed against Amazon. These models were estimated to compare which series exhibits greater volatility and to study how volatility patterns differ between the individual firm and the broader market. Both Amazon and Nasdaq 100 show high ARCH coefficient, indicating strong immediate shock impact on volatility. The GARCH term for Nasdaq is much higher and significant, indicating that past volatility plays a more persistent role in market volatility compared to Amazon. The high GARCH term shows that Nasdaq's volatility appears more persistent which means that the market volatility clustering is strongly influenced by past volatility. While Amazon's volatility is more influenced by immediate shocks but less by the persistence of past volatility. Thus, Amazon is more reactive.

Table 4. GARCH Results

	Amazon (Amazon	Nasdaq 100 (Market Proxy)	Amazon vs Nasdaq 100
Model	**GARCH**	**GARCH**	**GARCH**
Panel A: Mean Equation			
μ - Intercept	0.434118***	3.818878***	-
Φ – ebay	0.359727***	-	-
ʒ - etsy	0.071564***	-	-
Ᵽ – temu	-0.015465***	-	-
α – ar (1)	0.996678***	0.989136***	-
β – ma (1)	0.642459***	0.687268***	-
Panel B: Variance Equation			
ϕ – intercept	6.46E-11#	1.03E-10#	0.034539***
w - ARCH(-1)	0.815204***	0.997774***	0.988536***
Ʊ - GARCH(-1)	0.357067***	0.322573***	0.032419#
Panel C: Diagnostic test			
ARCH-LM	0.9832	-	-

*Note: 1*** indicates a statistical significance level of 1%*

Source: Authors' own estimation (2025)

4.2.3. Correlation Analysis

Table 5 presents the Covariance matrix which shows the correlation coefficients between Amazon and its competitors eBay, Etsy and Temu. eBay and Etsy have a positive and statistically significant correlation with Amazon which means that their stock return tend to move in the same direction, while the correlation between Amazon and Temu is negative, suggesting a weak or insignificant relationship between them. The negative correlation between Amazon and the control variable inflation posits that as inflation raises Amazon's return tend to decrease, controlling for macroeconomic factors. The positive correlation means that when the competitors returns (eBay and Etsy) increase, Amazon's tend to increase as well. Suggesting that market-wide factors and investor sentiments in the e-commerce sector affecting all players similarly. This essentially means that the positive correlations between Amazon and some of its competitors is because of they both get affected by economic conditions similarly and that the competitor's growth does not directly harm Amazon's returns.

While the weak correlation between Temu and Amazon may simply mean that because Temu is a relatively new platforms that it just emerged, its influence on the border-ecommerce market particularly Amazon may not yet be fully reflected in its stock price and return pattern. Furthermore, Temu might be targeting different consumer segments, or employing a business model that does not overlap with Amazon's operations. Therefore, because they respond to somewhat different consumer bases, market factors their stock returns may not move closely together.

Table 5. Covariance Matrix

Correlation						
Probability	**AMAZON**	**EBAY**	**ETSY**	**INF**	**M2**	**TEMU**
AMAZON	1.000000					

EBAY	0.451543	1.000000				
	0.0000	-----				
ETSY	0.328350	0.644708	1.000000			
	0.0000	0.0000	-----			
INF	-0.212471	-0.182694	-0.020953	1.000000		
	0.0000	0.0000	0.3104	-----		
M2	0.252808	0.386138	0.398043	-0.282971	1.000000	
	0.0000	0.0000	0.0000	0.0000	-----	
TEMU	0.018311	0.101550	0.115258	-0.128893	0.278138	1.000000
	0.3754	0.0000	0.0000	0.0000	0.0000	-----

Source: Authors' own estimations (2025)

4.3. Discussion of Results

This study's results reveal distinct in how Amazon's returns react to emerging competition and broader market dynamics, providing key insights for both investors and industry participants. The findings from the descriptive statistics and correlation analysis indicate that Amazon's mean return is lower than some of its major competitors, notably Temu, which has demonstrated the highest mean return and the most pronounced volatility among all e-commerce platforms. This suggests that newer and more aggressive competitors are capturing growth opportunities and reshaping the competitive landscape. These results align with earlier research by Mutlu and Bish, 2018 that indicated that newer and more aggressive online players have managed to capture significant market share by offering innovative solutions and responding swiftly to changing consumer preferences. The positive correlation between Amazon, eBay, and Etsy indicates that these firms are often influenced similarly by market and industry-wide forces, reflecting a sector where investor sentiment and macroeconomic trends drive collective performance.

In contrast, the weak and insignificant correlation between Amazon and Temu implies that Temu's impact is not yet fully integrated into Amazon's return dynamics. This could be due to Temu's recent entry into the market, differences in business models, or consumer segmentation, resulting in limited simultaneous movement between the two. Empirical results from the GARCH model demonstrate that Amazon's return volatility is highly sensitive to recent shocks, while the Nasdaq 100 market proxy exhibits greater volatility persistence, indicating sustained patterns of volatility clustering in the broader market. Yadav (2018), empirical findings also found that Amazon squared daily returns display volatility clustering where high volatility tends to be followed by high volatility and low volatility by low volatility. Amazon is more reactive meaning it responds quickly and sharply to new information or shocks, such as competitive disruption or regulatory events, whereas the market's volatility endures over longer periods as a result of prevailing macroeconomic conditions. This distinction underlines Amazon's heightened exposure to firm-specific risk drivers, especially those stemming from competition, compared to the broader market.

Collectively, these results illustrate that Amazon operates in an environment where sector-wide conditions and new entrant pressures can meaningfully affect stock returns and risk. The company's relatively lower mean return, greater exposure to downside shocks (high negative skewness and kurtosis), and more pronounced volatility response to immediate events highlight the challenges of maintaining dominance amidst intensifying competition and shifting consumer behaviour. For investors, this underscores the importance of monitoring emerging competitors and recognizing the potential for increased return variability and risk in Amazon's stock, compared to a more persistent market volatility backdrop.

The study's findings suggest that established e-commerce leaders like Amazon are now contending with a new era of heightened risk and competitive flux, driven by innovative entrants such as Temu. The findings align with Olugubeni et al. (2025) research that Temu's aggressive promotional strategies and focus on appeal especially for cost-conscious and young shoppers' contrasts Amazon's brand trust and extensive product offering. This dynamic compels both investors and corporate strategists to adjust their risk assessments and growth expectations.

5. Conclusion

This study sets out to analyse how emerging e-commerce competitors such as Temu, eBay, and Etsy influenced Amazon's stock returns and volatility between 2018 and 2024. Using covariance and GARCH-type models, the research found that Amazon's returns were significantly affected by market shocks and competitive pressures, revealing a strong presence of volatility clustering and asymmetric effects. The findings indicated that while eBay and Etsy moved in conjunction with Amazon, Temu's returns displayed an inverse relationship, suggesting that its rapid market expansion occurred partly at Amazon's expense. These outcomes validated the study's objective by demonstrating that intensified competition from new entrants altered investor sentiment and short-term stock performance in the global e-commerce landscape.

The results also bridged the gap between the Efficient Market Hypothesis (EMH) and Behavioral Finance by showing that investor reactions to competitive information were not always rational. And that herding tendencies and sentiment-driven responses appeared to amplify short-term volatility, implying that psychological and informational biases shape price movements in technology-driven markets. Amazon's sensitivity to immediate shocks, contrasted with the broader market's persistence of volatility, highlighted its heightened exposure to firm-specific risks and competitive dynamics. From a practical perspective, these findings carry several implications. Investors should monitor behavioral trends and market narratives surrounding emerging platforms, as these can influence valuation and risk beyond fundamental indicators. For e-commerce firms, the results emphasized the necessity of innovation, differentiation, and adaptive pricing strategies to maintain market share in a rapidly evolving industry.

Despite its contributions, the study was limited to a selected sample of competitors and a single geographic context, excluding other relevant factors such as exchange-rate dynamics and global political risks. Future research could expand the analysis by incorporating additional e-commerce firms, investor sentiment indices, or cross-country comparisons to deepen understanding of how competition and investor psychology interact in digital platform markets. Overall, the study demonstrated that emerging e-commerce platforms have materially reshaped the risk profile and stock performance of dominant players like Amazon, reinforcing the view that behavioural forces and competitive innovation jointly determine firm valuation in the modern digital economy.

Data Availability Statement

The data is available on reasonable request from the corresponding author.

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