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Financial Stress and Its Role in the New Trend of AI Investing

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Abstract: *Investment asset prices are increasingly more determined not only by economic fundamentals, but also by non-financial behavioral factors, such as the investor sentiment and emotions. One of key emotions in investing is financial stress, which tends to be high during economic crises and low during periods of growth. This paper aims to identify how strong is the impact of financial stress on the growth of technology stock prices during the current AI boom. Using regression analysis and econometric modeling, including a proxy variable of Financial Stress Index (FSI) from the Federal Reserve System of St. Louis, the results showed at 5% level of significance ($p < 0.05$) a negative correlation with a coefficient of ß1=-605,67 between financial stress and AI stock prices. These findings confirm that lower levels of stress contributed to AI investment growth and provide investors implications to incorporate not purely economic factors in decision-making and investment strategies.*

1. INTRODUCTION

Accelerated digitalization has emerged as one of the most significant consequences of the COVID-19 pandemic, the central point of which is also artificial intelligence (AI). Innovations that started in the technology sector gradually spread to other industries, which attracted considerable interest from investors and created a new trend of AI investing in companies such as NVIDIA, Microsoft and Apple. In this context, related spending on artificial intelligence, exceeded the mark of 150 billion dollars in 2023 (PwC, 2023; Bloomberg Intelligence, 2023).

Although companies developing artificial intelligence have benefited from this evolution, there are increasing concerns about the extent to which this growth is sustainable and not conditioned by irrational investor behavior. Given these circumstances, this paper aims to examine how a non-financial behavioral factor in the form of financial stress affects the development of technology stock prices during the current period of AI investing. Using regression analysis and econometric modeling, we will examine whether the current lower levels of financial stress, following after the high stress periods of COVID-19 pandemic, the war in Ukraine, or the recent inflationary crisis, contribute to the ongoing growth of investing in artificial intelligence. On this basis, the results will clarify to what extent is asset valuation growth driven solely by objective fundamentals or is also influenced by investor sentiment.

2. LITERATURE REVIEW

Artificial intelligence (abbreviation AI) refers to machines simulating human intelligence, with its use rapidly expanding in industries such as healthcare, finance, and manufacturing (Russell & Norvig, 2020). As AI technologies advanced, investors increasingly focused on companies such as NVIDIA, which as a result of elevated interest in new AI technologies saw a sharp

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increase in their valuation (Kochetkov & Akhatova, 2023). This phenomenon simultaneously gave rise to what some now call "AI investing" or the "AI bubble", as the market's enthusiasm led to an unprecedented valuation (Chakravarty & Michailidis, 2024).

The behaviour of investors is a critical part of financial decision-making. While traditional financial theories assume the rationality of investment decisions, behavioural finance research suggests that this is not always the case (Barber & Odean, 2000). Studies show that investors often act irrationally, driven by behavioural biases that can lead to phenomena such as asset bubbles (Shiller, 2022). These biases are essentially divided into two categories: cognitive, stemming from errors in reasoning such as overconfidence or herding, and emotional, arising from impulses or feelings such as fear and overreaction (Loewenstein et al., 2001; Shaji & Uma, 2024).

For our research, a key emotional bias is financial stress, during which individuals' logical processes are disrupted, leading to heightened emotional responses (Kleine et al., 2024). This phenomenon is particularly important in periods of market uncertainty, such as economic crises, where stress can impair emotional control and lead to suboptimal investment strategies (Montier, 2002). It is likewise interesting that lower levels of stress in markets can also contribute to the formation of financial bubbles, as investors are less cautious and more inclined to make speculative investments (Starcke & Brand, 2012).

The specific impact of financial stress on asset prices is mainly mentioned in literature addressing periods of strong emotions such as crises or booms (Baker & Wurgler, 2007; Kelley et al., 2023), when the purchase and sale of assets are irrational and mostly carried out without proper prior analysis (Akerlof & Shiller, 2009; Pástor & Veronesi, 2009). On this basis, previous empirical studies have shown a significant negative correlation between financial stress and investment prices. For example, a study by Ludvigson and Ng (2007) found a negative coefficient of -0.45 for the period of the global financial crisis in 2008. A more recent study by Zhang et al. (2020) and Cerqueti and Ficcadenti (2024) for the era of the COVID-19 pandemic further confirmed this negative impact of stress and anxiety on the performance of financial markets.

In the context of the technological development examined by us, the period of the Dotcom technology bubble from 2000 is relevant, where, according to Hong and Stein (2003), financial stress played a substantial part, in the sense that speculation together with rapid stress fluctuations contributed to the instability and subsequent crash of the stock market. Collectively, these examples illustrate the significant role of stress in triggering and amplifying market bubbles, particularly in high-growth industries such as technology, which is also the focus of the ongoing AI investing phenomenon that we will be researching.

3. METHODOLOGY AND DATA

The main aim of the research is to identify how the non-financial behavioural factor of financial stress affects the price development of technology stocks during the current period of AI investing. We proceed from the primary hypothesis that when abstracting from external shocks (ceteris paribus) a period of positive expectations from the future of AI innovation is reflected in lower investor stress, and thus contributes to the growth of asset valuations (Hong & Stein, 2003; Kleine et al., 2024; Taffler et al., 2024).

The research utilized secondary empirical data, where the set of variables shown in Table 1 had a character of time series with the investigated period following the beginning of the AI boom from October 2022 to June 2024. At the daily frequency, this represents a sample with 403 daily observations.

Table 1. List of used variables

Variable	Label	Type	Source
AI investment price	AI_invest	Dependent	Bloomberg markets
Financial stress (proxy)	fin_stress	Independent	FED
Bond yield	bonds	Control	Yahoo Finance
GDP growth	gdp_growth	Control	FED
Unemployment	unemploy	Control	FED
Inflation	inflation	Control	FED
Interest rates	interest_rate	Control	FED

Source: Own processing

The main independent variable of financial stress is measured through the proxy variable of the Financial Stress Index (FSI), which is officially published by the Federal Reserve Bank of St. Louis and U.S. Bureau of Economic Analysis (2023). The index is compiled from 18 individual data series: seven interest rate series, six yield spreads and five other indicators. The starting value of the index is designed at the zero level, where values below zero indicate below-average tension in the market, while values above zero indicate above-average tension and a high incidence of stress.

The dependent variable in this study represents the price of the NASDAQ Composite (^NDX) technology stock index, which is quoted in US dollars and is market-capitalization weighted. The index consists of over 3,000 technology companies, including major big-tech companies such as Apple, Microsoft, Alphabet, NVIDIA and others. A detailed composition of the index, listing the first 100 companies ranked by market capitalization, is presented in Table 2.

Table 2. Structure of the AI stock index

Composition of ^NDX (by market capitalization)			
Apple Inc.	Arm Holdings plc	DoorDash, Inc.	Keurig Dr Pepper Inc.
NVIDIA Corporation	PDD Holdings Inc.	O'Reilly Automotive	Electronic Arts Inc.
Microsoft Corporation	Vertex Pharmaceutical	Workday, Inc.	Lululemon Athletica
Amazon.com, Inc.	Starbucks Corporation	CSX Corporation	Honeywell Inc.
Alphabet Inc.	Micron Technology,	Autodesk, Inc.	Exelon Corporation
Meta Platforms, Inc.	Gilead Sciences,	The Trade Desk, Inc.	Solutions Corporation
Tesla, Inc.	Analog Devices,	Charter, Inc.	The Kraft Heinz
Broadcom Inc.	Intel Corporation	Roper Technologies,	GE HealthCare
Costco Wholesale	Lam Research Corporation	Copart, Inc.	Coca-Cola
Netflix, Inc.	Cintas Corporation	NXP Semiconductors	Microchip Technology
T-Mobile US, Inc.	CrowdStrike Holdings,	Diamondback Energy,	IDEXX Laboratories,
ASML Holding N.V.	Airbnb, Inc.	Monster Beverage	CoStar Group, Inc.
Cisco Systems, Inc.	Mondelez International,	American Electric	Zscaler, Inc.
Adobe Inc.	PayPal Holdings,	Power Company, Inc.	ON Semiconductor
Advanced Micro Devices	Synopsys, Inc.	Paychex, Inc.	DexCom, Inc.
PepsiCo, Inc.	Marvell Technology,	Datadog, Inc.	Warner Bros.
Linde plc	Regeneron Pharmaceuticals	Ross Stores, Inc.	GlobalFoundries Inc.
AstraZeneca PLC	Marriott International	Line, Inc.	Biogen Inc.
Intuitive Surgical, Inc.		Bloomberg markets	Moderna, Inc.
QUALCOMM		ANSYS, Inc.	Illumina, Inc.
Booking Holdings Inc.		Xcel Energy Inc.	Dollar Tree, Inc.
		Verisk Analytics, Inc.	Walgreens Alliance, Inc.

Source: Own processing and Yahoo Finance (2024)

The applied methodology is primarily graphical and regression analysis to quantify the influence of the independent variable (x) on the development of the dependent variable (y). We implemented the initial regression in the form of a Pearson correlation matrix, where we examine the strength of the linear correlation between the variables according to the following formula originating from Benesty et al. (2009):

$$\boldsymbol{r} = \frac{\sum(x_i - \bar{x}) * (y_i - \bar{y})}{\sum(x_i - \bar{x})^2 * \sum(y_i - \bar{y})^2} \tag{1}$$

In the second step of the analysis, was used the OLS multivariable linear regression (MLR) econometric model in the below depicted expression inspired by Khan and Zaman (2012) and Long et al. (2024):

$$AI_{invest} = \beta_0 + \beta_1 * fin_{stress} + \beta_2 * bonds + \beta_3 * gdp_{growth} + \beta_4 * unemploy + \\ + \beta_4 * inflation + \beta_5 * interest_{rate} + u \tag{2}$$

Where $ß_0$ = intercept, $ß_{1,2...k}$ = regression coefficients and u = error term.

The selected methodology intends to enable the quantification of predictors of the influence of chosen behavioural factors and at the same time control the estimates for other confounding elements.

4. RESEARCH RESULTS

The initial analysis of the descriptive statistics in Table 3 provides an overview of the key variables participating in this study. The dependent variable *AI_invest* exhibits a high mean value of 13,570.27 and substantial variability, as evidenced by the standard deviation of 1,858.86, which reflects significant fluctuations in AI-related investments over the observed period. In contrast, the independent variable of financial stress has a mean value of -0.525, suggesting a relatively stable environment closer to the baseline zero, though extreme peaks are associated with major crises. Other control variables, such as GDP growth and inflation, likewise demonstrate relatively stable mean values of 1.368 and 5.364, respectively, which consistently aligns with moderate economic conditions in this timeframe.

Table 3. Descriptive statistics for the variables used

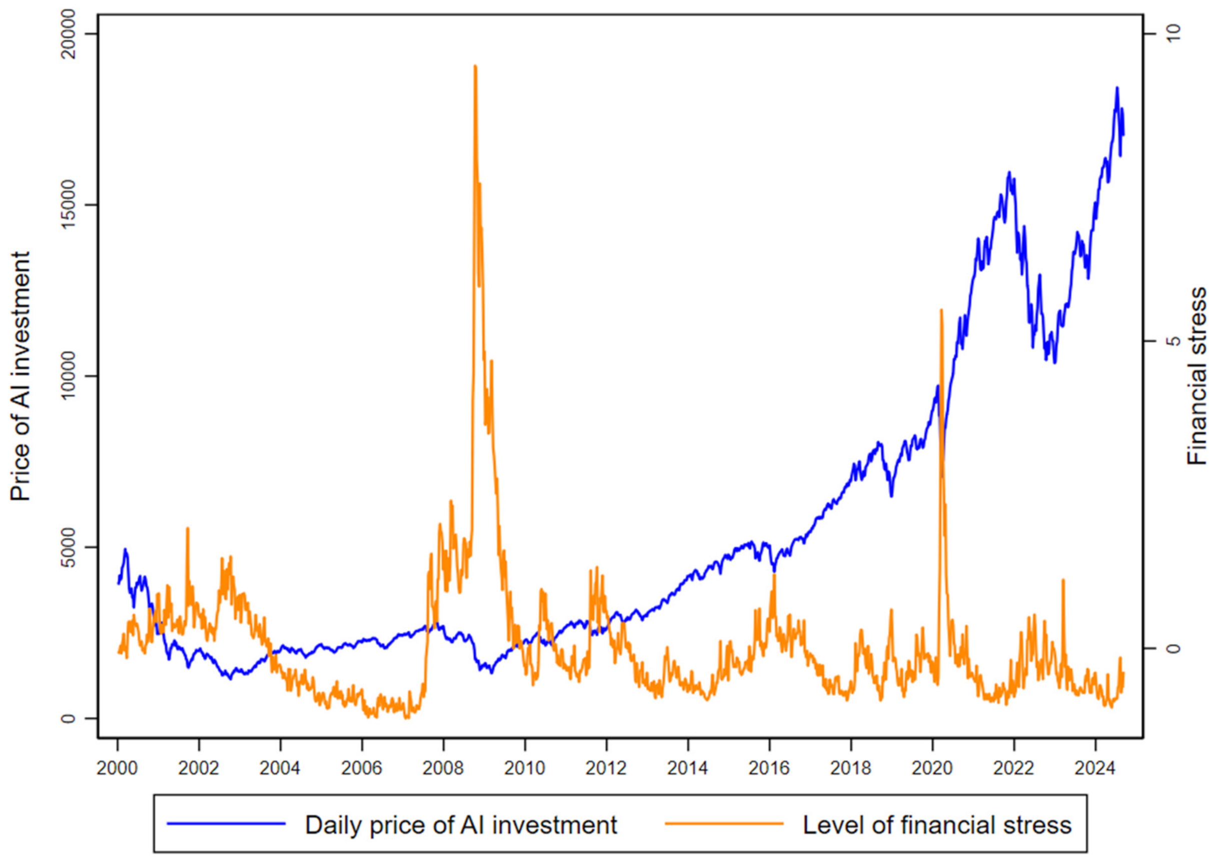
Variable	Obs	Mean	Std. Dev.	Min	Max
AI_invest	403	13570.271	1858.855	10213.29	17187.9
fin stress	403	-.525	.324	-.967	1.204
bonds	403	4.036	.402	3.287	4.988
gdp_growth	403	1.368	.356	.93	2.022
unemploy	403	3.714	.172	3.4	4
inflation	403	5.364	.826	4.403	6.538
interest_rate	403	4.99	.473	3.83	5.33

Source: Own calculations

In the subsequent long-term graphical display on Graph 1, we observe an inverse relationship between financial stress and stock prices. During major crises, such as the global crisis of 2008, the COVID-19 pandemic, or the war in Ukraine and the inflationary crisis of 2022, the level of financial stress has increased sharply, causing a smaller or larger drop in share prices. On the contrary, periods of low financial stress, such as the Internet euphoria at the beginning of the Dot-com bubble in 2000, saw a significant increase in the value of the investment. Together, these trends show that increased levels of stress lead to market declines, while low stress correlates with rising stock prices, as can potentially also be the case in the rising pattern of the ongoing AI technology phenomenon.

To quantify the current relationships in more detail, Pearson's correlation matrix was first used. Based on its results summarized in Table 4, we identify that there is a strong negative correlation

(-0.684) between AI investment return and financial stress, further supporting the inverse relationship identified earlier. Additionally, there is a strong negative correlation between the investment price and inflation (-0.925), as well as interest rates (-0.807), indicating that stock market performance weakens during periods of high inflation and rising interest rates. It then becomes all the more significant that even in such a period of economic slowdown, technology assets can achieve abnormal returns, most likely also thanks to the positive investor sentiment and lower stress levels stemming from previous arguments.



Graph 1. Long-term development of financial stress and price of technology stock index

Source: Own processing, Bloomberg Markets (2024) and Yahoo Finance (2024)

Table 4. Correlation matrix of dependencies within selected variables mix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) AI_invest	1.000						
(2) fin_stress	-0.684	1.000					
(3) bonds	0.599	-0.475	1.000				
(4) gdp_growth	-0.288	0.100	0.011	1.000			
(5) unemploy	0.866	-0.653	0.652	-0.089	1.000		
(6) inflation	-0.925	0.626	-0.771	0.232	-0.823	1.000	
(7) interest_rate	-0.807	-0.596	0.620	-0.226	0.694	-0.866	1.000

Source: Own calculations

In the last part of the research, we interpret the results of the OLS multivariate econometric model. The results summarized in Table 5 once more confirm the negative relationship between financial stress and technology stock index prices, even when taking into account the effects of other macroeconomic factors represented as control variables. The regression coefficient for financial stress reached a statistically significant value of -605.67, at the significance level of 5% ($p < 0.05$). This indicates that a unit increase in the level of financial stress ceteris paribus results in a decrease in the price of the AI stock index by 605 units (at the current price meaning approximately 3.51%). Together with the earlier correlation analysis, we can conclude that increased financial stress negatively affects the performance of AI stock market. The AI boom is in this sense however benefiting from the opposite scenario of low stress that prompts higher investment prices, as was also observed in the graphical analysis. This is driven primarily by the optimism surrounding innovation, as well as recent mitigation of highly stressful periods such as the COVID-19 pandemic and the Ukraine crisis. All in all, these conditions then collectively create a favourable narrative for growth, particularly evident in AI-related markets.

Beyond the primary focus on financial stress, the control variables in the model likewise reveal notable impacts, similar to the correlation matrix. Both inflation (-1854.97) and interest rates (-131.38) show significant negative coefficients, underscoring their detrimental effect on investment prices. The negative coefficient for GDP growth (-327.55) further reflects the connection with a lower likelihood of interest rate cuts, indirectly pressuring AI-related investments, while unemployment remains statistically insignificant. Collectively, these results highlight the intertwined nature of investment asset prices, affirming that even in AI-driven markets, stock prices are deeply connected with broader economic factors.

Table 5. Econometric model results
Model 1: OLS, using observations 2022-10-31:2024-06-07 (T = 403)
Dependent variable: AI_invest

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	16800.1	1627.36	10.32	<0.0001	***
fin_stress	−605.606	100.653	−6.017	0.0379	**
bonds	−1240.72	98.6648	−12.58	0.1701	*
gdp_growth	−327.548	73.3140	−4.468	0.0791	*
unemploy	3368.96	2167.367	1.971	0.3071	
inflation	−1854.97	88.0898	−21.06	<0.0001	***
interest_rate	−131.379	17.3751	−2.271	0.0205	**

Mean dependent var	13570.27	S.D. dependent var	1858.855
Sum squared resid	90137.110	S.E. of regression	477.0943
R-squared	0.535109	Adjusted R-squared	0.537127
F (6, 396)	9.2753	P-value(F)	$1.1e^{-3}$
Log-likelihood	−3053.890	Akaike criterion	6121.781
Schwarz criterion	6149.773	Hannan-Quinn	6132.863
rho	0.920540	Durbin-Watson	1.169092

Source: Own calculations

In terms of model quality, the R^2 value of 0.5351 demonstrates a relatively higher level of explanatory power, which means that over 53.51 % of the variability in investment prices is due to the included variables. Regarding further econometric tests, the stationarity of the time series was confirmed, thanks to which it was not necessary to transform the data, as well as the initial assumptions about homoscedasticity, normality of residuals, and absence of autocorrelation were verified. The high F-statistic (9.2753) and highly significant p-value for the overall model ($1.1e\text{-}^{3}$) further attest to the robustness and overall quality of the model as a reliable tool for understanding how financial stress, along with other factors, affect the current formation of AI investment prices.

5. FUTURE RESEARCH DIRECTIONS

One of the main limitations of our research is the use of the FSI (Financial Stress Indicator) indicator itself, which has undergone changes in its calculation over time and therefore may affect the long-term consistency of the data. In addition, other factors that were not included in the models can also influence the formation of stock prices, which opens up space for improvements in the researched topic through future endeavours.

Future research could therefore expand on the findings by incorporating additional control variables, such as other behavioural biases like herding, fear, or overconfidence, to better understand the full spectrum of non-financial influences on stock prices. Comparing the impact of stress across different geographic regions would also provide valuable insights into how investor sensitivity varies among cultural contexts. Additionally, analysing the role of financial stress during other speculative bubbles, such as those in real estate, cryptocurrencies, or commodities markets, could help identify patterns even across sectors. Future studies may furthermore employ more qualitative methods, such as surveys or behavioural experiments, to gain deeper causal insights into investor sentiment and decision-making processes.

6. CONCLUSION

In this article, we have focused on examining how financial stress affects the continued growth in investment prices during the current wave of investor euphoria around artificial intelligence (AI). Given that previous studies have shown a significant impact of financial stress, especially in periods of crisis, the objective of our research was to identify how strong is the role of low stress in the price formation of technology stocks during this period of AI expansion.

The carried out econometric analysis revealed at the 5% level of significance ($p < 0.05$) a significant negative correlation between financial stress and the price of the AI stock index with coefficient $ß1 = -605.67$. The results therefore show that financial stress plays an important role in the current AI era, where AI companies benefit from low investor stress that leads to euphoria-motivated buying of shares and subsequent growth of investment prices.

The key contribution of the results lies in the investigation of a highly current financial phenomenon, where previous studies usually limited their research to crisis periods, while our paper clarified the role of stress even in times of speculative boom. The research findings therefore present important implications for investors to include behavioural factors in their investment analyses, as well as for policymakers and companies, for which an understanding of the role of emotions in decision-making allows for more realistic and effective strategies.

At a time when investment prices are increasingly influenced not only by fundamentals but also by the emotions of investors, who dangerously often make irrational decisions, it can be concluded that it has become necessary to take into account the impact of behavioural factors. In light of recent stress-inducing external shocks, such as the COVID-19 pandemic and the war in Ukraine, it is crucial to recognize how both low and high levels of stress can enhance or disrupt the trajectories of investment trends, which was in this paper emphasized the positive case of AI investing.

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