The Dynamic Interaction Between Geopolitical Risk and Herd Behavior: Evidence From The Dow Jones Industrial Average

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Summary: This paper investigates the dynamic influence of global geopolitical risks on herd behavior among stock market investors. The analysis includes 30 companies listed on the Dow Jones Industrial Average (DJI) index from January 2010 to March 2024. To establish the presence of herd behavior, the cross-sectional absolute deviation (CSAD) model was employed. Subsequently, the conditional dynamic correlation between geopolitical risks and herd behavior was examined using the BEKK-GARCH and DCC-GARCH models. The results provide strong evidence of herding bias among investors in the DJI index over the study period. Furthermore, the findings reveal a dynamic conditional relationship between geopolitical risks and herd behavior, with prior geopolitical risk shocks having a positive effect on market herding behavior. Finally, given the evidence that herding behavior, as a form of behavioral distortion, can drive security prices away from equilibrium values supported by fundamentals and cause price bubbles, our findings have important implications for policymakers and investors to mitigate herding effects and misvaluations.

Keywords: Geopolitical Risk; Herding Behavior; CSAD; DCC-GARCH Model.
Jel Classification Codes : F51; G41; C58; C32

I- Introduction :

Investor behavior has been a focal point of interest for researchers and practitioners in the fields of economics and finance when analyzing price movements in financial markets. The aim is to understand the factors that lead to fluctuations and distortions in the prices of financial assets. This interest also extends to explaining phenomena associated with noise trading, recurrent financial crises, and bubble bursts. Experts in behavioral finance argue that investors' decisions are not always rational, as they are influenced by various behavioral biases. Among the most prominent of these biases is herd behavior (De Bondt, Muradoglu, Shefrin, & Staikouras, 2008), which is one of the most common biases in financial markets due to its significant impact on asset pricing, market efficiency, portfolio diversification, as well as financial stability and economic crises in general (Dang & Lin, 2016).

Herd behavior in investors refers to the tendency of investors, whether intentionally or unintentionally, to mimic the actions of a large group of investors in the market when making decisions. Individuals believe that by doing so, they can reduce the risks associated with their personal decisions by disregarding their own private information and opting for the same decisions made by the majority (Bikhchandani & Sharma, 2001). This behavior may be driven by a range of behavioral factors, such as optimism and pessimism, or the fear of loss and the desire to avoid the associated emotional pain. Alternatively, it could simply be a result of emotional contagion.

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Moreover, this behavior is influenced by various factors such as market conditions, economic shocks, and geopolitical issues (Bougatef & Nejah, 2024). These factors contribute to reinforcing this behavioral pattern, which can have wide-ranging effects on the performance of financial markets, including the formation of price bubbles or the acceleration of financial crashes. Therefore, understanding this behavior is essential for analyzing long-term financial stability and addressing the sharp fluctuations experienced by financial markets.

Geopolitical conflicts are among the most prominent challenges facing countries worldwide in recent years, especially following the outbreak of the COVID-19 pandemic. These include the war between Russia and Ukraine, the border dispute between China and India, ongoing conflicts in the Middle East, and escalating trade tensions between major powers, particularly between China and the United States. Additionally, the United Kingdom's exit from the European Union and other geopolitical and economic conflicts have contributed to a rise in global political and economic uncertainty.

The Global Risks Report published by the World Economic Forum in 2021 highlighted geopolitical risks as one of the most serious threats facing the global economy, particularly in the context of financial globalization and the rapid spread of its consequences on a widescale. These risks are expected to remain a key concern in the coming years due to their impact on financial and economic stability. Additionally, major international financial institutions, such as the European Central Bank, the International Monetary Fund, and the World Bank, have increasingly prioritized the regular monitoring of geopolitical tensions due to their extensive economic implications.

Among the most prominent consequences of these geopolitical tensions are the rising oil prices and inflation rates, which directly impact the stability of financial markets and the global economy as a whole (IMF, 2023; Bank World, 2021). The effects of these geopolitical tensions are not confined to specific geographical boundaries but extend to influence various aspects of the global economy. This makes it crucial to understand and manage these risks to ensure market stability and enhance resilience in the face of future challenges.

Studies have shown that financial markets are often highly sensitive to geopolitical threats and are significantly affected by international political tensions. Numerous studies have examined the impact of these geopolitical risks on markets through the lens of returns and volatility (Caldara & Iacoviello, 2022; Salisu, Ogbonna, Lasisi, & Olaniran, 2022; Zhang, He, He, & Li, 2023). However, research that explores the impact of geopolitical risks on financial markets from the perspective of herd behavior among investors remains relatively limited. Some researchers suggest that geopolitical risks significantly influence investor behavior and sentiment, ultimately driving them to adopt herd behavior in their investment decisions (Mertzanis & Allam, 2018). When political or economic tensions escalate on the global stage, investors experience uncertainty and fear of future risks, which prompts them to imitate the actions of others in the market rather than relying on their own individual analyses. Thus, literature review refers to following hypothesis:

- *H1: The primary hypothesis of this study is that geopolitical risks influence the herding behavior of investors in the Dow Jones Index (DJI) from January 2010 to March 2024.*

Accordingly, this research aims to examine whether investors in the New York financial market exhibit herd behavior in the presence of geopolitical conflicts. The goal is to provide findings that can aid in the development of more effective hedging strategies, risk management, and portfolio management. Furthermore, the research seeks to offer insights that governments, regulatory bodies, and policymakers can leverage to address market volatility caused by geopolitical tensions.

Through this, the study aims to fill the existing gap in the current literature, given the limited research addressing the relationship between geopolitical risks and financial markets from the perspective of herd behavior among investors. Therefore, the study focuses on measuring and analyzing the dynamic impact between these two factors in the New York financial market during the period from 2010 to 2023. The goal is to provide precise analyses of how geopolitical risks influence investor behavior and offer recommendations that could enhance financial market stability and improve investment strategies in a challenging geopolitical environment.

II– Theoretical Framework:

II.1. Herd Behavior in Financial Markets:

Herd behavior has garnered significant attention from researchers and policymakers due to its prevalence as a common bias and its substantial impact on investment decision-making in global markets. Christie and Huang (1995) defined herd behavior as the tendency of investors to make decisions based not on their own rational analyses but on the actions of others (Marietza, Nurazi, & et al, 2021). This behavior is a manifestation of John Maynard Keynes's concept of "animal spirits" introduced in 1936, referring to non-rational factors and emotions that influence economic decisions. Investors often follow the crowd instead of making independent decisions. Herd behavior can be described as a psychological phenomenon within social learning processes, where investors buy or sell financial assets based on the actions of a large group of market participants over a specific period, without conducting their own analyses or assessing the intrinsic value of financial products. These investors believe they can minimize decision-related risks by following the collective decision.

Bikhchandani and Sharma (2001) classified herd behavior into two types: false herd behavior and deliberate herd behavior. False herd behavior refers to a situation where the reactions of investors in the market are similar but not coordinated in response to new fundamental information. In this case, a group of investors in the same situation makes similar decisions unintentionally. On the other hand, deliberate herd behavior involves investors intentionally mimicking the actions of a large group of investors in the market. This type often leads to excessive volatility and systemic risk at the market level. Additionally, Bikhchandani and Sharma (2001) presented three reasons that lead to herd behavior: these are informational cascades, reputation-based herding, and compensation-based herding. Informational cascades refer to investors monitoring the outcomes of previous decision-makers and replicating those actions in their own decisions, believing such an approach is beneficial for decision-making. Reputation-based herding indicates that investors tend to follow the decisions of other managers. Compensation-based herding suggests that if a manager's compensation is linked to their performance, they may manipulate information, which could mislead regarding their compensation. This highlights the contribution of herd behavior to the divergence of a stock's price from its equilibrium price.

Devenow and Welch (1996) categorized deliberate herd behavior into rational and irrational types (Wong, 2018). Rational herd behavior involves investors making similar decisions simultaneously due to concerns related to reputation or the financial performance of companies. This type of herd behavior enhances market efficiency, as investors do not lose their rationality when making investment decisions; rather, they believe that most individuals possess good analytical skills regarding information trends and therefore have intentional motives. Consequently, rational herd behavior is based on the premise that investors do not lose their rational characteristics when making investment decisions. In some cases, it is intentional because investors believe that the best approach for making sound investment decisions in securities is to follow the majority's choice, as they possess better information or analytical skills.

The second type pertains to irrational behavior related to personal instincts (Sibande, 2024), where market participants disregard their own analyses and prefer to blindly follow others in trading, even when the available information in the market is dissimilar. Investors favor this behavior because it provides them with confidence and security against psychological and social pressures in the market. Bernales et al. (2016) argue that irrational herd behavior causes significant effects; it not only leads to asset prices deviating from their true values but also increases volatility, destabilizes markets, and heightens the fragility of the financial system. Noise traders play an important role in irrational herd behavior; these are investors who base their activities on rumors and incorrect information.

Herd behavior bias in financial markets is measured using two main methods. The first method analyzes the behavior of investors who follow the actions of others in the market, with these investors being characterized as rational for following a group of other investors who have access to better information. The second method relies on aggregate price data and market activities to determine the extent to which investors align with market consensus (Mahfouz, 2021).

Lakonishok et al. (1992) proposed a simple measure known as the difference between the buy and sell sides, which is based on the idea of disproportionate buying or selling of stocks by

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specific investors within the herd in the market. Herd behavior is revealed when there is a tendency among investors in the market, particularly money managers, to buy or sell individual stocks disproportionately (Wong, 2018). This measure is calculated by the ratio of net buyers (money managers who increase their holdings in stocks during a specific quarter) to the total number of money managers trading a particular stock, adjusted by an adjustment factor. This factor decreases as the number of money managers trading the same stock increases (Mahfouz, 2021).

Many studies investigating herd behavior in financial markets have utilized the models of Christie and Huang (1995) and Chang et al. (2000), which are based on the Capital Asset Pricing Model (CAPM). Through herd behavior, investors align their rational beliefs with collective market decisions, causing stock returns to converge towards market returns. Since herd behavior diverges from the CAPM, it leads to a testable hypothesis based on the difference between stock returns and market returns (Ramadan, 2015).

Christie and Huang (1995) suggested that the best measure of market effects due to herd behavior is dispersion, which gauges the proximity of stock returns to the market return. Dispersion, when negative, increases as stock returns diverge from the market return. If investors adhere to market expectations, dispersion will be significantly lower than average. Consequently, herd behavior at the market level results in reduced return dispersion. Typically, individual stocks exhibit variability in performance and sensitivity to market reactions, leading to deviations from the overall market return. However, when investors follow market trends, individual stock returns tend to converge around the market return (El-Gayar, 2021).

II.2. The Relationship Between Geopolitical Risks and Herd Behavior:

Geopolitical risks are one of the main factors that significantly influence investment decisions, serving as a critical element in driving financial markets and determining economic growth trends. What makes these risks unique is their unpredictability, as they often arise from unforeseen events characterized by complexity and interconnectivity. High geopolitical risks are expected to lead to negative impacts on investment outcomes, including decreased returns, increased likelihood of economic disasters, and diminished growth forecasts, as well as their adverse effects on stock returns (Caldara & Iacoviello, 2022).

Geopolitical risks arise from a wide range of local and international events, including wars, military conflicts, political crises, terrorist attacks, trade disputes, cyberattacks, and unwanted foreign interventions, as well as changes in laws and regulations that can directly impact the investment environment (Blackrock Investment Institute, 2023). Geopolitical risks are a major source of uncertainty and risk in the global economy, significantly affecting financial markets. The impact of these risks can be classified into two types: short-term effects and long-term effects. In the short term, geopolitical risks lead to sharp market fluctuations, increased levels of uncertainty, higher risk premiums, and a decline in investor confidence. In the long term, they may result in changes in trade policies, disruptions in supply chains, and the emergence of new economic powers.

Researchers have given considerable attention to studying the impact of geopolitical events on stock returns and their volatility. Numerous studies have shown that these risks negatively affect stock returns and increase volatility, although this impact varies from country to country. However, the study of the effects of these risks from a behavioral perspective has not received adequate attention.

The literature indicates that the performance of the stock market is a critical factor in investors' decisions, which in turn affects their confidence. Therefore, geopolitical tensions can induce abnormal fluctuations in the markets, prompting investors to engage in herd behavior when making their investment decisions (Mertzanis & Allam, 2018). This behavior may ultimately lead to sharp market movements and significant economic disruptions.

II.3. Literature Review:

Recently, the literature analyzed the connectedness of geopolitical risks and herd behavior, but the results are inconclusive. (Chong, Liu, & Zhu, 2016) investigated the presence of herd behavior. The global financial crisis caused volatility in the Chinese stock market during the 2007-2008 period. The study employed a nonlinear model and the cross-sectional absolute deviation (CSAD) model to analyze investor behavior. The results indicated that herd behavior was evident in both bull and bear markets. The primary reason for this behavior was attributed to the short-term outlook of investors, analyst recommendations, and the risks associated with the Chinese market. Investors tended to move together, driven by fear or anxiety. Contrarily, the study by (Mertzanis & Allam, 2018) provided evidence of traditional herd behavior in the Egyptian stock market during 2011 and earlier. However, the study revealed the presence of negative herds. Behavior, which explained the limited reaction of investors during times of political crises. Nonetheless, herd behavior was not observed during periods of market rises and falls, suggesting that herd behavior may be a short-term phenomenon influenced by specific political factors.

The analysis of herd behavior in financial markets during political and economic crises highlights the significant role of geopolitical events in influencing investors' decisions. Using the ICSS algorithm, the study by (Yildirim & Eren, 2024) analyzed herd behavior in the Istanbul Stock Exchange during periods of structural breaks as well as economic, political, and geopolitical crises from 1993 to 2019. The findings indicated that herd behavior was more pronounced during periods marked by political and geopolitical volatility. This behavior was particularly stronger in bear markets, especially during economic and political crises.

Other studies have also indicated that economic and political risks play a significant role in guiding investors' collective decision-making behavior in financial markets. This behavior is usually more apparent during periods of high volatility or market uncertainty. For example, the study by (Mallek, Albaity, & Molyneux, 2022) focused on the impact of economic and political risks on herd behavior in the stock markets of the Gulf Cooperation Council (GCC) countries from 2004 to 2020. The results revealed a positive relationship between economic risks and herd behavior in the stock markets of Kuwait, Bahrain, Saudi Arabia, and Oman. Regarding political risks, the study showed a positive correlation with herd behavior in the Saudi, Omani, and Abu Dhabi markets, while a significant negative correlation was found in the Kuwaiti market.

On the other hand, studies have varied in their examination of the impact of economic and political factors before and during the COVID-19 pandemic to assess the resilience of financial markets in the face of crises. Among these studies is the work by (Ooi Kok & Zamri, 2023), which aimed to explore the influence of economic and political factors on Shariah-compliant and conventional stocks in the Gulf Cooperation Council (GCC) countries during the period 2016-2021. The results indicated that economic factors had a greater influence on herd behavior during the pandemic, reflecting the impact of economic shocks caused by the global health crisis on investment decisions. As for political factors, they were influential only before the pandemic, which may suggest that the priority given to economic crises during the pandemic diminished the effect of political factors. Meanwhile, the study by (Nouri-Goushki & Hojaji, 2023) found that the COVID-19 pandemic was a major factor in shaping herd behavior, which was exacerbated by market volatility.

In a recent study conducted by (Aljifri, 2024) on the impact of the COVID-19 pandemic and the Russia-Ukraine conflict on herd behavior in the Saudi stock market, the results concluded that herd behavior did not appear before the pandemic but became evident during the pandemic and then disappeared afterward. One interesting aspect of this study is the failure of the Russia-Ukraine conflict to trigger herd behavior, indicating that economic and political crises have varying effects on investor behavior depending on the local and international context. The absence of significant differences between bullish and bearish markets or between high and low volatility days suggests a relative psychological stability among Saudi investors during these periods, potentially reflecting investor confidence in the Saudi government’s crisis response. Moreover, The impact of the turmoil in local politics on the country’s economy and therefore on the stock markets is undeniable. In addition to the foregoing, election periods are also at the most important point of the changes that may occur in economic policies. the study by (Godwin, Domeher, & Alagidede, 2022) highlighted the impact that presidential elections can have on herd behavior in African stock markets. Using the cross-sectional absolute deviation (CSAD) model, the results showed that herd behavior increases in Nigeria's consumer services sector before elections, while it becomes prominent in Ghana's consumer goods and services sector after elections. This can be explained by political cycles and the expectations related to economic policies that are formulated before elections. For instance, investors in Nigeria might make moves based on the expectation that a change in government will impact the consumer services sector. In contrast, after elections in Ghana, the political effect becomes more apparent as markets react to actual changes in government policies. (Białkowski, Gottschalk, & Wisniewski, 2008) examining 27 OECD

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countries, found that the country-specific portion of the stock index yield spread rose significantly during national election periods.

Other studies have focused on the impact of major geopolitical crises on investor behavior. The study by (Indārs, Savin, & Lublóy, 2019) provided an in-depth analysis of herd behavior in the Russian market, particularly during periods of heightened political and economic risks surrounding the Ukrainian crisis and the annexation of Crimea. Meanwhile,(Carter & Steinbach, 2024)examined the effects of the Russian invasion of Ukraine on grain futures markets, focusing specifically on wheat and corn futures contracts. Additionally, (Bougatef & Nejah, 2024) analyzed herd behavior on the Moscow Exchange during the Russia-Ukraine war by examining the daily closing prices of 40 companies comprising the MOEX index. While each study addressed different aspects of the crisis, the findings were aligned in several ways. The studies demonstrated that political crises, such as Russia’s annexation of Crimea or the Russia-Ukraine war, significantly shape herd behavior in financial markets. This suggests that investor behavior is not solely driven by psychological or social factors but is a rational response to increasing risks. Furthermore, it was shown that herd behavior does not necessarily manifest in all markets or during all periods. This investigates (Blasco, Casas, & Ferreruela, 2024). The influence of the Russia-Ukraine conflict on herding behavior in global stock markets. Examining MSCI World and MSCI Emerging indexes alongside Russia, the study explores imitation tendencies before the invasion, immediately after commencement of war, and during an extended war period. Findings reveal that emerging markets facing heightened geopolitical risk, either due to their proximity to the conflict or to commercial interests in energy markets, exhibit herding during the initial war phase. (Omar, Wisniewski, & Nolte, 2017) analyzed the impact of 43 wars, which were defined as direct cross-border violence. They found that the stock markets were negatively affected in periods in the event windows where they observed the change in the 50 trading days before and after the outbreak of the war. (Carter & Steinbach, 2024) offered a different perspective, showing that grain futures markets were able to rationally absorb the risks without being influenced by herd behavior. This suggests that the nature of financial assets may play a role in determining the extent to which geopolitical risks impact investor decisions. (Akçaalan, Dindaroğlu, & Binatlı, 2020) found that herding behavior strengthened as the trading volume of international investors increased and market volatility and political tensions encouraged herding behavior in BIST during the 2001–2016 period. There are other studies that have addressed herd behavior in the face of political instability. For example, the study (Le, Nguyen, & Thien, 2024), which examined herding behavior in the cryptocurrency market during the period of the Russia and Ukraine conflict using intraday cryptocurrency price data of the five largest cryptocurrencies in terms of market capitalization. The empirical results indicate an anti-herding behavior during the whole period of the confict, especially after the confict ofcially happens.

The findings of the study by (Krishna & Suresha, 2022) supported the theory that investors tend to act collectively during periods of political instability. This study highlighted the significance of geopolitical risks and their impact on financial markets. Using the MFDFA methodology, it was found that herd behavior generally emerged in key sectors listed on the Indian Stock Exchange (NIFTY) during the geopolitical clashes between India and China in 2020. This result was corroborated by the study of (Khan, Natchimuthu, & Krishna, 2023), which employed the same MFDFA methodology during the geopolitical events between Russia and Ukraine. This confirmation added further strength to the findings, demonstrating that herd behavior is not limited to a specific geopolitical crisis but is a general feature of financial markets during major crises. Additionally, other studies have examined the relationship between political uncertainty and geopolitical risks in financial markets. The studies by (Pastor & Veronesi, 2012) and (Gavriilidis, Kallinterakis, & Montone, 2021) shed light on the effect of political uncertainty on investor behavior and stock prices, illustrating how geopolitical risks can lead to herd behavior (Pastor & Veronesi, 2012) focused on two main types of political uncertainty: the first related to uncertainty about changes in government policies, and the second concerned with uncertainty about the impact of government policies on the private sector. They concluded that both types of uncertainty could increase market volatility and decrease stock values. (Gavriilidis, Kallinterakis, & Montone, 2021) revealed that herd behavior might act as a channel through which political uncertainty transmits its effects on financial markets, leading to increased market efficiency. A recent study by (Gavriilidis, Kallinterakis, & Montone, 2024) explored whether institutional investors herded in response to political uncertainty, Using U.S. equity holdings data from 13F filings, we find that institutional investors herd during politically uncertain times. This trading behavior is stronger when U.S. presidents are unpopular due to their proclivity for controversial policies and among riskier stocks. We also find that this mechanism, despite generating some excess trading, helps incorporate a risk premium into stock prices.

III- Methods and Materials:

III.1. Data and Sources:

The data for this study includes daily time series of the Geopolitical Risk (GPR) index, developed by Caldara and Iacoviello (2022). This index quantifies the frequency of negative geopolitical events by counting the number of related articles each month, derived from automated text searches of 10 global newspapers. The study also utilizes daily return series for the Dow Jones Industrial Average (DJI) and monthly returns of 30 companies listed in this index to calculate the cross-sectional absolute deviation (CSAD) model. The GPR index data was obtained from www.matteoiacoviello.com, while the CSAD model calculations follow the methodology established by Chang, Cheng, and Khorana (2000). The study covers the period from January 1, 2010, to March 30, 2024, chosen for its significant volatility and increasing geopolitical risks and uncertainties.

III.2. Measurement Model:

To achieve the study's objective, the BEKK-GARCH and DCC-GARCH models will be employed to demonstrate the dynamic correlation between geopolitical risks and herding behavior in the market. The initial step involves examining the presence of herding behavior in the Dow Jones Industrial Average (DJI) by evaluating return dispersion. In normal conditions, rational asset pricing models predict that cross-sectional return dispersion increases with the absolute value of market returns, as individual investors act based on their own information. However, during periods of market movement, individual investors may start to mimic others.

To measure herding bias in the market, the cross-sectional absolute deviation (CSAD) model will be used. This model assesses the relationship between stock returns and the weighted average market return using the following formula by (Chang, Cheng, & Khorana, 2000):

$$\boldsymbol{CSAD_t} = \frac{\sum_{t=1}^{N} |R_{i,t} - R_{m,t}|}{N}$$

Where:

$CSAD_t$**:** the cross-sectional absolute deviation of individual stocks' returns around the market (market return dispersion);

$R_{i,t}$**:** is stock i's return at time t;

$R_{m,t}$: the average return of the sample at time t;

N**:** the number of companies included in the sample.

Based on the previous CSAD model, (Chang, Cheng, & Khorana, 2000) estimated a multiple regression equation that measures the relationship between $CSAD_t$ and $R_{m,t}$ as follows:

$$\boldsymbol{CSAD_t} = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \varepsilon_t$$

The relationship described allows for the detection of investors' herding tendencies relative to market conditions. According to capital asset pricing models (CAPM), a positive linear relationship between CSAD and $|R_{m,t}|$ is expected, which would result in a positive and statistically significant coefficient γ_1. Conversely, a negative nonlinear relationship between returns and market return dispersion, indicated by a negative and statistically significant coefficient γ_2 suggests the presence of herding behavior in the market.

Empirical studies have shown that trading volume (TV) is a variable often associated with herding behavior. When herding is present in the market, a relationship between TV and the cross-sectional absolute deviation (CSAD) model is expected. Specifically, a decrease in CSAD (return dispersion) implies that investors are engaging in herding behavior, leading to a very small deviation of individual stock returns from the average market return. The relationship can be described by the following equation:

$$\boldsymbol{CSAD_t} = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \gamma_3 |TV_t| + \gamma_4 (TV_t)^2 + \varepsilon_t$$

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- The BEKK-GARCH model:

This model was developed by Baba, Engle, Kraft, and Kroner to estimate volatility spillovers and shock transmissions for interest rates, gold, crude oil, and exchange rates. The equation for the BEKK model is given as follows (Engle & Kroner, 1995):

$$H_t = C'C + A'\varepsilon'_{t-1}\varepsilon_{t-1}A + B'H_{t-1}B$$

Where H_t is the 2×2 conditional variance matrix of errors at time t, C is a 2×2 constant matrix, A is a 2×2 matrix measuring the autoregressive parameters reflecting the impact of previous shocks ε_{t-1} on current conditional volatility, and Bis a 2×2 matrix measuring its autoregressive parameters reflecting the impact of previous volatilities H_{t-1} on current conditional volatility.

- The DCC-GARCH model:

This model was developed by Engle (2002) to detect potential changes in conditional correlations over time. This model assumes that the time series follows a normal distribution with a mean equal to zero and a conditional variance H_t. It operates in two steps: first, estimating the GARCH model, and then estimating the conditional correlations as follows (Naas, Bensania, & Bendob, 2019):

$$r_t = \mu_t + \varepsilon_t ; \frac{\varepsilon_t}{\Omega_{t-1}} \rightarrow N(0, H_t)$$

$$H_t = D_t R_t D_t$$

Where r_t represents a matrix of order (K×1), ε_t are the residuals and represent a matrix of order (K×1), Ω_{t-1} represents a matrix of all information available up to time t, H_t is the conditional covariance matrix, D_t is a diagonal matrix of order (K×K) for the time-varying standard deviations derived from the GARCH model, and R_t represents the time-varying conditional correlation matrix (K×K). The matrices D_t and R_t are determined as follows:

$$D_t = diag\left(\sqrt{\sigma_{ii,t}}, \dots\dots, \sqrt{\sigma_{kk,t}}\right)$$

$$R_t = \left(diag(Q_t)\right)^{-\frac{1}{2}} Q_t \left(diag(Q_t)\right)^{-\frac{1}{2}}$$

$Q_t = (q_{ij,t})$ represents a symmetric and positive-definite conditional covariance matrix of order (K×K) and is expressed as follows:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha(\mu_{t-1}\mu'_{t-1}) + \beta Q_{t-1}$$

μ_{t-1} represents the standardized residuals, while $\bar{Q} = E(\mu_{t-1}\mu'_{t-1})$ represents the unconditional covariance matrix of the errors μ_{it} of order (K×K). α and β are the unknown parameters to be estimated in the model. For the conditional covariance matrix to be positive definite, it must hold that α>0; β≥0; and β+α<1. If β+α is close to 1, it indicates the persistence of volatility in the conditional variance.

$(Q_t)^{-½}$ represents a diagonal matrix composed of the square roots of the inverses of the diagonal elements of Q_t:

$$\left(diag(Q_t)\right)^{-\frac{1}{2}} = diag\left(\frac{1}{\sqrt{q_{ii,t}}} \dots\dots . \frac{1}{\sqrt{q_{mn,t}}}\right)$$

As for the dynamic conditional correlation coefficient, it is given as follows:

$$p_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}}, \quad i,j = 1,2, \dots .n, \quad / i \neq j$$

$$p_{12,t} = \frac{(1-\alpha-\beta)\bar{q}_{12} + \alpha\mu_{1t-1}\mu_{2,t-1} + \beta q_{12,t-1}}{\sqrt{\left[(1-\alpha-\beta)\bar{q}_{12} + \alpha\mu_{1t-1}\mu_{2,t-1} + \beta q_{12,t-1}\right]}\sqrt{\left[(1-\alpha-\beta)\bar{q}_{12} + \alpha\mu_{1t-1}\mu_{2,t-1} + \beta q_{12,t-1}\right]}}$$

Where q_{ij} are the elements forming the matrix Q_t with i rows.

IV- Results and discussion :

IV.1. Descriptive Analysis of the Study Variables:

Before conducting the econometric study, we present the descriptive statistics of the study variables for the period 2010–2023. The following table illustrates this:

Table (1): Descriptive Statistical Properties of the Studied Variables During the Study Period

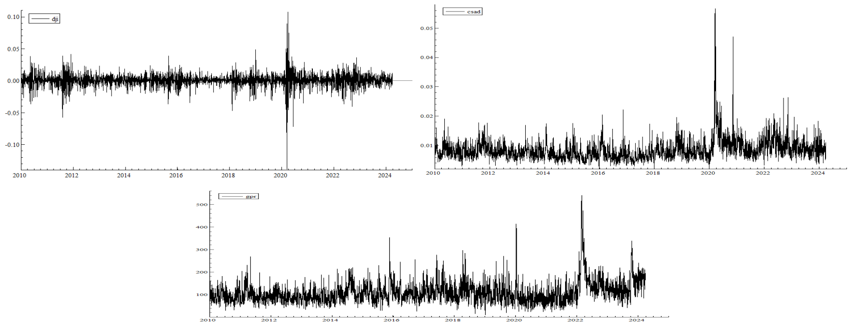
	CSAD	Dji	R_m2	GPR	TV
Mean	0.008445	0.000367	0.000113	109.2738	2.308832
Maximum	0.056662	0.107643	0.019160	540.8274	2.965051
Minimum	0.002381	-0.138418	0.000000	9.491598	1.526856
Std. Dev.	0.003568	0.010627	0.000525	48.85573	0.259067
Skewness	3.579587	-0.853610	21.57557	2.118724	-0.234730
Kurtosis	33.80569	22.71824	632.0963	12.86189	2.036688
Prob Jarque-Bera	149161.4***	58415.59***	5929570***	391091***	171.2426***
(ADF) test t-Statistic	-11.58385***	-19.65197***	-11.44690***	-10.89032***	12.36531***
(P-P) test t-Statistic	-52.1288***	-67.56199***	-57.46485***	-48.76656***	-16.49078***

The source: Oxmetrics.

Note: (***) indicates statistical significance at the 1% level. The table also shows the results of the ADF and P-P tests with constants and trends.

Table (1) illustrates that the variables exhibited positive values and high risk throughout the study period, as reflected by their high mean and standard deviation values. The positive skewness coefficients indicate that the distribution of these variables is right-skewed. Additionally, the excess kurtosis coefficients, which exceeded three, suggest deviations from a normal distribution. This is further supported by the significant Jarque-Bera test statistic, indicating that the variables deviated from normality during the study period. The following section highlights the evolution of the study variables from 2015 to 2023.

Figure (1): Evolution of the Studied Variables During the Study Period



The source: Oxmetrics.

The results show that the computed values of the ADF and PP tests for the absolute values of the CSAD, GPR, Rm^2, and TV indices are lower than the critical values from the Mackinnon distribution and the LM statistic at the 5% significance level. This suggests the absence of unit roots in the studied series, indicating that the series are stationary at the I(0) level.

IV.2. Checking for Herding Behavior in the Dow Jones Index:

Before examining the relationship between geopolitical risks and herding behavior, it is essential to first determine whether herding behavior is present in the Dow Jones Index during the study period using a multiple linear regression model estimation.

The results of the multiple regression, as presented in Table (2), indicate that the coefficient y^2 for the market return variable Rm^2 is positive and statistically significant at the 5% level.

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Conversely, the coefficient y^4 for trading volume (TV) is negative, with its probability value below the 5% significance level, suggesting no conclusive evidence of herding behavior in the market.

Table (2): Results of the Multiple Linear Regression Model Estimation

Variable	Coefficient	t-Statistic	Prob
C	0.0350	9.6323	0.0000
Rm	0.1259	13.6380	0.0000
Rm^2	1.2068	8.5518	0.0000
TV	0.00741	10.4505	0.0000
TV^2	-0.02927	-9.0757	0.0000
R-squared = 0.4213	F-Statistic = 651.2801	Prob (F) = 0.0000	

The source: Oxmetrics.

The Fisher F-statistic indicates that the model is statistically acceptable, as the p-value is below the 5% significance level. Additionally, the coefficient of determination R^2 is 42%, suggesting that the model has some explanatory power. One of the assumptions for model acceptance is the presence of homoscedasticity in error variance. To test this, an ARCH test was conducted. The results, shown in Table (3), reveal that the computed value of the Lagrange multiplier test statistic is significantly greater than the critical value of the $x^2_{\alpha}\,q$ distribution at the 5% significance level with 1 degree of freedom. The associated probability value is well below the 5% significance level, indicating the rejection of the hypothesis of stable conditional variance. Therefore, the previous model is not suitable for interpreting the relationship between the study variables due to the presence of heteroscedasticity. To address this issue, it is advisable to apply a generalized autoregressive conditional heteroscedasticity (GARCH) model.

Table (3): Results of the ARCH impact test

F-statistic	146.2765
Prob. F	0.0000
Obs*R-squared	140.6114
Prob. Chi-Square (1)	0.0000

The source: Oxmetrics.

IV.3. Results of the GARCH (1,1) Model Estimation:

According to Table 4, which presents the results of estimating the GARCH (1,1) model with the market return index Rm, its square Rm^2, and the trading volume index (TV) and its square TV2 included in the mean equation, the model is statistically acceptable at the 1% significance level. This conclusion is supported by the majority of the estimates for the univariate GARCH parameters being both acceptable and statistically significant.

Table (4): Results of the GARCH Model Estimation with Variables Included in the Mean Equation

Dependent Variable: CSAD		
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)		
Included observations: 3582		
GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*GARCH(-1)		
Mean equation	C	0.010433 (0.0014)
	Rm	0.101376 (0.0000)
	Rm^2	-1.009989 (0.0000)
	TV	0.002351 (0.0002)
	TV^2	-0.006814

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		(0.0177)
Variance Equation	ω(Constant)	5.68E-07 (0.0000)
	α(ARCH effect)	0.137521 (0.0000)
	β(GARCH effect)	0.780576 (0.0086)
	α+β	0.918097
R-squared		0.3940
Log likelihood		16461.21
ARCH Test		0.169413 (0.6807)

The source: Oxmetrics.

Note: The values enclosed in parentheses indicate p-values. All coefficients are statistically significant at the 1% significance level.

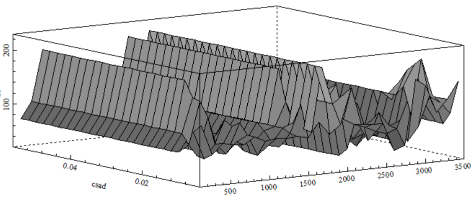
The results presented in Table (4) reveal a statistically significant inverse relationship at the 5% level between the coefficient y^2 for the market return variable Rm^2 and the cross-sectional absolute deviation (CSAD) index. Additionally, the coefficient y^4 for trading volume TV^2 is negative, with its p-value below the 5% significance level. These findings provide evidence of herding behavior in the market during the study period. Specifically, higher values of Rm^2 and TV2 are associated with a decrease in CSAD, indicating that market participants are engaging in herding behavior. A decrease in CSAD suggests reduced variability in returns, which aligns with the presence of herding behavior.

Furthermore, there is a statistically significant negative relationship between market return, trading volume, and CSAD. The coefficient α of 0.13 indicates that CSAD fluctuations are highly sensitive to events or shocks. The high value of the coefficient β at 0.7805 suggests that periods of high volatility are followed by continued high volatility. The sum of these coefficients, totaling 0.918, implies that fluctuations in CSAD exhibit persistence and that the effects of such fluctuations are long-lasting.

IV.4. Results of the Dynamic Conditional Correlation Between Geopolitical Risks and Herding Behavior:

After confirming the presence of herding behavior among investors in the Dow Jones Index during the study period, we proceeded to measure the dynamic correlation between geopolitical risks (GPR) and herding behavior using the BEKK-GARCH and DCC-GARCH models from 2010 to 2024.

Figure (2) Graphical representation of the two series



The source: Oxmetrics.

Table (5) presents the parameter estimates of the BEKK-GARCH model's diagonal for the cross-sectional absolute deviation (CSAD) index and geopolitical risks (GPR). The results indicate a significant negative effect of previous geopolitical risks on CSAD, suggesting an inverse relationship between geopolitical risks and herding behavior. This finding implies that geopolitical

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events impact economic activities and financial markets, potentially causing increased market volatility. As a result, investors may become more cautious, leading them to base their decisions on market movements and the behavior of other investors rather than on economic fundamentals.

The table also reveals that parameter AAA, representing the impact of previous shocks or innovations on volatility, is statistically significant and positive. This indicates that the current conditional variance depends on the square of previous shocks. Additionally, the significance of parameter BBB suggests that high volatility is followed by another period of high volatility. Furthermore, the results demonstrate that previous shocks from geopolitical risks have a significant effect on the variance of CSAD.

Table (5) BEKK-GARCH Model Estimation Results

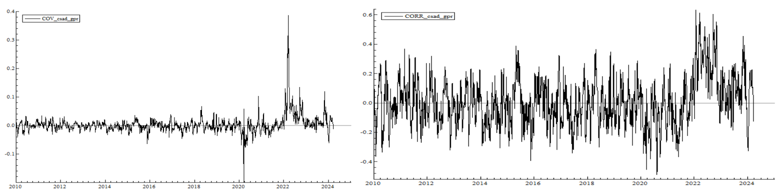
Variable	Coefficient	t-Statistic	Prob
C (1)	0.0078	72.3066	0.0000
C (2)	-1.66E-06	-2.3010	0.0217
C (3)	6.5325	35.3294	0.0000
C (4)	0.39817	25.75291	0.0000
Transformed Variance Coefficients			
C (1.1)	5.41E-07	9.0011	0.0000
C (1.2)	-0.000347	-2.1475	0.0322
C (2.2)	9.7796	7.3811	0.0000
A1(1.1)	0.3840	35.0547	0.0000
A1(2.2)	0.2703	25.2410	0.0000
B1(1.1)	0.8927	129.8787	0.0000
B1(2.2)	0.9278	133.8094	0.0000
Log Likelihood	12411.72		
AIC	-6.925841		

csad = c(1)+c(2)*gpr(-1)
gpr= c(3) +c(4)*gpr(-1)

The source: Oxmetrics.

Note: The values in the table indicate the statistical significance of the parameters, with all coefficients being statistically significant at the 1% level.

Figure (3): Conditional Correlation Between Variables



The source: Oxmetrics.

IV.5. Results of the DCC-GARCH Model Estimation:

Table (6) presents the results of the Dynamic Conditional Correlation (DCC-GARCH) model, examining the relationship between herding behavior and geopolitical risks. The results are statistically significant, indicating notable findings:

IV.5.1. Dynamic Conditional Correlations: The DCC-GARCH model reveals significant and negative dynamic conditional correlations between herding behavior and geopolitical risks over time. This means that fluctuations in herding behavior are inversely related to changes in geopolitical risks.

IV.5.2. Sensitivity: The sensitivity of herding behavior to changes in geopolitical risks is relatively weak, with a coefficient of 0.8%. This suggests that while there is a dynamic sensitivity of herding behavior to geopolitical risks, the effect is modest. In other words, events that influence herding behavior tend to affect geopolitical risks in the opposite direction.

Table (6): Results of the DCC-GARCH (1.1) Model

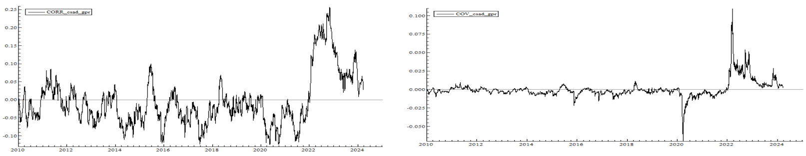
#1: csad			
#2: gpr			
Conditional Variance: Dynamic Correlation Model (Engle)			
Variable	Coefficient	t-Statistic	Prob
rho_21	-0.008455	-10.21	0.0000
Alpha	0.007190	3.115	0.0019
Beta	0.987758	128.5	0.0000
Model Diagnostics:			
Hosking (10)	548.298 [0.0677290]		
Li-McLeod (10)	547.913 [0.0679452]		

The source: Oxmetrics.

Note: The values within parentheses represent the associated probabilities. All coefficients are considered non-significant at the 5% significance level.

From Table (6), it is evident that the combined value of coefficients alpha and beta is 0.99, reflecting a sustained correlation over the long term. Additionally, the probabilities for the Hosking, Li, and McLeod tests exceed the 5% significance level, indicating no autocorrelation in the squared residuals at lag intervals of 10.

Figure (4)*:* Dynamic Conditional Correlation (E)



The source: Oxmetrics.

The figure reveals that correlations among the studied variables experienced significant fluctuations over time, ranging from high to low correlations. Notably, there was a sharp increase in correlations during periods of financial instability and economic disruption.

The study's findings suggest that investors in the New York financial market tend to exhibit herd behavior, with geopolitical risks having a positive dynamic impact on this behavior. As indicators of geopolitical risk rise, American investors are more likely to engage in herd behavior. This response can be attributed to significant geopolitical risks causing anxiety and uncertainty among investors, complicating the acquisition of accurate information about complex global events and potential policy changes. This uncertainty disrupts market forecasting and return expectations, leading investors to act irrationally, undermining confidence in financial markets, and increasing price volatility. Consequently, investors tend to avoid risks and follow herd behavior, adopting prevailing opinions or actions without thorough evaluation of available information. Geopolitical risks also have important implications for firms. When political uncertainty is high, firms find it more advantageous to postpone investment until the uncertainty is resolved. Our results suggest that institutional investors' trading behavior during times of political uncertainty can exacerbate this problem. Politically motivated herding generates a higher cost of capital for firms more exposed to political uncertainty, thus creating a stronger incentive to postpone investment.

In essence, heightened concern and fear over geopolitical risks can prompt investors to collectively sell stocks or seek safer investments like gold or short-term assets. This behavior may exacerbate market volatility, leading more investors to align their actions with the prevailing trend. The study's results are consistent with the findings of (Mertzanis & Allam, 2018) and (Ooi Kok & Zamri, 2023) and (Yildirim & Eren, 2024) and (Nouri-Goushki & Hojaji, 2023) (Indārs, Savin, & Lublóy, 2019) (Krishna & Suresha, 2022), but differ from (Mallek, Albaity, & Molyneux, 2022), which found a positive relationship between political tensions and herd behavior. The empirical results validate the study's conclusions. Events such as the Russian military intervention in

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Ukraine, US-China tensions, supply chain disruptions, and energy shocks have contributed to significant volatility in US financial markets, driven by increased concerns about economic instability. This has made it difficult for investors to maintain rational investment behavior. Due to uncertainty in economic policies, such as central bank monetary policy plans, there has been widespread hedging, with liquidity shifting from high-risk assets like stocks to safer instruments such as government bonds and gold. This shift has led to lower yields on Treasury bonds and declines in stock prices.

V- Conclusion:

This paper investigated the dynamic impact of geopolitical risks on investor herd behavior within the Dow Jones Index from January 2010 to March 2024, employing univariate GARCH, BEKK-GARCH, and DCC-GARCH models. The findings reveal a statistically significant inverse relationship at the 5% level between market return squared (Rm^2), trading volume squared (TV^2), and the cross-sectional absolute deviation (CSAD). This indicates that investors tend to follow the market consensus and exhibit herd behavior during periods of heightened geopolitical risk.

The study highlights that fluctuations in CSAD are highly responsive to market shocks and geopolitical events. Specifically, a significant negative relationship was observed between geopolitical risks and CSAD at lag 1, suggesting that an increase (or decrease) in geopolitical risks in the prior period corresponds to a decrease (or increase) in CSAD in the current period. A reduction in CSAD signifies diminished return volatility, further reflecting herd behavior among investors.

Moreover, the analysis identified significant negative dynamic conditional correlations over time between herd behavior and geopolitical risks. This finding confirms the hypothesis that investor herd behavior in the New York market is influenced by global geopolitical risks.

Based on these results, further research is recommended to explore how geopolitical tensions impact investment trends. Such research will aid analysts and investors in developing more informed and strategic approaches in a volatile economic environment. Investors should carefully evaluate geopolitical risks and their potential market effects before making decisions, understanding how these risks interact with traditional factors such as interest rates, liquidity, and market conditions. While completely avoiding herd behavior may be challenging, awareness and independent decision-making can help manage geopolitical risks more effectively.

To address the risks associated with herd behavior, regulatory bodies should implement mechanisms such as early warning systems and trading limits during periods of geopolitical conflict to stabilize the market. Additionally, regulators should focus on identifying, measuring, managing, and mitigating geopolitical risks to enhance overall market stability.

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