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Measuring AI-driven Risk with Stock Prices

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Abstract

We propose an empirical approach to identify and measure AI-driven shocks based on the co-movements of relevant financial asset prices. For that purpose, we first calculate the common volatility of the share prices of major US AI-relevant companies. Then we isolate the events that shake this industry only from those that shake all sectors of economic activity at the same time. For the sample analysed, AI shocks are identified when there are announcements about (mergers and) acquisitions in the AI industry, launching of new products, releases of new versions, and AI-related regulations and policies.

1 Introduction

The World Economic Forum surveys professionals on the likelihood and impact of global risks every year. According to the global risks perception survey, the top risk most likely

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to present a material crisis in 2024 on a global scale is extreme weather, closely followed by AI-generated misinformation and disinformation (WEF, 2024).

Artificial intelligence (AI) has the potential to revolutionize various aspects of human life, from healthcare and education to transportation and finance. Its rapid development raises significant concerns about potential risks which can have global implications due to the interconnectedness of our world. Several reasons can be pointed out for why AI risks are important globally.

1. Economic disruption: AI could automate many tasks, leading to job losses in certain sectors (Acemoglu and Restrepo (2019), WEF (2023), Harayama et al. (2021)), and economic inequality as the benefits of AI may not be distributed evenly, exacerbating existing economic disparities (Gmyrek et al., 2023).

2. Social and ethical concerns: The collection and use of large amounts of personal data can raise privacy concerns (see e.g., O'Neil (2016), IEEE (2020)).

3. Security and governance: AI can be used to develop more sophisticated cyberattacks, posing a threat to national security and critical infrastructure; AI development can outpace the development of appropriate regulations and governance frameworks (see e.g., CSET (2023), SIPRI (2019)).

4. Environmental impact: AI systems can be energy-intensive, contributing to climate change, and the mass production of AI hardware can deplete natural resources (Strubell et al. (2019), GPAI (2021)).

5. Existential risks: The development of superintelligent AI systems that surpass human capabilities can pose an existential threat to humanity if not controlled or aligned with human values (see e.g., Bostrom (2014)).

Addressing these global AI risks requires international cooperation, ethical guidelines, and ongoing research to ensure that AI is developed and used responsibly. But how to identify and measure global AI risks empirically and consistently over time?

Some events impact volatilities of a wide range of assets, asset classes, sectors and countries, with implications for risk management, portfolio allocation and policy-making. The magnitude of such shocks has been defined as global common volatility, or simply COVOL, by Engle and Campos-Martins (2023), which is a broad measure of global financial risk. Because a single factor may not be sufficient to fully capture the structure of the common variation in the volatilities of financial asset returns, Campos-Martins and Engle (2024) paper introduced an extension of the statistical formulation of COVOL to include multiple volatility factors, which allows for clustering structures in the co-movements of global financial volatilities that may exist at the industry or regional levels. In addition, this work is also motivated by **?** who identified climate change risk drivers in the global carbon transition from analysing common volatility of relevant share prices (e.g., of oil and gas companies).

Financial markets are difficult to predict accurately. Large unexpected outcomes are frequent and often common to a wide range of assets across markets. There is strong evidence of international co-movement of asset prices and uncertainty (see, among others, Bekaert et al. (2020), Bollerslev et al. (2014), Miranda-Agrippino and Rey (2020)). Correlated financial volatilities cannot be explained by traditional factor pricing models (Herskovic et al., 2016). But they do using COVOL (Engle and Campos-Martins, 2023). We use common factors to reduce the dimensionality of financial asset prices worldwide while extracting meaningful information about the driving forces behind AI-driven shocks. The multiplicative decomposition that we consider implies a factor structure of the squared innovation covariance matrix to which factor analysis can be applied. This not only should be more efficient than principal component analysis, it also overcomes the issue of getting negative values for the principal components when dealing with variances.

Principal component analysis cannot deal with missing values and has no end point for the optimal number of factors. Moreover, using numerical methods is much easier to implement and to replicate (than, for instance, text-based indicators).

Textual analysis of newspapers is becoming very popular (see Caldara and Iacoviello (2022) for measuring geopolitical risk and Ahir et al. (2022), Baker et al. (2016), Davis (2016) on global uncertainty). Newspapers tend however to reflect what people are worried might happen and not necessarily what has happened. Studies based solely on news reports may thus not address the materiality of news and shocks. An empirical approach using multiplicative volatility factors applied to financial asset prices provides a systematic analysis of global risks that is consistent over time, and that measures in real time big risks as perceived by not only the press, but also the public, global investors, and policy-makers. When assessing the effectiveness of various methods in promptly detecting (shifts in) geopolitical risks, Karagozoglu et al. (2022) found that measures derived from asset prices such as global COVOL are quicker in capturing changes in geopolitical risk compared to textual analysis.

By focussing on particular vocabulary, text-based measures may leave out many events that shake our world. The measure introduced here extends to phenomena such as major political events (e.g., Brexit), global economic occurrences (e.g., COVID-19 and the global financial crisis), climate change (Campos-Martins and Hendry, 2024) or cyberattacks. These events are all of global nature. If the interest lies in identifying and measuring the magnitude of purely AI-driven shocks, one must control for these other events.

We propose a novel methodology to measure common movements of the AI industry and to identify those which have been driven by unexpected increases in AI risks. The model of global COVOL is applied to the daily share prices of AI-relevant companies in the US. We establish the common events that have made these AI equity prices move at the same time and that have had the greatest impact on the industry in the last two decades.

The paper is organised as follows. In Section 2, we review the related literature. The dataset is present in Section 4 and the results, including the AI risk index, are shown in Section 4.2. Finally, Section 5 concludes the paper.

2 Literature review

The literature of AI and how it relates to the financial markets is a recently explored field. For instance, Khalfaoui et al. (2022) points out a static spillover network, which exhibited a high spillover transfer between markets at extreme market states. Naeem et al. (2024) also emphasizes a strong contagion effect from Al to other innovative sectors, as its examination of tail-risk spillovers highlights Al as one of the most influential risk transmitters during market tumult, while cryptocurrency and blockchain consistently function as net risk receivers. Specifically, Bitcoin uncertainty, and global carbon indices were found to be net receipts of shock spillovers, while most green commodities acted as net contributors. Jareño and Yousaf (2023) further explores the extreme connectedness between AI-based tokens and stocks. The fact that Al-based stocks and tokens may have relatively low levels of connectedness makes Bitcoin to be the dominant hedging positions (Huynh et al., 2020) and leading to the conclusion that these technological assets would present a good diversification mechanism (Tiwari et al., 2021). Most existing studies employ the quantile connectedness approach (Abakah et al., 2022, Jareño and Yousaf, 2023, Khalfaoui et al., 2022, Yousaf et al., 2024b, Zeng et al., 2024).

Abakah et al. (2022) conducted a series of empirical analyses with daily log-returns of the NASDAQ Financial Technology Index and AI Index, and Bitcoin price index from March 9, 2018 to January 27, 2021. They used a non-parametric causality-in-quantile modelling technique to assess the sensitivity of distributional predictability between Bitcoin, Fintech, and AI. The directional predictability across the markets was explored by employing a cross quantilogram correlation framework. This method has the superiority in its ability to measure extreme value dependence and that it allows for the use of arbitrary quantiles and large lags capable of detecting directions, intensity, and duration of the dependence among variables. They also employed the quantile VAR estimation technique to examine connectedness and transmission across assets under different market conditions. From the results of the distributional predictability test, the authors documented the existence of bidirectional causality-in-variance between the variables in a normal market, suggesting an endorsement of the information content efficiency. Based on the QVAR connectedness approach, Abakah et al. (2022) observed a very strong price connectedness for highly positive and negative changes, with the level of connectedness appearing to be strongly event-dependent.

Darehshiri et al. (2022) and Ghosh et al. (2023) focus on the dynamics and risk transmission between firms in the digital technology industry. Darehshiri et al. (2022) used two empirical methods: the quantile coherency model and the time-varying parameter-vector autoregressive model. They found a diverse pattern of interdependency between Future Payments and the Future Communication companies, which depends on market conditions and investment horizons. Investors should exercise caution while investing in Future Payments and Digital Communities throughout the normal market state (vs bear markets) and Virtual Reality, particularly on the monthly horizon, owing to their high interconnection. An investor can ignore the negative shocks associated with Future Payments while benefiting from the positive shocks related to Future Communication, thanks to their lack of coherence. The net connectedness indicates that Future Payments are net transmitters of shocks to other firms in the system, where firms play a leading role in the general contactless digital technology industry.

Ghosh et al. (2023) applied explainable artificial intelligence frameworks and found digital assets seemed to be immune to economic policy uncertainty, exhibited persistent trends and were relatively less sensitive to macroeconomic shocks.

Huynh et al. (2020) collected daily data for eight financial asset classes for the period from 19 December 2017 to 16 January 2020. They modelled tail-dependence as copulas and volatility interconnectedness via the generalized forecast error variance decomposition. The authors explored portfolio diversification in the presence of AI, blockchain or cryptocurrencies, green bonds as well as the pre-industrial revolution assets such as gold, and traditional assets like common stocks. Such portfolio exhibited heavy-tail dependence: in the times of economic and financial turbulences the worst case happens, as all alternative investments have a high probability of significant losses at the same time. The volatility transmission were higher in the short term than in the long term: short-term shocks can cause higher volatility in the other financial assets in the portfolio, whereas holding this portfolio in the long run would decrease the volatility transmission among the assets. The Bitcoin and gold appear to be dominant hedging positions, with the limitation that the Bitcoin is also affected by its past volatility. This characteristic of volatility persistence is also found in green bonds and NASDAQ AI index. Finally, the total volatility transmission of all financial assets is considerably high, around 50%, with two spikes close to 90%, indicating the portfolio has an inherent self-transmitting risk that requires appropriate diversification.

Tiwari et al. (2021) employed time-varying Markov switching copula models from December 2017 to July 2020. Their results provided evidence of a time-varying Markov tail dependence structure and dynamics between AI and carbon prices such as EU ETS. The nature of dependence between AI and carbon is negative, suggesting that their prices co-move in the opposite direction. In other words, AI can play a hedging role for the EU ETS. Therefore, these technological assets could present a good diversification mechanism. Motivated by the uncertainty of global economies, the paper investigates the possible effects of geopolitical and global economic policy uncertainty indices, and the outbreak of the novel coronavirus on the correlation between AI and carbon prices. The uncertainty of the markets caused by these factors exerts a negative effect on AI and carbon prices, especially at lower and higher quantiles.

Naeem et al. (2024) applied the conditional autoregressive value-at-risk and time-varying parameters vector auto-regressions to daily data spanning from 1 June 2018 to 11 October 2023, encompassing twelve stock indices representing each industry. They found a strong contagion effect from AI to other innovative sectors. Democratized banking and the metaverse emerge as key recipients of this contagion. The authors also examined tail-risk spillovers highlighted AI as one of the most influential risk transmitters during market tumult, while cryptocurrency and blockchain consistently function as net risk receivers throughout the sample period.

Jareño and Yousaf (2023) examined the extreme connectedness between AI-based tokens and AI-based stocks using a quantile VAR model to estimate tail connectedness between the returns of five leading AI stocks and tokens from 6 May 2019 to 27 January 2023. The period covers various global events, including the COVID-19 pandemic, the Russian invasion of Ukraine, and the energy crisis examine both static and dynamic spillovers in the lower and upper tails of the return distribution. AI-based stocks and tokens may have relatively low levels of connectedness, which also varies over time and increases during periods of economic turbulence. In line with previous work analysing other financial markets and assets, Jareño and Yousaf (2023) found the system is more sensitive to the tails of the distribution (i.e., the lower and upper quantiles) than to the median. The finding is consistent with expectations, and measures of dynamic connectedness change over time, with the intensity of spillovers increasing at the extremes of the distribution.

Zeng et al. (2024) were the first to analyse the volatility connectedness and time-frequency interdependence between an AI index and a clean energy index. They used a QVAR frequency connectedness, wavelet local multiple correlations and Granger causality quantile methods to check the risk spillovers and multivariate time and frequency relationships among eight clean energy indices and the AI index over the period from 18 December 2017 to 4 April 2023. In downturn conditions, the S&P Global Clean Energy Index is the largest net shock sender. The AI Index exports shocks at all frequencies. In addition, market connectedness among markets is stronger under extreme market conditions. The AI index predominantly exhibited positive co-movements with clean energy indices, primarily concentrated within the long-term frequency domain. However, they displayed robust cooperative dynamics across all frequency domains within the context of multivariate wavelet interconnections. Below the extreme bullish threshold, the an AI index can predict changes in the risk associated with all clean energy indices. The effect is partly robust under extremely bullish quantile conditions. Overall, risk spillover activities in extreme market conditions were more pronounced compared to normal conditions

Sharma et al. (2023) studied the time and frequency connectedness using Wavelet Coherence and applied network analysis as a robustness check. The results captured that FinTech was the most resilient asset class during the pre- and post-outbreak of COVID-19, followed by AI-based fund and finally by Green fund. FinTech provides superior diversification opportunities among all with MSCI emerging market: AI and Green funds are captured to be invested in the long term for diversification, whereas FinTech is suitable for both long- and short-term assets.

Yousaf et al. (2024b) examined volatility connectedness between AI stocks, AI tokens, and fossil fuel markets over the period from 6 May 2019 and 8 July 2023. They applied a novel three-dimensional framework in which they model time-domain and frequency-domain volatility spillovers at the median-, lower- and upper-quantiles. They considered both static and dynamic settings. AI tokens and stocks can be either recipients or transmitters of the spillovers at the median quantile. They alert that this result that is not always consistent. Short-term fluctuations predominantly influence the network's overall shock transmission, while the longer-term aspect has the potential to alter the role of a net transmitter or receiver of shocks.

Yousaf et al. (2024a) applied a quantile connectedness approach to highly capitalized AI tokens, AI exchange traded funds (ETFs), and other traditional assets classes from 1 August 2019 to 27 January 2023. The results indicated that during normal market conditions, AI tokens may offer utility as diversifiers for portfolios of traditional assets. AI tokens offer effective low-cost hedging when portfolio weights are properly set. During extreme market conditions, AI tokens and ETFs stop being diversifiers, as both asset types become highly sensitive during extreme shocks.

A short note on AI's impacts on the financial markets and the economy. Acemoglu (2024) highlighted the macroeconomic implications of new advances in AI. The potential effects that AI technologies can have in the medium run include quickly revolutionize every aspect of the economy, and lead to massive improvements in productivity. While this is a possibility that cannot be completely ruled out, there is so far no evidence of such revolutionary effects. AI can also impact wages and inequality because of their automation effects, or conversely, lead to large wage increases, especially for lower-pay workers. Other adverse effects are *deepfakes*, misinformation, and manipulation. On the impacts on economic growth, Aghion et al. (2019) introduced AI in the production function of goods and services and tried to reconcile evolving automation with the observed stability in the capital share and per capita GDP growth over the last century. Automation is taken to be exogenous and the incentives for introducing AI in various places clearly can have first order effects. Exploring the details of endogenous automation and AI in this setup is a crucial direction for further research. Even if many tasks are automated, growth may remain limited due to areas that remain essential yet are hard to improve. If some steps in the innovation process require human R&D, then super AI may end up slowing or even ending growth by exacerbating business-stealing which in turn discourages human investments in innovation. Such possibilities and other implications such as cross-country convergence and property right protection remain promising directions for future research as well. AI may in part discourage future innovation by speeding up imitation; similarly, rapid creative destruction, by limiting the returns to an innovation, may impose its own limit on the growth process.

3 The modelling approach

To measure common shocks to the volatilities of AI-relevant assets, we build upon the model of global common volatility (COVOL) of Engle and Campos-Martins (2023). This is a statistical formulation based on a multiplicative volatility factor decomposition of the standardised residuals. We briefly introduce the simple model with one global factor and then focus on the identification and measurement of AI-relevant shocks.

Consider the vector of AI equity excess returns $\boldsymbol{r}_t = (r_{1,t}, \ldots, r_{N,t})'$ where $r_{i,t} = \tilde{r}_{i,t} - r_{f,t}$, $\tilde{r}_{i,t}$ is the observed return and $r_{f,t}$ is the risk-free return, $i = 1, \ldots, N$. To account for time-dependence in the first two moments of the data, we specify a factor model with AR(1)-GARCH(1,1) errors for each time series of excess returns as follows:

$$r_{i,t} = c_i + \delta_i r_{i,t-1} + \boldsymbol{\beta}_i' \boldsymbol{f}_t + u_{i,t}, \quad |\delta_i| < 1, \tag{1}$$

where c_i is a constant, δ_i is the first-order auto-regressive (AR) coefficient, $\boldsymbol{\beta}_i$ is a $(p \times 1)$ vector of risk exposures, $\boldsymbol{f}_t$ is a $(p \times 1)$ vector of risk factors and $u_{i,t}$ is an error term. If factors are sufficient to reduce the contemporaneous correlations of returns to zero[1],

[1]To reduce the contemporaneous correlations of returns to zero, the cross-sectional mean returns will

the volatility standardised residuals $\boldsymbol{e}_t = (e_{1,t}, \ldots, e_{N,t})'$ will have zero covariances and unit variances. This assumption does not mean that residuals are independent in the cross-section, only uncorrelated.

The key and testable observation of the model is that, although the standardised residuals are orthogonal with unit variance, their squares (or absolute values) are correlated in the cross-section. The co-movement of volatilities is then most likely caused by the positive correlation between shocks to those volatilities (Engle and Campos-Martins, 2023).

We define a variance shock to the ith AI stock as follows:

$$\phi^{\sigma}_{i,t} \equiv \frac{u^2_{i,t} - h_{i,t}}{h_{it}} = e^2_{i,t} - 1, \tag{2}$$

where $e^2_{i,t} = u^2_{i,t}/h_{i,t}, i = 1, \ldots, N$, generally denotes the squared standardised innovation, in this setting from factor model (1). We use the superscript σ to emphasize that these are volatility shocks.[2] The variance shock $\phi^{\sigma}_{i,t}$ is the proportional difference between the squared idiosyncrasy and its expectation. For each stock, the realised squared idiosyncrasy is on some days larger than one and on other days smaller. If many AI equities around the world have squared idiosyncrasies larger than usual at the same time, this can be interpreted as a common variance shock to the AI industry. These global common events are associated with geopolitical news that we will later identify as AI common volatility shocks.

We denote the global AI variance (latent) factor by $f^{\sigma}_{\mathrm{AI},t}, t = 1, \ldots, T$, a positive scalar random variable with $\mathbb{E}[f^{\sigma}_{\mathrm{AI},t}] = 1$. Moreover, $f^{\sigma}_{\mathrm{AI},t}$ is independent of $\boldsymbol{\epsilon}_t = (\epsilon_{1,t}, \ldots, \epsilon_{N,t})'$, where $\epsilon_{i,t} \sim \mathrm{IIN}(0, 1)$ i.e., independently and identically normally distributed with zero mean and unit variance, $i = 1, \ldots, N$. The factor loadings are denoted by $s_i, i = 1, \ldots, N$,

be used as a factor in model (1).

[2]Because volatility is the square root of the variance these two terms can be used interchangeably when interpreting results.

and interpreted as parameters (or fixed effects). The standardised residuals are then assumed to have the multiplicative decomposition of Engle and Campos-Martins (2023),

$$e_{i,t} = \sqrt{g(s_i, f^{\sigma}_{\mathrm{AI},t})}\epsilon_{i,t}, \tag{3}$$

where

$$g(s_i, f^{\sigma}_{\mathrm{AI},t}) \equiv s_i(f^{\sigma}_{\mathrm{AI},t} - 1) + 1, \tag{4}$$

$f^{\sigma}_{\mathrm{AI},t} > 0, t = 1, \ldots, T$, and $0 \leq s_i \leq 1, i = 1, \ldots, N$. By choosing specification (4), $g(s_i, f^{\sigma}_{\mathrm{AI},t})$ is positive for every $t \in [1, T]$ and by assuming $\mathbb{E}[g(s_i, f^{\sigma}_{\mathrm{AI},t})] = 1$, $\mathbb{E}[e^2_{i,t}] = 1$ is satisfied for every i.

Let $f^{\sigma}_{\mathrm{AI},t}$ have strictly positive variance. Then, (3) implies $\boldsymbol{e}^2$ are positively correlated. Hence, the variance-covariance matrix of $\boldsymbol{e}^2$ averaged over t, Σ_{e^2}, will not be diagonal due to the cross-sectional dependence in $\boldsymbol{e}$. It is then straightforward to test for common variance shocks by testing whether Σ_{e^2} is diagonal. Under the alternative, $f^{\sigma}_{\mathrm{AI},t}$ varies over time inducing co-movements and positive correlations of $\boldsymbol{e}^2$.

Positive correlations mean that the off-diagonal elements of $\Sigma_{e^2,t}$ will also be positive. Moreover, we assume $s_i = 1, i = 1, \ldots, N$, under the alternative meaning all equities are equally affected by a shock. This means all $N(N-1)/2$ unique pairwise correlations will be the same. The null hypothesis is thus reduced to $\mathbb{H}_0 : \rho_{e^2} = 0$, where ρ_{e^2} is the equicorrelation of the squared standardised residuals, and tested against the alternative that this is positive i.e., $\mathbb{H}_1 : \rho_{e^2} > 0$. For that purpose, we will use the test statistic proposed by Engle and Campos-Martins (2023),

$$\xi_{e^2} = \frac{\sqrt{\frac{NT}{(N-1)/2}} \sum_{i>j,j=1}^{N} \sum_{t=1}^{T} (e^2_{it} - 1)(e^2_{jt} - 1)}{\sum_{i=1}^{N} \sum_{t=1}^{T} (e^2_{it} - 1)^2}, \tag{5}$$

which has a standard normal distribution under $\mathbb{H}_0$. Using Monte Carlo simulations, the test has good size and power in various settings. For the finite-sample properties of the test and further details, we refer to Engle and Campos-Martins (2023). In practice, the null hypothesis is tested by calculating the empirical variance-covariance matrix $\Sigma_{\hat{e}^2}$.

Assuming normality, the likelihood is constructed as if $f^{\sigma}_{\mathrm{AI},t}$ were observed and given by

$$L(s, f^{\sigma}_{\mathrm{AI}}; e) = -\frac{1}{2} \sum_{i=1,t=1}^{N,T} \left\{ \log g(s_i, f^{\sigma}_{\mathrm{AI},t}) + \frac{e^2_{i,t}}{g(s_i, f^{\sigma}_{\mathrm{AI},t})} \right\}. \tag{6}$$

Because the model formulation is multiplicative between two sets of unknowns $f^{\sigma}_{\mathrm{AI},t}, t = 1, \ldots, T$, and $s_i, i = 1, \ldots, N$, we estimate each conditional on the other by maximum likelihood as follows. The first-order conditions,

$$\frac{\partial L(s, f^{\sigma}_{\mathrm{AI},t}; e)}{\partial s_i} = 0, \quad \frac{\partial L(s, f^{\sigma}_{\mathrm{AI}}; e)}{\partial f^{\sigma}_{\mathrm{AI},t}} = 0,$$

give two heteroscedasticity relationships:

$$\begin{aligned} \text{Cross-Section: } e_{i,t} &= \epsilon_{i,t} \sqrt{\hat{s}_i \left(f^{\sigma}_{\mathrm{AI},t} - 1 \right) + 1} \text{ for } t = 1, \ldots, T, \\ \text{Time-Series: } e_{i,t} &= \epsilon_{i,t} \sqrt{s_i \left(\hat{f}^{\sigma}_{\mathrm{AI},t} - 1 \right) + 1} \text{ for } i = 1, \ldots, N. \end{aligned} \tag{7}$$

The cross-sectional regression allows us to estimate the unobserved value of $f^{\sigma}_{\mathrm{AI},t}, t = 1, \ldots, T$, using some starting values for $s_i, i = 1, \ldots, N$. For instance these could be the loadings on the first principal component of the squared standardised residuals. Then the time-series regression provides estimates for $s_i, i = 1, \ldots, N$, conditional on the estimates of the latent variable. There is thus an estimator for each $s_i, i = 1, \ldots, N$, given $\hat{f}^{\sigma}_{\mathrm{AI},t}, t = 1, \ldots, T$, using time-series and another estimator for each $f^{\sigma}_{\mathrm{AI},t}, t = 1, \ldots, T$, given estimated $\hat{s}_i, i = 1, \ldots, N$, for each cross-section. To gain efficiency, we iterate the estimation of the time-series and cross-sectional regressions until convergence. At that point, both first-order conditions are satisfied and a joint maximum can be achieved.

4 The AI relevant stocks and shocks

We use the daily closing prices of shares from March 08, 2004 until March 05, 2024 for AI-relevant companies. Table 1 summarises the full list of equities. The share prices are all from companies in the Information Technology, Communication Services, and Consumer Discretionary sectors, and are all traded in US stock exchanges to avoid asynchronous observations. This is an unbalanced panel (equities were launched on different dates) with some observations missing at the beginning of the sample. At each point in time we estimate the value of the global common factor using all the available observations in that cross section. Prices are converted to log-returns to remove stochastic trends.

Table 1: List of equities from Information Technology sector in USD.

Issuer Ticker	Name
AAPL	APPLE INC
NVDA	NVIDIA CORP
MSFT	MICROSOFT CORP
AVGO	BROADCOM INC
CRM	SALESFORCE INC
ADBE	ADOBE INC
AMD	ADVANCED MICRO DEVICES INC
ACN	ACCENTURE PLC CLASS A
CSCO	CISCO SYSTEMS INC
IBM	INTERNATIONAL BUSINESS MACHINES CO
INTC	INTEL CORP
GOOGL	ALPHABET INC CLASS A
META	META PLATFORMS INC
TSLA	TESLA INC
PLTR	PALANTIR TECHNOLOGIES INC

We first estimate a factor model for each series of AI returns. We use the market portfolio, namely the Standard & Poor's (S&P) 500 index and the cross-sectional mean of returns for the sample as the market pricing factors. Each factor model includes a lagged dependent variable and assumes GARCH(1,1) errors. This is supported by the Ljung-Box AR(1) and ARCH(1) tests of time independence in the first and second moments, respectively, which confirm these are necessary to capture time dependence.

The cross-sectional mean AI residuals from the factor models are shown in the upper panel of Figure 1, and the estimated conditional volatilities in the lower panel. For comparison, we also add the estimated volatility of the S&P 500 index. AI returns are heteroscedastic with large movements during periods of market distress, most notably over the 2007–2009 Great Recession and the COVID-19 pandemic. Though the S&P 500 is much more volatile, the volatilities of AI equities and the market tend to co-move especially during market turmoil.

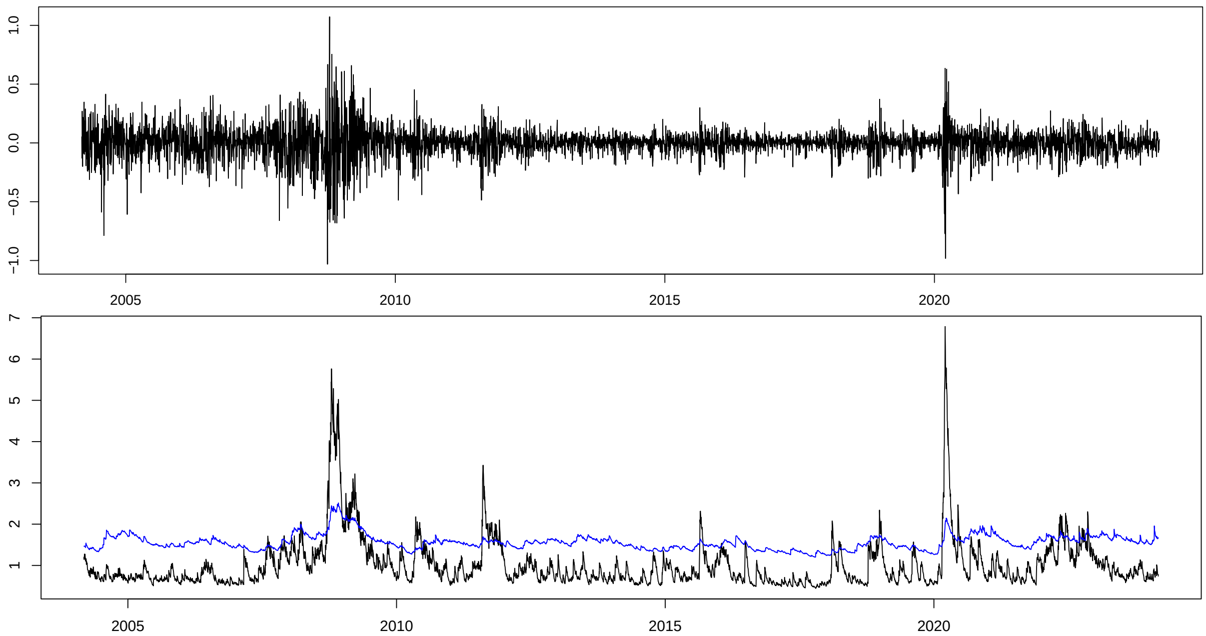

Figure 1: Cross-sectional mean AI residuals (upper panel) and estimated conditional volatilities (lower panel in blue). For comparison, the volatility of the S&P 500 index is also shown (lower panel in black).

After estimating the factor pricing models, we compute the volatility standardized residuals $e_{i,t}, i = 1, \ldots, N, t = 1, \ldots, T$. Before estimating the factor and factor loadings, we have to test the null hypothesis of no COVOL. We need to test whether the variance-covariance matrix of $\boldsymbol{e}^2$ is diagonal against the one sided alternative that its off-diagonal elements are positive. The empirical counterpart of the equi-correlation ρ_{e^2} is computed based on the squared estimated volatility standardized residuals and denoted by $\rho_{\hat{e}^2}$.

The average correlation of the squared standardised residuals and and the global COVOL test statistic (Engle and Campos-Martins, 2023) are presented in Table 2. For this sample, $\rho_{\hat{e}^2} = 0.034$ and the test statistic is $\xi_{\hat{e}^2} = 17.828$ ($p-$value $= 0.000$). The null hypothesis that the squared standardized residuals are uncorrelated is thus rejected. This result provides evidence that the squared standardized residuals are, in fact, positively correlated and we can then proceed to the estimation of the global COVOL model[3].

Table 2: Sample average correlation of $\hat{\boldsymbol{e}}^2$ and test result for the first factor.

	$\rho_{\hat{e}^2}$
Correlation	0.034
Test statistic	17.828***

Before we present the estimation results, we observe that extracting a single global volatility factor is sufficient to get the squared standardised residuals to be no longer positively correlated. This is an indication that one factor is enough to capture all the common variation in the volatilities. The empirical averaged correlation and the test statistic applied to the residuals standardized by not only the idiosyncratic volatilities but also the global common factor are presented in Table 3.

Table 3: Sample average correlation of $\hat{\boldsymbol{\varepsilon}}^2$ and test result for a potential second factor.

	$\rho_{\hat{\varepsilon}^2}$
Correlation	−0.021
Test statistic	−9.591

[3] To help estimate $f^{\sigma}_{\mathrm{AI},t}$, the cross-sectional mean standardized residuals may be added to the sample.

4.1 The naive approach

The estimated most extreme common AI variance shocks captured by $\hat{f}^{\sigma}_{\mathrm{AI},t}$ are summarised in Table 4. For comparison, the returns on the same day are shown for the cross-section average of AI stocks ($\bar{r}^{\mathrm{AI}}_t$), and the S&P 500 index (r^{SP500}_t). Several important dates can be recognised as when major events happened affecting global financial markets, including AI equities. Many extreme common variance shocks as measured by $\hat{f}^{\sigma}_{\mathrm{AI},t}$ coincide with large negative returns to the industry. Negative shocks seem to have greater potential than positive ones to have a global effect, but need not be matched by large negative shocks to the S&P 500. This difference suggests some shocks may be sector or AI specific. For instance, on July 21, 2004 (the day of the 4th largest shock in Table 4), the shares of Salesforce Inc–an American cloud-based software company for customer relationship management with artificial intelligence integrated across all products–fell 27% only days after the company went public, marking the stock's worst trading day for decades. The stock promptly plunged after the company's announcement that profit and revenue for the full year would be lower than expected.

More generally, in January 2006 Google acquires dMarc Broadcasting, a company specializing in automated advertising, which was an early step towards Google's AI-driven ad infrastructure. In April of the same year Google also releases Google Translate, a statistical machine translation service that can translate text between multiple languages. In January, 2008 Microsoft acquires Calista Technologies, which specialized in enhancing virtual machine technology, an important step towards improving AI applications in cloud computing. In July 2008 iPhone 3G is launched. Although not directly related to AI, the launch of the iPhone 3G contributed to the growth of mobile AI applications, particularly with the App Store enabling a surge in AI-powered apps. November 2010 is when Microsoft releases Kinect, a motion-sensing device for the Xbox 360, which utilized AI for gesture and voice recognition, marking a significant development in human-computer interaction. In November 2016, in the aftermath of the U.S. presidential election, there was significant discussion on the role of AI in data analysis, targeted advertising, and social media, raising concerns about its influence on democratic processes. In July 2020, there is much discussion about OpenAI release of GPT-3, a state-of-the-art language model that demonstrated unprecedented capabilities in natural language processing, generating significant attention and discussions about the future of AI. In 2020, AI is increasingly used in the COVID-19 vaccination efforts, to optimize the distribution of vaccines, manage supply chains, and predict vaccine efficacy.

Table 4: The largest estimated global shocks, $\hat{f}^{\sigma}_{\mathrm{AI},t}$, and the values of the returns on the same day. $\bar{r}^{\mathrm{AI}}_t$ denotes the cross-sectional mean return to the AI stocks in our sample, and r^{SP500}_t the return of the S&P 500 index.

Date	$\hat{f}^{\sigma}_{\mathrm{AI},t}$	$\bar{r}^{\mathrm{AI}}_t$	r^{SP500}_t
2004-08-06	65.699	-6.953	-1.560
2016-04-22	43.774	1.610	0.005
2008-07-03	40.157	-3.444	0.109
2004-07-21	35.948	-5.437	-1.343
2022-02-03	34.615	-5.134	-2.469
2006-04-28	33.870	-1.688	0.068
2018-07-26	33.520	-0.798	-0.304
2016-11-11	30.424	2.442	-0.140
2020-08-26	30.150	3.868	1.014
2010-11-11	29.271	-2.298	-0.425
2013-10-18	27.631	0.682	0.653
2015-07-17	27.513	1.105	0.111
2020-07-24	25.548	-1.142	-0.621
2008-01-23	24.988	1.282	2.121
2018-07-12	24.901	0.538	0.871
2006-01-18	24.721	-0.638	-0.391
2022-09-15	24.681	-2.358	-1.138
2008-01-16	23.538	-2.841	-0.563
2022-10-27	23.521	-2.752	-0.610
2020-03-18	22.055	-5.368	-5.323

Table 4 also notes some of the major global economic and financial events, political elections, climate and pandemic-related policy changes and terrorist attacks likely to influence shocks to the AI industry.

All the events discussed above caused large absolute returns across the AI equities at the same time showing up in the common volatility factor as some of the biggest common shocks affecting the AI industry. The monthly averaged estimated AI global common variance factor, $\hat{f}^{\sigma}_{\text{AI},m}$, where m indicates the calendar month, is plotted in Figure 2 where some of the major events affecting the AI industry are labelled. Note that many other events could be labelled. Certainly, around the date of Russia's invasion of Ukraine in February 2022, others events of AI relevance could have been pointed out. Same applies to those that happened during the two most recent economic contractions, namely the COVID-19 pandemic and the global financial crisis. The next step in identifying AI-relevant shocks is to disentangle them from those arising in response to any other types of news.

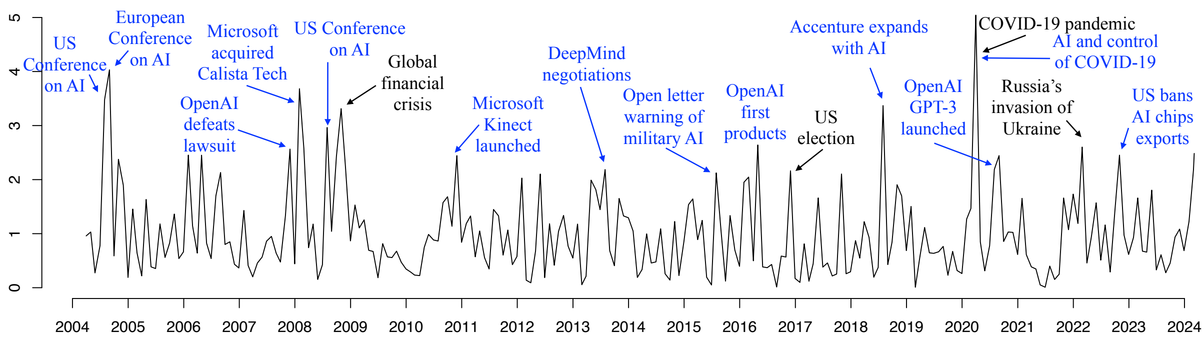

Figure 2: The monthly averaged AI common volatility index. Events in blue are AI-specific. Other events in black, where some culminated in economic recessions.

The empirical variances and covariances of the squared standardised residuals are not equal across AI equities as different equities have different loadings on $f^{\sigma}_{\text{AI},t}$. The estimated AI loadings are presented in Table 5 in descending order of magnitude showing the proportion of $f^{\sigma}_{\text{AI},t}$ that affects each assets' variance. Because the impact of $f^{\sigma}_{\text{AI},t}$ is heterogeneous across equities, AI companies have different exposures to common variance shocks. This heterogeneity may reflect equity specific factors security, sustainability and governance. Note that the loadings shown in Table 5 reflect exposure to all types of shocks that make all AI companies move at the same time, not only AI-specific.

Table 5: The estimated AI common variance factor loadings.

	$\hat{s}_i$		$\hat{s}_i$
CSCO	0.301	NVDA	0.254
META	0.300	ACN	0.253
IBM	0.291	INTC	0.251
GOOGL	0.284	PLTR	0.244
ADBE	0.283	AVGO	0.203
AMD	0.263	TSLA	0.200
MSFT	0.259	AAPL	0.199
CRM	0.257		

A glossary can be found in Table 1.

By construction of functions $g(s_i, f^{\sigma}_{\mathrm{AI},t}), i = 1, \ldots, N$, the loading s_i measures the exposure of company i to any common volatility shock. Thus, differences in the AI loadings make it possible to reduce exposure to broad risks: Engle and Campos-Martins (2023) examine portfolio optimality facing such common volatility shocks.

4.2 The two-step approach

To disentangle purely AI-driven shocks, we propose a two-step approach. In the first step, common volatility is model for a set of AI-relevant stocks and all US select sector SPDR funds[4]. This way we are able to identify the shocks that make all these asset prices move at the same time across all industries. Such shocks are driven by large events such as presidential elections, pandemics, major policy changes or extreme weather. The key observation is that the shocks are identified such that they impact not only the AI-relevant shocks, but also all other stocks in all sectors of economic activity.

[4]The select sector SPDR fund is a unique exchange traded fund that divides the S&P 500 into eleven sector index funds. Together they comprise the stocks of all companies included in the S&P 500.

Then, in the second step, we remove the common shocks from the AI-relevant stocks by standardizing the residuals by the square root of $f^{\sigma}_{\text{AI+Sectors},t}$. Using these re-scaled AI residuals, we re-estimate common volatility for the AI-relevant stocks only and obtain $f^{\sigma*}_{\text{AI},t}$. Assuming the global common shocks have been correctly identified, the common movements in all the AI asset prices should now be AI-specific.

We then iterate the two steps until convergence so gain efficiency and allow for any feedback effects between the two factors i.e., AI and AI+Sectors.

The estimated most extreme AI-driven variance shocks captured by $\hat{f}^{\sigma*}_{\text{AI},t}$ are summarised in Table 6. For comparison, the returns on the same day are shown for the cross-section average of AI stocks ($\bar{r}^{\text{AI}}_t$), and the S&P 500 index (r^{SP500}_t). By construction, the events should be mostly AI-specific.

All the events above caused large returns (in absolute value) across the AI equities at the same time. These are captured by the common volatility factor as some of the biggest common shocks affecting the AI industry. Note that some of the events remain as large as those impacting the AI industry in the previous sections, but, for others, the impact is actually much larger in the refined two-step analysis where global shocks have first been removed before identifying the AI-specific shocks. For instance, July 12th, 2018 is now at the top when Accenture expanded touchless testing platform with AI Technology from real time analytics Platform, Inc., the European AI alliance was launched and the high-level expert group on AI set up. In July 2020, OpenAI's GPT-3 was released, showcasing powerful language abilities at the same time as the impact assessment is created with ethical and legal requirements on AI, an EU initiative to ensure that AI is safe, lawful and in line with EU fundamental rights. Its overall goal is to stimulate the uptake of trustworthy AI in the EU economy. In January 2021, the White House Office of Science and Technology Policy announced the establishment of the National Artificial Intelligence Initiative Office to liaise with Federal AI activities and stakeholders in the private sector

Table 6: The largest estimated global shocks, $\hat{f}^{\sigma*}_{\text{AI},t}$, and the values of the returns on the same day. $\bar{r}^{\text{AI}}_t$ denotes the cross-sectional mean return to the AI stocks in our sample, and r^{SP500}_t the return of the S&P 500 index. See Table **??** for events that happened on or around each of the dates presented.

Date	$\hat{f}^{\sigma*}_{\text{AI},t}$	$\bar{r}^{\text{AI}}_t$	r^{SP500}_t
2016-04-22	50.720	1.610	0.005
2020-07-24	40.500	-1.142	-0.621
2018-07-12	36.535	0.538	0.871
2005-01-11	33.320	-4.581	-0.611
2013-07-25	32.895	2.072	0.256
2010-11-11	31.229	-2.298	-0.425
2013-06-28	31.166	-1.117	-0.430
2015-07-17	30.642	1.105	0.111
2013-10-18	29.489	0.682	0.653
2021-01-22	27.374	0.352	-0.302
2004-07-14	26.040	-2.141	-0.329
2017-05-02	25.304	-1.878	0.119
2011-02-10	25.284	-1.143	0.075
2022-05-19	25.173	-1.616	-0.585
2010-09-22	24.882	-1.844	-0.484
2024-02-06	24.433	1.128	0.231
2004-10-13	23.966	-0.245	-0.733
2009-01-22	23.463	-3.667	-1.529
2013-12-13	22.698	0.611	-0.010
2008-02-01	22.581	0.323	1.216

and academia. In February 2011, IBM's Watson competes on Jeopardy!, winning against two former champions. This event captured the public imagination and demonstrated AI's ability to understand and process natural language. While reportedly undergoing negotiations with DeepMind Technologies–which later is acquired by Google and becomes a significant player in AI research, known for its work in reinforcement learning and neural networks– in 2013, Facebook also reveals the future of AI with deep learning in December 2013.

News and events on or around the dates of the largest shocks in Table 4 shaking the share prices of AI relevant companies are hard to find in the media news articles.

It is important to note that the specific events on the dates highlighted may not have been widely publicized immediately. Also, AI development is often incremental, with significant advancements or announcements building upon previous research and events.

The monthly averaged estimated AI global common variance factor, $\hat{f}^{\sigma*}_{\mathrm{AI},m}$, where m indicates the calendar month, is plotted in Figure 3.

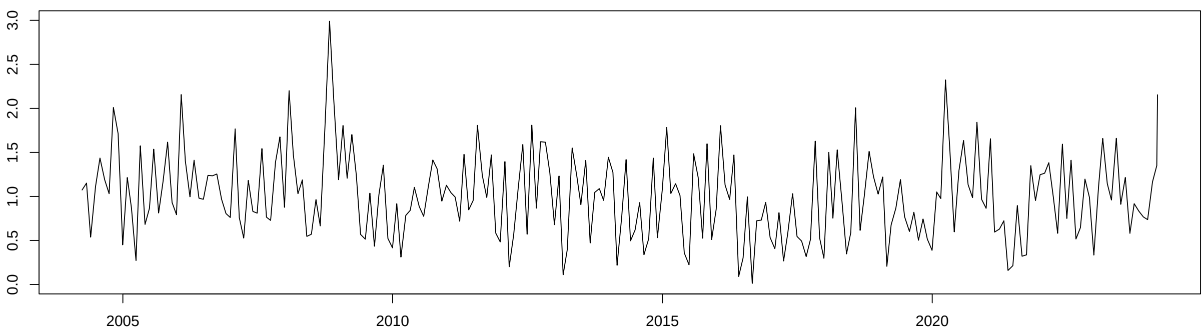

Figure 3: The monthly averaged AI-driven volatility.

The estimated AI loadings are presented in Table 7 in descending order of magnitude showing the proportion of $f^{\sigma*}_{\mathrm{AI},t}$ that affects each assets' variance. Note that the loadings shown in Table 7 reflect exposure to all types of shocks that make all AI companies move at the same time, only AI-specific.

Some AI-relevant assets have a zero loading meaning such assets are insensitive to changes in the common factor $\hat{f}^{\sigma*}_{\mathrm{AI},t}$. This result is surprising. The next steps will be to run some robustness checks and potentially refine the methodology and/or the analysis for disentangling AI-driven shocks.

5 Concluding remarks

We proposed a novel methodology to measure common movements of the AI industry and to identify those which have been driven by unexpected increases in AI risks. The

Table 7: The estimated AI sensitivities to the shocks common to AI stocks. These are obtained by first removing the global factor that is common to both AI and all sectors of economic activity. Then, we estimate the AI-specific factor and factor loadings on the standardized AI series.

	$\hat{s}_i$		$\hat{s}_i$
IBM	0.326	INTC	0.277
CSCO	0.325	MSFT	0.273
AMD	0.303	AAPL	0.259
META	0.300	AVGO	0.234
ADBE	0.296	NVDA	0.034
ACN	0.289	CRM	0.000
GOOGL	0.288	TSLA	0.000
PLTR	0.279		

A glossary can be found in Table 1.

model of global COVOL introduced by Engle and Campos-Martins (2023) was applied to the daily share prices of AI-relevant companies, all traded in US stock exchanges. We establish the common events that have made these AI equity prices move at the same time and that have had the greatest impact on the industry in the last two decades. AI-driven COVOL seems to peak around important acquisitions in the industry and major developments or AI product releases.

Improvements to identifying and measuring AI-driven COVOL include adding relevant stocks from various countries and regions of the world. This would implicitly make controlling for other shocks affecting the AI industry much more effective. As a robustness check, the next steps also include comparing our AI-driven COVOL index with other existing AI indices.

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