STRATOS
Research

Silver, AI Infrastructure and the Economics of Power

An empirical analysis of silver's economic link to AI infrastructure and market decoupling

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February 7, 2026

Abstract:
This paper empirically investigates the evolving economic relationship between silver and the rapidly expanding Artificial Intelligence (AI) infrastructure sector. The prevailing narrative of AI as a purely digital phenomenon overlooks its profound physical footprint, characterized by massive capital expenditures in power-hungry data centers. We hypothesize that this build-out has established a new, structural demand driver for silver, altering its traditional market correlations. Using Exchange-Traded Funds (ETFs) as liquid market proxies—iShares Silver Trust (SLV), Pacer Benchmark Data & Infrastructure Real Estate SCTR ETF (SRVR) and Consumer Staples Select Sector SPDR Fund (XLP)—this study employs correlation and multiple regression analysis on daily returns data from 2021 to 2025. The results reveal a fluctuating but persistent positive correlation between silver (SLV) and AI infrastructure (SRVR). More critically, a multiple linear regression model confirms a statistically significant positive relationship between the returns of SLV and SRVR (coefficient = 0.298, $p < 0.001$), while showing no significant link to the non-digital consumer staples sector (XLP, $p = 0.7174$). These findings suggest that silver is exhibiting a measurable decoupling from traditional economic segments, aligning more closely with the physical demands of the digital economy. The conclusions hold significant implications for commodity analysis, investment strategy and portfolio diversification, highlighting silver's emerging role as a key industrial commodity for the AI era.

1. Introduction

The proliferation of Artificial Intelligence (AI) is frequently framed as a software-driven revolution, a narrative that often obscures the immense physical and capital-intensive reality underpinning its growth. While the value of AI is realized through algorithms, its execution depends on a massive physical layer of high-performance semiconductors, power systems and data centers. Global technology hyperscalers are committing hundreds of billions of dollars in capital expenditures (CAPEX) toward building facilities designed to handle the unprecedented power and cooling demands of AI workloads[13].

This spending appears "relatively insensitive to the macro conditions," suggesting a persistent, non-cyclical demand driver [11]. The AI data center market is projected to grow at a compound annual growth rate (CAGR) of over 31% through 2030, a testament to this insatiable demand for computational power [7].

This global infrastructure build-out creates a significant and inelastic demand for energy and, consequently, for the raw materials essential to power generation, transmission and high-performance computing hardware. Among these materials, silver (Ag) holds a critical position due to its unique physical properties. Possessing the highest electrical and thermal conductivity of any metal, it is indispensable in high-density server environments for applications such as multi-layer circuit boards, high-frequency connectors and power distribution systems[15, 16]. This demand is occurring within the context of a tightening market; industrial demand for silver reached a record 680.5 million ounces in 2024 and the market has experienced a structural deficit for four consecutive years [17].

This paper posits that the physical demands of the AI revolution have created a new, measurable and structural demand layer for silver. We hypothesize that this has initiated a "decoupling" of silver's price behavior from traditional economic sectors, aligning it more closely with the growth of digital infrastructure. This challenges the conventional view of silver, which has historically been analyzed through its dual nature as both a precious metal, often correlated with gold and an industrial commodity tied to broad economic cycles. To test our hypothesis, we conduct a rigorous quantitative analysis of the relationship between silver and proxies for the AI infrastructure sector and the non-digital economy.

2. Methodology

This study employs a rigorous econometric framework to test the hypothesis that silver's price dynamics are increasingly influenced by the physical build-out of AI infrastructure. The methodology is designed to be transparent and replicable, utilizing established statistical techniques to analyze financial time-series data. We use Exchange-Traded Funds (ETFs) as liquid and transparent proxies for their respective asset classes.

2.1. Data selection and preparation

The analysis is based on daily closing prices for four ETFs, chosen to represent distinct market segments. Daily log-returns were calculated to ensure stationarity and to approximate continuously compounded returns, a standard practice in financial econometrics. The selected proxies are:

1. Silver: iShares Silver Trust (SLV). This ETF is physically backed by silver, providing a direct and liquid proxy for the commodity's spot price dynamics.

2. AI & Data Center Infrastructure: Pacer Benchmark Data & Infrastructure Real Estate SCTR ETF (SRVR). This thematic ETF tracks companies deriving revenue from data and infrastructure real estate, serving as a proxy for the capital-intensive AI infrastructure sector.

3. Non-Digital Economy (Control): Consumer Staples Select Sector SPDR Fund (XLP). This fund represents non-cyclical, traditional economic activity with minimal direct exposure to the digital infrastructure build-out, acting as a control variable.

4. Broader Technology Sector: Invesco QQQ Trust (QQQ). Tracking the Nasdaq-100 Index, this ETF is included to control for broader technology market sentiment and to provide a comparative benchmark.

The data for correlation analysis spans from January 1, 2021, to December 31, 2025[1]. The regression and EGARCH analyses utilize data from January 27, 2021, to December 31, 2025, comprising 1,286 daily observations. Both are based on daily returns based on their respective daily closing prices.[2]

2.2. Econometric models

2.2.1 Correlation analysis

To assess the co-movement between the assets, we compute Pearson product–moment correlation coefficients between the daily log-returns of the selected Exchange-Traded Funds. Let $r_{i,t}$ and $r_{j,t}$ denote the daily log-returns of assets i and j at time t. The Pearson correlation coefficient is defined as:

$$\rho_{ij} = \frac{\mathrm{Cov}(r_{i,t}, r_{j,t})}{\sqrt{\mathrm{Var}(r_{i,t})\ \mathrm{Var}(r_{j,t})}} = \frac{\sum_{t=1}^{T}(r_{i,t} - \bar{r}_i)(r_{j,t} - \bar{r}_j)}{\sqrt{\sum_{t=1}^{T}(r_{i,t} - \bar{r}_i)^2}\sqrt{\sum_{t=1}^{T}(r_{j,t} - \bar{r}_j)^2}} \tag{1}$$

where $\bar{r}_i$ and $\bar{r}_j$ denote the sample means of the respective return series and T represents the number of observations within the estimation window.

The full-sample correlation provides a baseline measure of linear dependence between asset returns. To capture temporal variation in co-movement and to identify potential structural changes over time, we additionally estimate rolling-window correlations. Specifically, the correlation coefficient is recomputed for each window of approximately 30 trading days, allowing the correlation structure to evolve dynamically. This rolling estimation approach enables the analysis of time-varying relationships between silver, AI infrastructure and traditional economic sectors and facilitates the identification of periods of strengthening or weakening co-movement.

2.2.2 Multiple linear regression

To quantify the explanatory power of the selected factors on silver's returns, we specify a multiple linear regression model using Ordinary Least Squares (OLS). The model is designed to isolate the impact of AI infrastructure while controlling for the broader technology market and the traditional economy. The formal specification is as follows:

$$R_{SLV,t} = \alpha + \beta_1 R_{SRVR,t} + \beta_2 R_{XLP,t} + \beta_3 R_{QQQ,t} + \varepsilon_t \tag{2}$$

Where:

- $R_{SLV,t}$ is the log-return of SLV on day t.
- $R_{SRVR,t}$, $R_{XLP,t}$ and $R_{QQQ,t}$ are the log-returns of the respective independent variables.
- α is the intercept term.
- β_1, β_2 and β_3 are the coefficients representing the sensitivity of silver's returns to each factor.
- ε_t is the error term, assumed to be independently and identically distributed.

[1]All correlation tables are the result of calculations made with "Portfolio Visualiser": https://www.portfoliovisualizer.com/

[2]Data were provided by Nasdaq's historical quotation and calculated using EViews

2.2.3 Conditional volatility modeling (EGARCH)

To analyze the volatility dynamics of silver, we employ an Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model, originally proposed by Nelson (1991). This specification is preferred to the standard GARCH framework due to its ability to capture two key empirical regularities commonly observed in financial return series: volatility clustering, whereby periods of high volatility tend to persist over time and asymmetric volatility responses, often referred to as leverage effects. In addition, the model is estimated under the assumption of Student's t-distributed innovations in order to accommodate the heavy-tailed (leptokurtic) nature of daily silver returns, a well-documented characteristic of precious metal markets.

The conditional variance of silver returns is modeled using an EGARCH$(1,1)$ specification augmented with exogenous variables, allowing volatility to respond not only to past shocks and past variance, but also to external market dynamics linked to the technology sector and AI infrastructure. The variance equation is specified as follows:

$$\ln(\sigma_t^2) = \omega + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta \ln(\sigma_{t-1}^2) + \delta_1 \, QQQ_{t-1} + \delta_2 \, SRVR_{t-1} \tag{3}$$

where σ_t^2 denotes the conditional variance of silver returns at time t and ε_{t-1} represents the lagged innovation from the mean equation. The logarithmic formulation of the variance ensures that the conditional variance remains strictly positive without imposing non-negativity constraints on the parameters.

The coefficient α captures the magnitude effect, measuring the impact of the absolute size of past standardized shocks on current volatility and thereby modeling volatility clustering. The parameter β represents volatility persistence, indicating the extent to which past conditional variance propagates into the present. Values of β close to unity are indicative of highly persistent volatility, a common feature in commodity markets.

The parameter γ governs the asymmetric response of volatility to past shocks. A statistically significant and positive value of γ implies that positive return shocks generate a stronger increase in volatility than negative shocks of the same magnitude, highlighting an asymmetric volatility structure in silver price dynamics.

Finally, the inclusion of lagged exogenous variables in the variance equation allows for direct testing of volatility spillovers from related financial markets. The term QQQ_{t-1} captures volatility transmission from the broader technology sector, while $SRVR_{t-1}$ proxies the influence of AI and data center infrastructure dynamics. This extended EGARCH framework enables an assessment of whether the digital infrastructure build-out affects not only the level of silver returns, but also the uncertainty surrounding those returns.

3. Results

This section presents the statistical findings from the correlation, regression and EGARCH analyses, based on market data for the specified time periods.

3.1. Correlation analysis results

The correlation matrix for the full 2021–2025 period is presented in Table 1, followed by the annual evolution of silver's correlation with the other assets in Table 2. These tables illustrate the evolving relationship between silver (SLV), AI infrastructure (SRVR), consumer staples (XLP) and the broader technology sector (QQQ).

Table 1: Asset correlation matrix (Jan 1, 2021 – Dec 31, 2025)

Asset	SLV	SRVR	XLP	QQQ
SLV	1.00	0.28	0.13	0.19
SRVR	0.28	1.00	0.41	0.65
XLP	0.13	0.41	1.00	0.52
QQQ	0.19	0.65	0.52	1.00

Table 2: Annual evolution of silver's correlation

Year	Correlation (SLV vs. SRVR)	Correlation (SLV vs. XLP)	Correlation (SLV vs. QQQ)
2021	0.32	0.31	0.41
2022	0.35	0.25	0.21
2023	0.31	0.21	0.17
2024	0.19	-0.11	0.05
2025	0.25	0.06	0.11

3.2. Multiple linear regression analysis results

The results of the multiple linear regression analysis, with SLV returns as the dependent variable, are summarized in Table 3. The analysis was conducted on February 3, 2026, using data from January 27, 2021, to December 31, 2025.

Table 3: Silver's returns regression results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C (Intercept)	0.000389	0.000211	1.840211	0.0660
SRVR	0.298371	0.053268	5.601312	0.0000
XLP	-0.025243	0.069722	-0.362049	0.7174
QQQ	0.153055	0.043020	3.557751	0.0004

Model Summary Statistics:

- R-squared: 0.080185
- Adjusted R-squared: 0.078032
- F-statistic: 37.25281

- Prob(F-statistic): 0.000000
- Observations: 1286

3.3. Conditional volatility analysis results

The results of the EGARCH(1,1) model with a Student's t-distribution are presented in Table 4. The model was estimated using data from January 28, 2021, to December 31, 2025.

Table 4: EGARCH Model Results for Dependent Variable SLV

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
C	0.000329	0.000196	1.679374	0.0931
Variance Equation				
Constant	-0.329759	0.129684	-2.542781	0.0110
ARCH Term	0.053820	0.025673	2.096350	0.0361
Leverage Term	0.052150	0.017554	2.970860	0.0030
GARCH Term	0.970248	0.012764	76.01460	0.0000
QQQ(-1)	-6.694531	3.483017	-1.922049	0.0546
SRVR(-1)	-2.286951	3.446294	-0.663597	0.5069
T-Distribution Parameter				
DOF	6.784172	1.438884	4.714885	0.0000

The high and statistically significant GARCH term ($C(5) = 0.970$) indicates strong volatility clustering. The positive and significant leverage term ($C(4) = 0.052$) suggests the presence of an asymmetric response, where positive shocks have a greater impact on volatility than negative shocks. The significant degrees of freedom (DOF) parameter confirms that the Student's t-distribution is a better fit for the fat-tailed nature of silver returns than a normal distribution.

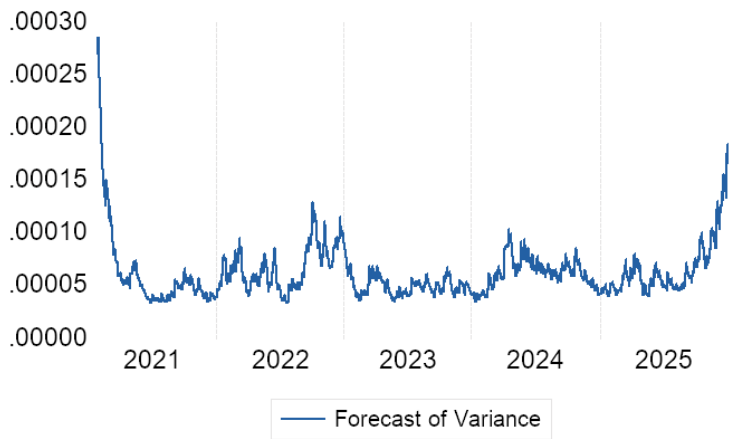

Figure 1: Forecasted conditional variance of silver based on historical returns

Figure 1 illustrates the conditional variance over the sample period, highlighting periods of heightened volatility, particularly in late 2024 and 2025.

4. The Hyperscaler CAPEX Cycle as a Fundamental Catalyst

The statistical relationship identified in our results is underpinned by a powerful fundamental driver: an unprecedented capital expenditure cycle led by technology hyperscalers. In 2024 alone, Amazon, Google and Microsoft collectively spent over $180 billion on CAPEX, with a significant portion allocated to AI infrastructure [13].

Projections for 2025–2026 indicate a further acceleration, with combined annual spending from major tech firms expected to exceed $200 billion and some estimates placing total hyperscaler CAPEX near $600 billion by 2026[3, 6, 9]. This spending is not discretionary; it is a strategic necessity to build the computational capacity required for next-generation AI models.

This "physical" build-out creates what Morgan Stanley has termed an "AI memory super cycle," characterized by demand that is less sensitive to price and traditional economic cycles [10]. The sheer scale of this investment establishes a high and inelastic demand floor for the specialized components and raw materials required for data center construction. As McKinsey analysis highlights, AI data centers require more advanced materials than traditional facilities, intensifying pressure on supply chains for critical inputs like silver[8]. This sustained, non-cyclical demand from a handful of the world's largest corporations acts as a powerful catalyst, fundamentally altering the demand-side equation for key industrial commodities.

5. Supply-Side Structural Deficits and Industrial Dominance

The demand shock from the AI sector is colliding with a silver market already defined by tight supply. For the fourth consecutive year, the global silver market recorded a structural deficit in 2024, with demand exceeding supply by 148.9 million ounces[17]. This imbalance is driven by record-breaking industrial demand, which reached 680.5 million ounces in 2024 and now accounts for over half of total silver consumption[1, 17]. This marks a profound shift from silver's historical role, where investment and jewelry were dominant drivers.

This trend is fueling a "decoupling" theory, where silver's price dynamics are becoming less correlated with its traditional monetary counterpart, gold and more aligned with its industrial utility [14]. Silver's unique properties—its unmatched electrical and thermal conductivity—make it virtually irreplaceable in high-performance applications such as high-frequency connectors, multi-layered circuit boards and power distribution systems essential for AI hardware [15]. As Goldman Sachs' former head of commodities research, Jeff Currie, has argued, the global economy is entering a new "super-cycle" driven by decarbonization and AI, leading to a "metallic transition" where the value of physical commodities essential for this infrastructure rises [2]. This structural shift, combined with persistent supply deficits, suggests that the industrial demand component of silver's valuation is becoming increasingly dominant.

6. Discussion

The empirical results, contextualized by the fundamental drivers of CAPEX and supply, provide compelling evidence that silver's market behavior is undergoing a structural transformation. The AI infrastructure build-out is not merely another source of demand; it represents a physical demand shock that is fundamentally altering the metal's economic identity.

The correlation analysis demonstrates a clear and progressive trend. The annual data in Table 2 shows that while the correlation between SLV and SRVR fluctuates, it remains consistently positive. More strikingly, the correlation between silver (SLV) and the consumer staples sector (XLP) shows a marked decline, falling from a positive 0.31 in 2021 to negative territory in 2024 (-0.11) before settling at a negligible 0.06 in 2025. This sharp decline signals that silver's role as an industrial commodity tied to technological expansion is beginning to eclipse its traditional, broader economic sensitivities. As Goldman Sachs Research has noted in a parallel context for copper, a significant portion of industrial metal demand growth is now driven by "grid and power infrastructure," a sector directly linked to data center expansion[5].

The multiple regression analysis reinforces this conclusion with greater statistical rigor. The model reveals that both AI infrastructure (SRVR) and the Nasdaq-100 (QQQ) are statistically significant positive predictors of silver's returns. The SRVR coefficient of 0.298 ($p < 0.001$) and the QQQ coefficient of 0.153 ($p = 0.0004$) confirm a strong link to the high-tech economy. Conversely, the consumer staples sector (XLP) remains statistically irrelevant ($p = 0.7174$), effectively isolating silver's sensitivity to the digital and technological spheres while demonstrating its detachment from the non-digital, defensive economy.

While an adjusted R-squared of 0.078 indicates that the model explains a modest portion of silver's total price variance, this is expected for a multifaceted commodity also influenced by monetary policy, investor sentiment and its role as a precious metal. The significance of the finding lies not in explaining all of silver's volatility, but in identifying a new, statistically robust and economically intuitive set of drivers. The fact that both the specific infrastructure (SRVR) and the broader tech index (QQQ) are significant suggests that silver is becoming a "high-tech industrial" commodity. The AI infrastructure build-out represents a significant incremental demand layer for silver, one that is relatively inelastic due to the metal's unique physical properties and the lack of viable substitutes in high-performance applications.

This emerging relationship challenges traditional asset allocation frameworks that categorize silver primarily as a precious metal correlated with gold or as a simple industrial commodity tied to the broad business cycle. Our findings suggest a more nuanced view is required, where silver acts as a hybrid asset with a growing beta to the high-growth, capital-intensive technology infrastructure sector.

7. Conclusion

This research paper set out to empirically test the relationship between silver and the physical infrastructure of the AI revolution. By transforming the narrative of AI's material demands into a testable hypothesis, we have moved beyond anecdotal evidence to provide quantitative validation.

Our analysis, based on correlation, multiple regression and EGARCH models using ETF proxies, yields several key conclusions. First, there is a clear decoupling of silver from traditional defensive sectors, with its correlation to consumer staples (XLP) diminishing toward zero over the 2021–2025 period. Second, regression analysis confirms that returns from both AI infrastructure (SRVR) and the broader technology sector (QQQ) are statistically significant, positive predictors of silver's returns. Third, this relationship persists even when controlling for the influence of the broader, non-digital economy, which shows no significant statistical link in our model. Finally, the EGARCH analysis reveals significant volatility clustering and an asymmetric response to market shocks, with a notable increase in conditional variance in the most recent period, suggesting heightened uncertainty.

The implications of these findings are significant. For investors and portfolio managers, this research highlights a potential new avenue for gaining exposure to the second-order effects of the AI boom, beyond software and semiconductor stocks. The demonstrated decoupling from traditional sectors suggests that silver may offer unique diversification benefits in portfolios, acting as a hedge against downturns in non-tech sectors while capturing upside from the digital infrastructure build-out. For commodity analysts, this study underscores the necessity of incorporating technology-driven industrial demand and its associated volatility into forecasting models for silver, as this new demand layer is structural, growing and relatively inelastic.

While this study provides a robust statistical foundation, further research could explore this relationship using more granular data, such as specific company revenues or physical commodity offtake figures. Nonetheless, the evidence presented strongly suggests that the AI revolution, while digital in output, is increasingly metallic in its inputs. Silver has emerged as a critical enabler of this transformation and its market dynamics are beginning to reflect this new economic reality.

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