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Causal analysis of macroeconomic shocks on financial markets through machine learning methods

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ABSTRACT

Macroeconomic announcements often trigger sharp market reactions; however, their causal impact is difficult to measure. This study quantifies the causal effects of the consumer price index (CPI), non-farm payrolls (NFP), and Federal Open Market Committee (FOMC) decisions on the S&P 500, Gold, and the VIX using daily data from 2022 to 2024. Three estimators are applied: Ordinary Least Squares, Propensity Score Matching, and Double Machine Learning. The results show limited price adjustments but strong and statistically meaningful volatility responses. FOMC shocks generate the most persistent effects, whereas CPI and NFP impacts are short-lived. Overall, the findings indicate that volatility, rather than prices, is the primary transmission channel of macroeconomic news, highlighting the value of causal machine learning in identifying structural market responses.

Keywords: double machine learning; macroeconomic announcements; propensity score matching; S&P 500

1. INTRODUCTION

The causal relationship between macroeconomic shocks and financial markets has long been a central matter in empirical economics and finance (Andersen et al., 2003; Boyd et al., 2005; Bernanke & Kuttner, 2005). Macroeconomic announcements, such as the consumer price index (CPI), non-farm payrolls (NFP), and Federal Open Market Committee (FOMC) decisions, are often associated with significant market reactions; thus, identifying the relationship between them remains a methodological challenge (Andersen et al., 2003). This study contributes to the literature by adopting a causal machine learning perspective to quantify the structural effects of these macroeconomic shocks on asset prices and volatility.

In recent years, the link between macroeconomic announcements and financial markets has become even stronger due to persistent inflationary pressures, tightening monetary policies, and rising uncertainty about the future of the economy, which have characterized global economic conditions. During periods such as 2021–2024, markets have shown how rapidly, and often in a non-linear way, they can react to new information, as investors continuously adjust their expectations to realized macroeconomic outcomes. In this environment, macroeconomic news such as CPI, NFP, and FOMC decisions play a significant informational role, providing signals on price stability, labor market conditions, and monetary policy orientation. These announcements influence both expectations related to the future path of interest rates and economic activity and risk perception and overall market sentiment. Therefore, understanding how markets react to these signals and whether such relationships can be interpreted as causal rather than correlational is extremely important.

Financial markets are highly responsive to macroeconomic news, particularly during periods of high inflation, changes in monetary policy, and as recently happened with the COVID-19 pandemic. Prior research has widely examined how economic announcements shape market behavior using different approaches, such as event studies to measure unusual returns (Boyd et al., 2005; Flannery & Protopapadakis, 2002) and econometric models like VAR and GARCH to analyze volatility dynamics (Engle, 1982; Sims, 1980; Baumeister & Hamilton, 2015). More recent studies have introduced advanced econometric and data–driven frameworks, including structural VARs for policy identification (Baumeister & Hamilton, 2015), regime switching and stochastic volatility models (Kim & Nelson, 1999), and machine learning-based models for high-dimensional prediction (Gu et al., 2020). However, both traditional and modern methods often rely on statistical associations rather than causal relationships, as they depend on linear specifications and have limited capacity to manage complex, high–dimensional data to identify the true causal effects of macroeconomic shocks on asset returns and volatility.

The choice of the 2022–2024 period is a key factor in the analysis as it incorporates an exceptionally unstable environment. These years were characterized by episodes of high inflation, aggressive monetary policies, and geopolitical uncertainty, which reshaped market expectations. Therefore, financial markets suffered from frequent repricing and high volatility, making announcement days highly informative regarding how investors absorb new information about inflation dynamics, labor market strength, and policy direction. This analysis offers a unique opportunity to study how the market reacts to specific phases, providing highly relevant settings for understanding how macroeconomic news and financial assets are linked.

The motivation for this research stems from the limitations of traditional econometric techniques. Recent advances in machine learning have provided new tools for causal inference that allow flexible modelling while maintaining statistical rigor (Chernozhukov et al., 2018). This study aims to bridge the gap between traditional econometric approaches and modern data–driven causal inference by applying double machine learning, propensity score matching, and OLS least squares backdoor estimation to financial market data.

Despite the growing interest in machine learning applications in finance, few studies have explicitly addressed causal estimation in the context of macroeconomic shocks. Most research focuses on predictive accuracy rather than on identifying true structural relationships. Recent advances in deep learning and ensemble models have improved the prediction of asset prices, volatility, and risk (Gu et al., 2020; Chen et al., 2021), these methods primarily uncover correlations rather than causal mechanisms. Consequently, they provide limited insight into how macroeconomic events effectively drive financial market behavior.

Addressing some of these issues, this work proposes employing causal machine learning methods to isolate the direct effects of CPI, NFP, and FOMC announcements (D_t^j) on key financial assets (Y_t^i) (S&P 500, Gold (XAUUSD), and the VIX index) during the 2022–2024 period. We aim to provide both methodological advancements and practical insights into how markets process new economic information. In doing so, the analysis reduces potential bias from confounding factors and misspecification by relying solely on causal interpretations. While maintaining a strict statistical framework, the use of double machine learning and propensity score matching allows more flexibility in handling high–dimensional data, non–linear relationships, and heterogeneous market responses, resulting in a more accurate evaluation of the impact of macroeconomic announcements on financial markets.

The diverse ways in which macroeconomic announcements impact financial markets provide an additional reason for their relevance. Equity indices, such as the S&P 500, reflect expectations regarding economic growth, corporate profitability, and general business conditions, making them highly sensitive assets that alter perceptions of the macroeconomic outlook. In contrast, gold is often associated with a safe asset and a store of value, particularly during periods of high inflation or uncertainty, providing valuable insights into how markets hedge against macroeconomic risk. In addition, the VIX index provides direct information on implied volatility and investor risk perception, reflecting how markets assess uncertainty. By analyzing these three assets together, it is possible to understand how macroeconomic shocks propagate through prices and risk sentiment rather than focusing on a single dimension.

The remainder of this paper is organized as follows. Section 2 describes the dataset and preprocessing steps. Section 3 illustrates the causal machine learning frameworks employed, including OLS, Propensity Score Matching (PSM), and Double Machine Learning (DML). Section 4 presents the empirical findings, comparing the benchmark estimates obtained from linear models with causal results and robustness checks. Section 5 discusses the economic and methodological implications of these results, outlines directions for future research, and concludes the study.

2. DATA SOURCES, VARIABLES, AND PREPROCESSING

The analysis was based on publicly available financial time-series data obtained from Kaggle.com. Three representative assets were selected to capture different market behaviors: the S&P 500 index, CBOE volatility index (VIX), and gold (XAU/USD).

The analysis covers a period from January 2021 to April 2024 to ensure that periods with inflation shocks, monetary policy shifts, and post-pandemic stabilizations were included; 2021 data were included later for robustness checks. Observations were collected daily, providing sufficient precision to capture market responses to macroeconomic announcements. The main sample comprises 505 daily observations, including 16 CPI releases, 9 NFP releases, and 9 FOMC meetings, plus 223 daily observations and 5 CPI shocks for the 2021 robustness period.

2.1. Financial Variables

For each asset i, the following variables were formulated. First, we used **logarithmic returns** as the outcome variable.

$$r_t^i = \ln\left(\frac{P_t^i}{P_{t-1}^i}\right) \tag{1}$$

With P_t^i indicating the price of asset i at time t.

Second, **momentum indicators**, such as the Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD). The Relative Strength Index measures the magnitude of recent price changes for asset i based on its price series P_t^i. Defined as:

$$\mathrm{RSI}_t^i = 100 - \frac{100}{(1+RS_t^i)} \quad (2), \quad \mathrm{RS}_t^i = \frac{Average\ Gain_t^i}{Average\ Loss_t^i} \tag{3}$$

where *Average Gain* and *Average Loss* are computed from the positive and negative variations in P_t^i over a fixed window (14 periods) (Wilder, 1978). The MACD indicator captures momentum by comparing short- and long-term exponential moving averages (EMA) of the price P_t^i. Defined as:

$$MACD_t^i = EMA_{12}(P_t^i) - EMA_{26}(P_t^i) \tag{4}$$

A signal line is then computed as a 9-period exponential moving average of $MACD_t^i$, used to identify trend reversals (Appel, 1979).

Third, **historical volatility** is computed as the rolling standard deviation of returns. Historical volatility reflects the dispersion of returns for asset i over a moving window of n observations, computed as the rolling standard deviation of past logarithmic returns r_t^i:

$$\sigma_t^i = \sqrt{\frac{1}{n-1}\sum_{k=t-n+1}^{t}\left(r_k^i - \bar{r}^i\right)^2} \tag{5}$$

where $\bar{r}^i$ denotes the mean return of asset i over the same window (Hull, 2018).

Fourth, **trading volume** is used as a proxy for market activity. Trading volume represents the total quantity of asset i traded during period t. To ensure comparability across assets, it can be normalized by the sample mean volume.

$$Vol_t^i = \frac{V_t^i}{\bar{V}^i} \tag{6}$$

where V_t^i is the raw trading volume and $\bar{V}^i$ its average over the sample period (Hull, 2018).

Fifth, **lagged return** levels capture short-term dependencies. Lagged returns capture short-term temporal dependence in asset performance and serve as control variables in causal models. They are defined as:

$$Lag_r^i = \{r_{t-1}^i, r_{t-2}^i, \ldots, r_{t-p}^i\} \tag{7}$$

where p is the number of lags considered

2.2. Data Cleaning

The data cleaning process involved data alignment across assets, correction of formatting irregularities (as for the VIX), and removal of missing entries or duplicate observations. All variables were then aligned to a common tradingday calendar to ensure consistency and comparability across the dataset.

3. METHODS

3.1. Macroeconomic Shocks and Treatment Framework

Macroeconomic shocks were labelled as binary treatment variables defining the occurrence of three major macroeconomic announcements. First, **the Consumer Price Index (CPI)**, representing inflation shocks (U.S. Bureau of Labor Statistics, 2024). The CPI measures the average change in the prices paid by consumers for a basket of goods and services in a given period. The corresponding inflation rate is computed as:

$$\pi_t = \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}} \times 100 \tag{8}$$

Second**, Non-Farm Payrolls (NFP)**, which represent labor-market shocks (U.S. Bureau of Labor Statistics, 2024). NFP measures the monthly change in total paid employment, excluding the farm, household, and non-profit sectors. Expressed as:

$$NFP_t^{growth} = \frac{NFP_t - NFP_{t-1}}{NFP_{t-1}} \times 100 \tag{9}$$

Third**, the Federal Open Market Committee (FOMC)** represents interest rate shocks (Board of Governors of the Federal Reserve System, 2024). The FOMC sets the target federal funds rate (i^{target}); the corresponding policy shock is expressed as:

$$\Delta i_t = i_t^{target} - i_{t-1}^{target} \tag{10}$$

For each macroeconomic event type j, a treatment indicator $D_t^{(j)}$ takes the value 1 on announcement days and 0 otherwise.

$$D_t^j = \begin{cases} 1, & \text{if a macroeconomic announcement of type } j \text{ occurs on day } t, \\ 0, & \text{otherwise.} \end{cases} \tag{11}$$

This framework allows the estimation of the **Average Treatment Effect (ATE)** of macroeconomic news on financial returns Y_t^i using observational data. The ATE measures the expected difference in outcomes between treated and untreated states and is defined as

$$ATE^j = \mathbb{E}(Y_t^i(1) - Y_t^i(0)) \tag{12}$$

where: (1) $Y_t^i(1)$ represents the potential outcome (return) of asset $i$when exposed to a macroeconomic shock of type j, (2) $Y_t^i(0)$represents the outcome in the absence of that shock, and (3) $\mathbb{E}()$denotes the **expected value operator**, which averages the causal effect across all observations.

The analysis considers three financial assets ($i \in \{\text{S\&P 500, VIX, Gold}\}$) and three macroeconomic shocks ($j \in \{\text{CPI, NFP, FOMC}\}$), allowing cross-asset evaluation of causal market reactions; with 9 treatment–outcome pairs.

3.2. Econometric and Causal Framework

Three complementary approaches were used to estimate the treatment effects and to assess robustness. First, **we used Ordinary Least Squares (OLS) with backdoor adjustment.** OLS (Wooldridge, 2010) is used as a Benchmark model for the control of pre-treatment covariates (X_t) (lagged returns, lagged VIX, and technical indicators). The estimated regression equation is as follows:

$$Y_t^i = \alpha + \beta D_t^j + \gamma' X_t + \varepsilon_t \tag{13}$$

where: (1) Y_t^i is the return of asset i at time t; (2) D_t^j is the treatment variable indicating exposure to the macroeconomic shock of type j; (3) X_t is the vector of pre-treatment controls, and (4) ε_t is the error term.

To reduce autocorrelation and heteroskedasticity, Newey–West HAC standard errors were applied (Newey & West, 1987). This specification isolates the direct causal relationship and minimizes bias by controlling for mediators. First, **Propensity Score Matching (PSM)** was performed. As Rosenbaum and

Rubin (1983) explained the **propensity score** represents the conditional probability of receiving the treatment given observed covariates X_t, and is defined as:

$$p(X_t) = \Pr(D_t = 1 \mid X_t) \qquad (14)$$

Where D_t is a binary variable equal to 1 if the observation is exposed to the macroeconomic shock and 0 otherwise, and Pr () stands for probability of Dt = 1 conditioned to X_t. The propensity score $p(X_t)$ was estimated using **logistic regression**, and treated observations were then matched to the nearest untreated neighbours within a predefined caliper distance. This procedure balances the covariate distribution between the treated and control units, approximating the conditions of a randomized experiment.

The **Average Treatment Effect on the Treated (ATT)** is then computed as

$$ATT = \mathbb{E}(Y_t(1) - Y_t(0) \mid D_t = 1) \qquad (15)$$

where $Y_t(1)$ and $Y_t(0)$ denote the potential outcomes under treatment and non-treatment, respectively.

3.3. Double Machine Learning (DML)

The DML method estimates the treatment effects while controlling for potential confounders. In the first step, machine learning (ML) models, such as Random Forest, are used to predict both the treatment and outcome using all available covariates. In the second step, the remaining unexplained parts (i.e., the residuals) are used to estimate the causal effects. This two-step approach reduces bias and overfitting, and the use of cross-fitting helps keep the estimation independent and reliable.

Formally, the DML estimator follows a two-stage orthogonalization procedure.

$$\tilde{Y}_t = Y_t - \widehat{m}(X_t), \qquad (16)$$
$$\widetilde{D}_t = D_t - \hat{g}(X_t), \qquad (17)$$
$$\hat{\theta}_{DML} = \frac{\mathrm{Cov}(\tilde{Y}_t, \widetilde{D}_t)}{\mathrm{Var}(\widetilde{D}_t)} \qquad (18)$$

where: (1) $\widehat{m}(X_t)$ and $\hat{g}(X_t)$ are machine learning predictions of the outcome and the treatment, respectively, given covariates X_t; (2) $\tilde{Y}_t$ and $\widetilde{D}_t$ are their residuals, and (3) $\hat{\theta}_{DML}$ represents the estimated.

3.4. Average Treatment Effect (ATE).

All estimations were performed in Python, using EconML for DML, Statsmodels for OLS, and Scikit learn for auxiliary models (Chernozhukov et al., 2018).

4. RESULTS AND DISCUSSION

4.1. Results

4.1.1. Benchmark Results (OLS)

The results show heterogeneous market responses to macroeconomic shocks across assets and event types. Preliminary diagnostics confirmed that the time series were stationary and properly aligned after preprocessing. As illustrated in Figure 1, the benchmark OLS estimates indicate that CPI and NFP announcements have limited and mostly statistically insignificant short-term effects on both returns and volatility, whereas FOMC decisions generate more persistent impacts. Specifically, the S&P 500 shows small coefficients following unexpected CPI increases and weaker employment releases, consistent with investor expectations that are sensitive to inflation and growth conditions. The VIX displayed mild positive responses around the same events, confirming its countercyclical nature. Gold tends to appreciate during periods of higher inflation or labor market uncertainty, supporting its role as a defensive asset.

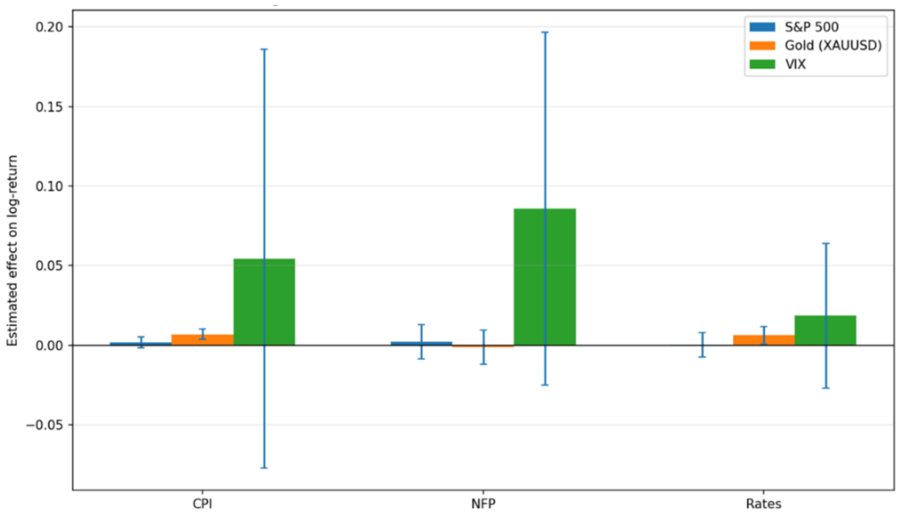

Figure 1. OLS Benchmark Estimates of CPI, NFP, and FOMC Shocks on S&P 500, Gold, and VIX (2022–2024)

4.1.2. Causal Results: PSM and DML

The causal estimators reinforce the evidence from the benchmark model while improving precision. The PSM framework (Rosenbaum & Rubin, 1983) confirms that matched treated observations experience larger absolute return responses than their matched controls, particularly following NFP and, more moderately, CPI shocks and FOMC rate decisions. This implies that market reactions are not purely correlational but reflect genuine causal effects once the pre-event conditions are balanced.

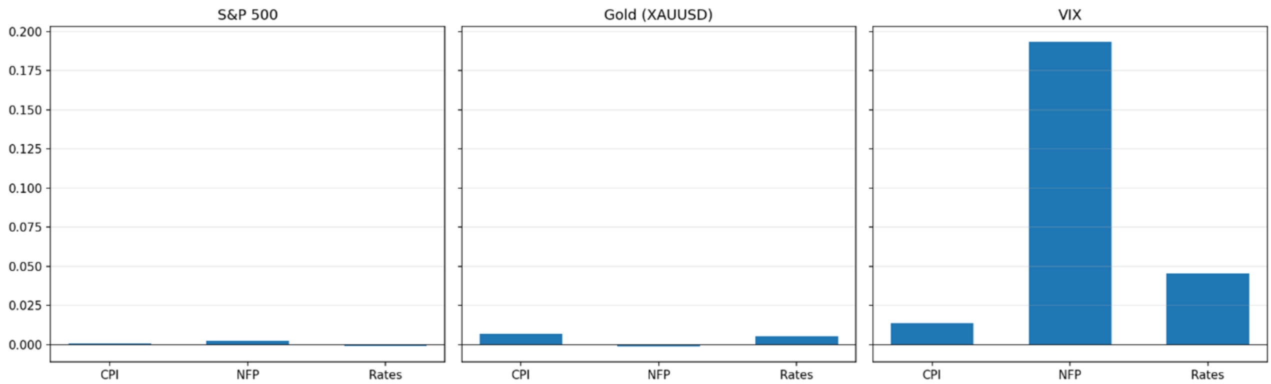

Figure 2. Average Treatment Effects Estimated Via Propensity Score Matching (PSM) Across Assets and Shocks

The DML results extend these findings by accounting for nonlinearities and high-dimensional confounding (Chernozhukov et al., 2018). The estimated treatment effects generally have a stronger magnitude and are more stable across specifications. DML detects interaction effects between volatility indicators and lagged returns, showing asymmetric responses: large inflation surprises generate stronger volatility spikes in the VIX than in the proportional declines in the S&P 500. Across all assets, DML generated more precise and directionally consistent estimates, confirming its robustness compared to traditional econometric methods.

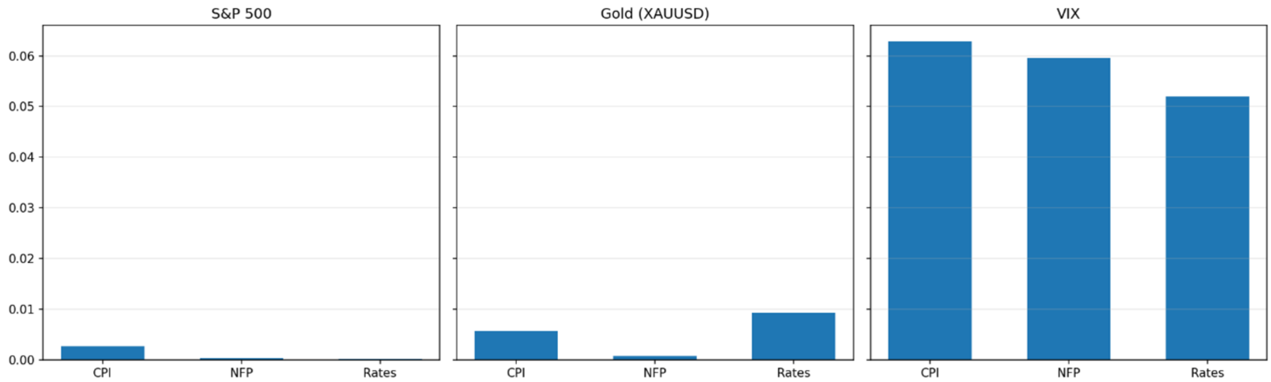

Figure 3. Double Machine Learning (DML) Causal Estimates Controlling for Nonlinearities and Confounding

4.1.3. Robustness Checks

Several robustness checks validate the consistency of the estimated causal relationship. Re-estimations over two distinct subperiods (2021–2022 and 2023–2024) show broadly stable effects for the S&P 500 and gold, while the VIX exhibits stronger and directionally different responses in the more recent period, reflecting increased sensitivity to macroeconomic shocks. Alternative model specifications, including adjustments in hyperparameters and window lengths, generate qualitatively similar conclusions. The persistence of the FOMC effect across time horizons, together with the transitory nature of CPI and NFP shocks, suggests that monetary policy decisions exert a deeper and more prolonged influence on financial markets. Overall, the results provide consistent evidence of economically meaningful causal effects on major financial assets, with heterogeneous sensitivities that align with their underlying market functions.

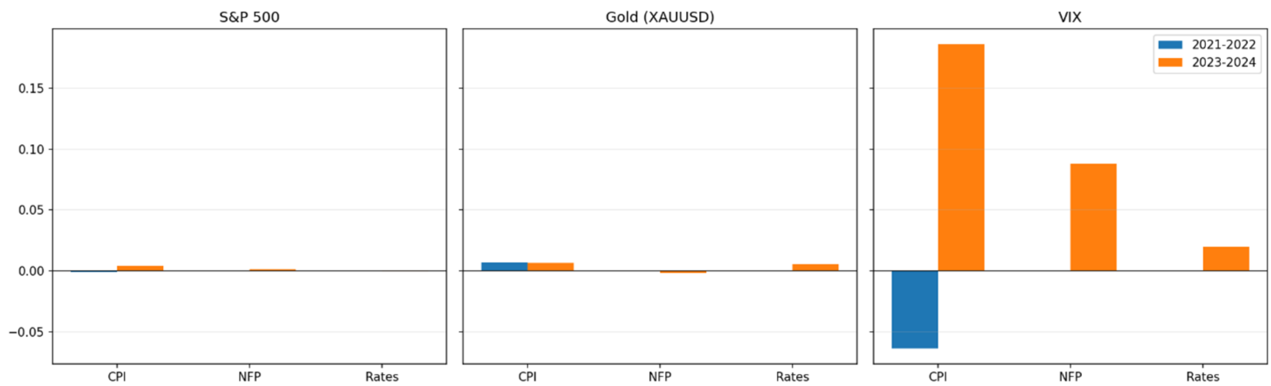

Figure 4. Temporal Robustness of Causal Effects: Comparison Between 2021–2022 And 2023–2024

4.2. Discussion

4.2.1. Market Dynamics

As illustrated in Figure 1, the analysis reveals that the impact of major macroeconomic shocks on financial markets is predominantly nonlinear and heterogeneous. The OLS coefficients, which are weak and statistically insignificant, confirm that traditional linear models fail to capture short-term market adjustments, as asset prices usually react asymmetrically to the latest information. Commodities and equity returns tend to be partially anticipatory, whereas volatility reacts more directly to uncertainty. This pattern suggests that financial markets gradually adjust to new macroeconomic information, with volatility acting as the primary channel through which these shocks are transmitted.

4.2.2. Causal Evidence and Temporal Robustness

As shown in Figure 2 and Figure 3, causal estimators provide stronger and more interpretable evidence. By balancing pre-event conditions and accounting for non-linear dependencies, PSM and DML isolate the genuine causal effect that may be obscured by traditional approaches. Both methods show that inflation and labor market shocks mainly influence volatility rather than price levels, reinforcing the view that short-term market dynamics are driven more by uncertainty than by the news itself. Temporal robustness analysis (see Figure 4) further indicates that volatility has become increasingly sensitive to macroeconomic information in the post-pandemic period, whereas gold and equity responses have remained relatively stable. The lasting effect of FOMC decisions suggests that monetary policy communication remains a key stabilizing factor for market expectations.

A wider interpretation of the results highlights the key role of expectations in the market when reacting to macroeconomic news. Instead of reacting mechanically to released data, financial markets seem to react by updating their expectations of inflation, monetary policy, and growth. This is coherent with the logic that investors re-evaluate their expectations and update their perceptions of risk. In this regard, the fact that volatility has a stronger reaction to macroeconomic news than returns shows that uncertainty and risk are the primary factors used by the market to distribute the effects of the news itself. In addition, the diversified reactions distributed across equity markets, gold, and implied volatility suggest that investors are continuously reallocating capital and modifying their hedge exposure sentiment, resulting in multiple adjustments rather than a simple price reaction.

These dynamics highlight that macroeconomic announcements operate as a coordination tool for the financial market rather than a simple information delivery device. Announcement days create crucial moments for investors to reorganize their beliefs and realign their strategies. This is why immediate and permanent price adjustments are rarely seen in the market. As a result, market corrections tend to present changes in sentiment, hedging strategies, and strategic positioning rather than through direct price movements.

4.2.3. Comparisons with State-of-the-Art Methods

To clearly position the proposed methodology within the existing empirical finance and economics literature, this section provides a structured comparison with state-of-the-art approaches commonly adopted to analyze the effects of macroeconomic announcements on financial markets, with a specific emphasis on the distinction between predictive and causal machine learning frameworks. Earlier contributions to the macro–financial literature have primarily relied on event-study methodologies (Andersen et al., 2003; Boyd et al., 2005), linear and structural VAR models (Sims, 1980; Bernanke & Kuttner, 2005; Baumeister & Hamilton, 2015), and GARCH-type models for volatility dynamics (Engle, 1982). While these approaches provide valuable insights into average market responses and dynamic interactions, they are largely correlation-based and depend on strong parametric and linear assumptions. Consequently, their ability to isolate structural causal effects is limited, particularly in the presence of nonlinearities, heterogeneous responses, and high-dimensional confounding. Recently, predictive machine learning methods have been introduced into asset pricing and financial forecasting, demonstrating substantial gains in out-of-sample predictive accuracy (Gu et al., 2020; Chen et al., 2021). These models, including random forests, neural networks, and ensemble learners, are particularly effective at capturing complex, nonlinear patterns and interactions in large datasets. However, their primary objective was prediction rather than inference. As such, the estimated relationships are not directly interpretable as causal effects, limiting their usefulness for policy analysis and structural economic interpretations.

The methodological novelty of this study lies in explicitly bridging predictive machine learning and causal inference within a unified empirical framework. By combining traditional OLS backdoor adjustment with Propensity Score Matching (Rosenbaum & Rubin, 1983) and Double Machine Learning (Chernozhukov et al., 2018), the proposed approach leverages the flexibility of modern ML algorithms while preserving a well-defined causal interpretation. In particular, predictive ML models are employed as auxiliary tools within the DML framework to partially out high-dimensional confounders rather than as final predictive models. This distinction is crucial because machine learning is used here to improve the identification and robustness of causal estimates, not merely to maximize forecasting performance. Table X summarizes the key differences between representative state-of-the-art approaches and the proposed framework, highlighting the contribution of this study in addressing the predictive–causal trade-off that characterizes much of the recent financial machine learning literature (see Table 1).

Table 1. Key Differences between Representative State-of-the-Art Approaches and the Proposed Framework

Methodological Approach	Representative References	Primary Objective	Treatment of Nonlinearities	Causal Interpretability	Limitations	Contribution of This Paper
Event Studies	Andersen et al. (2003); Boyd et al. (2005)	Short-term reaction measurement	Low	Weak	Window sensitivity; correlational	Used as conceptual benchmark only
VAR / SVAR Models	Sims (1980); Bernanke & Kuttner (2005); Baumeister & Hamilton (2015)	Dynamic interactions	Low–Medium	Medium (model-dependent)	Strong parametric assumptions	Replaced by data-driven causal ML
GARCH-type Models	Engle (1982)	Volatility dynamics	Low	Weak	No direct causal isolation	Complements causal volatility analysis
Predictive ML	Gu et al. (2020); Chen et al. (2021)	Forecasting accuracy	High	None	Lack of economic interpretation	Embedded within causal estimation
PSM	Rosenbaum & Rubin (1983)	Causal inference	Medium	Strong (CIA)	Matching sensitivity	Applied to macro announcements
DML	Chernozhukov et al. (2018)	Structural causal effects	High	Strong	Computational complexity	Core methodological contribution

Overall, the comparison highlights that the main advancement of this study relative to the state of the art is the explicit separation between predictive power and causal interpretation. By embedding machine learning within a principled causal inference framework, this study focuses on interpretability and policy relevance, providing robust evidence on how macroeconomic announcements causally affect asset prices and market volatility, rather than merely predicting their co-movements.

5. CONCLUSION AND FUTURE RESEARCH

This study investigated the causal impact of major macroeconomic shocks, such as CPI, NFP, and FOMC announcements, on primary financial assets (S&P 500, gold, and the VIX), to gain a better understanding of how financial markets absorb and transmit macroeconomic information through price and volatility dynamics. The analysis combined traditional econometric techniques with causal ML approaches, including OLS, Propensity Score Matching (PSM), and Double Machine Learning (DML), using data from 2021 to 2024 to capture multiple global events to distinguish causal effects from simple correlations.

These findings demonstrate the value of combining causal inference with machine learning algorithms to identify the structural effects in complex financial data. The proposed framework enhances the reliability and interpretability of estimates, effectively linking ML prediction with economic theory. From an investor's perspective, the results highlight the role of volatility and gold as hedges against this uncertainty. In particular, the market's sensitivity around announcement days suggests that investors should incorporate macroeconomic calendars and policy expectations into their risk management strategies. The VIX appears to be an important transmission channel of uncertainty, which indicates that different expectations and sentiments can be as important as movements in prices. These insights can support portfolio allocation, hedging strategies, and short–term positions not only in turbulent periods but also in normal situations. From a policymaker's standpoint, the importance of clear communication to avoid destabilizing markets is emphasized. The results indicate that macroeconomic releases influence both price levels and risk perception; therefore, transparency and factual guidance can help reduce volatility and prevent re-pricing episodes.

Future research could extend this approach to cross-market or high-frequency data and alternative shock types (geopolitical, fiscal, or environmental) to better understand how global uncertainty propagates through financial systems. Further developments may also explore heterogeneous effects across investor categories, market regimes, and geographical regions, as well as the role of alternative financial instruments, such as bonds, exchange rates, and derivatives. From a methodological standpoint, the current framework can be improved with additional causal machine learning techniques to improve the robustness and applicability of the results. Finally, by distinguishing more precisely between expectation and driven and surprise–driven components of announcements, we can understand the mechanism through which macroeconomic shocks affect financial markets.

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Ethical approval

Not Applicable

Informed consent statement

Not Applicable

Authors' contributions

SC contributed to the conceptualization of the study, research design, data collection, implementation of empirical models, formal analysis, interpretation of the findings, and drafting of the manuscript. FB contributed to the development of the methodology, supervision of the analytical framework, critical review of the results, and revision and editing of the manuscript. Both authors contributed substantially to the study's development and approved the final version of the manuscript.

Disclosure statement

The authors declare no conflicts of interest.

Data availability statement

The data presented in this study are available on request from the corresponding author due to privacy reasons.

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REFERENCES

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Vega, C. (2003). Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American Economic Review, 93*(1), 38–62. https://doi.org/10.1257/000282803321455151

Appel, G. (1979). *The moving average convergence divergence (MACD) trading method*. Financial Insights.

Baumeister, C., & Hamilton, J. D. (2015). Sign restrictions, structural vector autoregressions, and useful prior information. *Econometrica, 83*(5), 1963–1999. https://doi.org/10.3982/ECTA12356

Bernanke, B. S., & Kuttner, K. N. (2005). What explains the stock market's reaction to Federal Reserve policy? *The Journal of Finance, 60*(3), 1221–1257. https://doi.org/10.1111/j.1540-6261.2005.00760.x

Board of Governors of the Federal Reserve System. (n.d.). *Meeting calendars and information*. Retrieved December 30, 2025, from https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm

Boyd, J. H., Hu, J., & Jagannathan, R. (2005). The stock market's reaction to unemployment news: Why bad news is usually good for stocks. *The Journal of Finance, 60*(2), 649–672. https://doi.org/10.1111/j.1540-6261.2005.00742.x

Chen, L., Pelger, M., & Zhu, J. (2024). Deep learning in asset pricing. *Management Science, 70*(2), 714–750. https://doi.org/10.1287/mnsc.2023.4695

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W. K., & Robins, J. M. (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal, 21*(1), C1–C68. https://doi.org/10.1111/ectj.12097

Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*(4), 987–1007. https://doi.org/10.2307/1912773

Flannery, M. J., & Protopapadakis, A. A. (2002). Macroeconomic factors do influence aggregate stock returns. *The Review of Financial Studies, 15*(3), 751–782. https://doi.org/10.1093/rfs/15.3.751

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies, 33*(5), 2223–2273. https://doi.org/10.1093/rfs/hhaa009

Hull, J. C. (2018). *Options, futures, and other derivatives* (10th ed.). Pearson. https://books.google.com/books/about?id=vpIYvgAACAAJ

Kim, C.-J., & Nelson, C. R. (1999). *State-space models with regime switching: Classical and Gibbs-sampling approaches with applications*. MIT Press. https://mitpress.mit.edu/9780262112383/state-space-models-with-regime-switching/

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica, 55*(3), 703–708. https://doi.org/10.2307/1913610

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica, 48*(1), 1–48. https://doi.org/10.2307/1912017

U.S. Bureau of Labor Statistics. (n.d.). *Economic news releases*. Retrieved December 30, 2025, from https://www.bls.gov/news.release/

Wilder, J. W. (1978). *New concepts in technical trading systems*. Trend Research. https://books.google.com/books/about?id=WesJAQAAMAAJ

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press. https://mitpress.mit.edu/9780262232586/econometric-analysis-of-cross-section-and-panel-data/