Do Federal Reserve Rate Decisions Increase Stock Market Volatility? An Empirical Analysis Using EGARCH and ARCH-X Models

Sejal Kalra[1]

[1]*University of Waterloo*
[1] *s27kalra@uwaterloo.ca* *

Keywords: *volatility, monetary policy, FOMC announcements, interest rate changes, GARCH, EGARCH, ARCH-X, financial markets, S&P 500, event-day effects, t-distribution*
JEL Classification Codes: *C22, C58, E44, E52, G14*

Compiled November 25, 2025

This paper investigates whether Federal Reserve monetary policy announcements—particularly interest rate decisions—generate measurable changes in U.S. equity market volatility. Using daily S&P 500 returns from 2010 to 2024, we estimate a series of volatility models and find that an asymmetric EGARCH (1,1) specification with heavy-tailed Student-t errors provides the best overall fit for the data, capturing strong volatility persistence, fat tails, and leverage effects (Engle, 1982; Bollerslev, 1986; Nelson, 1991). However, when announcement-day indicators are introduced directly into the EGARCH variance equation, their coefficients are statistically insignificant, reflecting the model's high persistence (Savor & Wilson, 2014). To better isolate short-run announcement effects, we employ simpler ARCH-X and ARX specifications that allow volatility to respond more flexibly to exogenous events (Bollerslev, 1987). Across these models, rate-change announcements are associated with a significant increase in realized volatility, whereas routine meetings show little effect (Bernanke & Kuttner, 2005; Kuttner, 2001). The evidence suggests that unexpected policy actions, rather than scheduled meetings that confirm expectations, generate meaningful volatility responses in equity markets (Gürkaynak, Sack, & Swanson, 2005; Bomfim, 2003).

1. INTRODUCTION

Monetary policy announcements made by the Federal Open Market Committee (FOMC) are among the most influential regularly scheduled information releases in global financial markets (Bernanke & Kuttner, 2005). While investors often anticipate broad policy trajectories, the precise details conveyed at each meeting—particularly changes to the federal funds target rate—can generate substantial uncertainty about future economic and financial conditions (Gürkaynak, Sack, & Swanson, 2005). This uncertainty does not necessarily appear in the direction of stock price movements but is frequently reflected in fluctuations in return volatility (Bomfim, 2003). Understanding how FOMC announcements affect equity-market volatility is therefore critical for evaluating the transmission of monetary policy, the pricing of risk, and the short-run behaviour of financial markets.

A large literature examines how markets respond to macroeconomic and policy announcements, with particular emphasis on the Fed's role in shaping risk sentiment. Studies such as Bernanke and Kuttner (2005) and Gürkaynak et al. (2005) highlight the strong influence of unexpected policy decisions on asset prices. More recent work documents that monetary policy shocks can generate sharp, short-lived bursts of volatility across equity, fixed-income, and foreign exchange markets (Savor & Wilson, 2014; Bomfim, 2003). However, evidence varies depending on the frequency of data, the choice of volatility model, and the way policy shocks are defined. While intraday studies often find large reactions around the announcement window, daily return analyses produce more mixed results, partly because daily volatility models absorb substantial persistence unrelated to specific events (Schwert, 1989).

In this paper, we examine whether FOMC announcements produce measurable increases in daily equity-market volatility over the 2010–2024 period. Using daily S&P 500 log-returns, we employ a set of complementary econometric models designed to isolate short-run volatility responses to monetary policy decisions. Our analysis begins with an AR(1)–EGARCH(1,1) specification with Student-t innovations, a model widely used to characterize the key statistical features of equity returns, including volatility clustering, negative shock asymmetry, and heavy tails (Engle, 1982; Bollerslev, 1986; Nelson, 1991). This baseline allows us to document the underlying dynamics of market volatility and evaluate whether announcement-day effects persist once long-memory volatility components are accounted for.

To capture event-driven volatility responses more precisely, we extend our analysis beyond the EGARCH framework using simpler, event-focused specifications. First, we estimate a variance regression based on log squared daily returns, analogous to an ARCH-X model, where FOMC announcement indicators enter directly into the variance equation (Engle, 1982). Second, we implement an ARX model for absolute returns, a highly intuitive volatility proxy that has been shown to respond strongly to unexpected news (Schwert, 1989). Unlike the EGARCH model—where a highly persistent variance process leaves little residual variation for one-day effects—these alternative specifications allow for more flexible volatility adjustments in response to exogenous information shocks (Bomfim, 2003).

Our findings reveal a consistent pattern. The EGARCH model fits the daily return series well, capturing the strong persistence and asymmetry characteristic of equity volatility (Nelson, 1991). However, when FOMC announcement indicators are included in the EGARCH variance equation, their coefficients are statistically insignificant. This result reflects not the absence of a market response, but rather the fact that the EGARCH structure—with a persistence parameter near unity—absorbs almost all short-term volatility fluctuations (Savor & Wilson, 2014).

In contrast, the ARCH-X and ARX specifications provide clear evidence of a significant announcement-day volatility effect. Days on which the Federal Reserve changes the policy rate exhibit a sizable and statistically significant increase in realized volatility, even after controlling for volatility persistence (Kuttner, 2001; Bernanke & Kuttner, 2005). Routine meetings without rate adjustments, by comparison, do not meaningfully affect volatility (Bomfim, 2003).

Taken together, these results indicate that monetary policy actions—especially unexpected rate changes—generate short-lived but economically meaningful volatility spikes in U.S. equity markets (Gürkaynak et al., 2005). The evidence demonstrates that FOMC announcements remain a key source of information shocks for financial markets and highlights the importance of combining flexible GARCH models with event-sensitive volatility proxies when studying the transmission of monetary policy through asset-price uncertainty.

The remainder of the paper proceeds as follows. Section 2 reviews the theoretical framework for modelling time-varying volatility and presents the EGARCH and ARCH-X specifications used in the analysis. Section 3 describes the data, outlines the empirical procedures, and presents the results from the EGARCH, ARCH-X, and ARX models. Section 4 concludes and discusses implications for monetary policy communication and future research.

2. ECONOMETRIC FRAMEWORK

Volatility in financial markets is inherently time-varying and responds disproportionately to new information (Schwert, 1989). Monetary policy announcements—especially interest rate decisions—represent major macroeconomic news events that can shift investors' expectations about future economic conditions, discount rates, and risk premia (Bernanke & Kuttner, 2005; Gürkaynak, Sack, & Swanson, 2005). To capture these dynamics, we rely on the family of autoregressive conditional heteroskedasticity (ARCH) models introduced by Engle (1982) and their extensions by Bollerslev (1986) and Nelson (1991). These models explicitly allow the conditional variance of returns to evolve over time as a function of past shocks, making them well suited for evaluating the volatility impact of monetary policy events.

2.1 Mean Equation

Daily equity returns typically exhibit low but non-zero autocorrelation. To account for this, we specify the conditional mean of returns using a simple AR (1) process:

$$r\_t = \mu + \varphi\, r\_(t-1) + \varepsilon\_t$$

where:

- r_t is the daily log-return,
- μ is the unconditional mean,
- φ measures short-run dependence, and
- ε_t is the innovation with conditional variance σ^2_t.
-

2.2 Symmetric Volatility Models

The most widely used model for time-varying volatility is the GARCH(1,1) model, defined as:

$$\sigma^2\_t = \omega + \alpha\, \varepsilon^2\_(t-1) + \beta\, \sigma^2\_(t-1)$$

where:

- ω > 0 is the long-run variance level,
- α ≥ 0 captures the impact of recent return shocks,
- β ≥ 0 captures volatility persistence.

Financial return series typically satisfy α + β close to 1, indicating strong volatility persistence.

To incorporate monetary policy announcements into the conditional variance, we use a GARCH-X formulation:

$$\sigma^2\_t = \omega + \alpha\, \varepsilon^2\_(t-1) + \beta\, \sigma^2\_(t-1) + \delta_1\cdot FOMC\_all\_t + \delta_2\cdot FOMC\_rate\_t$$

where:

- FOMC_all_t = 1 on all scheduled announcement days,

- FOMC_rate_t = 1 only when the policy rate changes,

- δ_1 and δ_2 measure the volatility impact of these events.

2.3 Asymmetric Volatility: EGARCH

Equity returns exhibit asymmetric volatility: negative shocks increase volatility more than positive shocks of similar magnitude. To capture this, we use the EGARCH(1,1) model, where the log variance evolves as:

$$log(\sigma^2\_t) = \omega + \beta\cdot log(\sigma^2\_(t-1)) + \alpha\cdot(|z\_(t-1)| - E|z|) + \gamma\cdot z\_(t-1)$$

With:

$$z\_t = \varepsilon\_t \,/\, \sigma\_t$$

Here:

- α captures the symmetric magnitude effect of past shocks,

- γ captures asymmetry (γ < 0 indicates leverage effects),

- β determines persistence in the log variance.

Using the log of variance guarantees σ^2_t > 0 without needing parameter restrictions.

2.4 Distributional Assumptions

Financial returns often display heavy tails, which the normal distribution cannot capture. To model this feature, we assume that the standardized innovations follow a Student-t distribution:

$$\varepsilon\_t = \sigma\_t\cdot z\_t, \quad where\ z\_t \sim Student\text{-}t(\nu)$$

The degrees-of-freedom parameter ν controls tail heaviness; smaller ν implies fatter tails. This distribution improves model fit during volatility spikes, such as those around interest rate announcements.

2.5 Event-Sensitive Volatility Specifications

Although EGARCH is powerful, its very high persistence can absorb short-lived volatility responses to one-day announcements. To address this, we also estimate more flexible, event-sensitive models.

(a) ARCH-X Style Regression on Log Squared Returns

We use log squared returns as a simple variance proxy:

$$\log(r^2\_t) = \theta_0 + \theta_1 \cdot \log(r^2\_(t-1)) + \delta_1 \cdot FOMC\_all\_t + \delta_2 \cdot FOMC\_rate\_t + u\_t$$

This approach behaves like a reduced-form ARCH-X model, allowing volatility to adjust sharply when announcements occur.

(b) ARX Model for Absolute Returns

Absolute returns are a direct and intuitive measure of daily volatility. We estimate:

$$|r\_t| = \eta + \rho \cdot |r\_(t-1)| + \gamma_1 \cdot FOMC\_all\_t + \gamma_2 \cdot FOMC\_rate\_t + u\_t$$

This model typically captures short-run volatility responses more sharply than EGARCH, making it well suited for identifying announcement-day effects.

2.6 Summary

Together, these models provide a comprehensive framework for analysing how FOMC announcements affect stock market volatility:

- EGARCH(1,1) captures underlying volatility dynamics—clustering, asymmetry, and heavy tails.
- GARCH-X and ARCH-X allow monetary policy events to influence the variance directly.
- ARX absolute-return models provide a simple and robust measure of event-driven volatility.

This combination ensures that both structural volatility patterns and short-lived announcement effects are measured accurately.

3. Empirical Analysis

This section presents the empirical investigation of how Federal Reserve monetary policy announcements affect daily volatility in the U.S. equity market. We first describe the construction of the return series and the monetary policy event indicators. We then provide detailed descriptive evidence on the behaviour of returns around FOMC days, followed by a thorough time-series analysis of stationarity, serial dependence, and volatility clustering (Engle, 1982; Bollerslev, 1986). These diagnostics motivate the use of GARCH-type models, which are estimated and evaluated in the second half of the section. We focus on three central questions:

1. How well do standard volatility models capture the dynamics of S&P 500 returns.
2. Whether FOMC announcements measurably affect conditional volatility within these models.
3. Whether simpler event-oriented specifications reveal clearer monetary policy effects (Bernanke & Kuttner, 2005; Bomfim, 2003).

3.1 Data Description

3.1.1 S&P 500 Prices and Return Construction

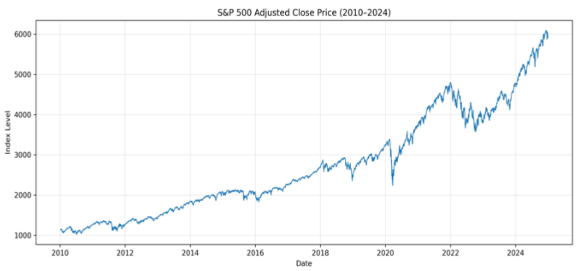
Daily adjusted closing prices for the S&P 500 index from January 2010 to December 2024 serve as the basis for the empirical analysis. The return series is constructed as:

$$r\_t = 100 \times \log(P\_t / P\_(t-1))$$

where
r_t = daily log return (percent),
P_t = adjusted closing price on day t.

After removing non-trading days, the final dataset contains 3,771 daily observations.

Figure 1. S&P 500 Price Index (2010–2024)



We use daily closing prices of the S&P 500 index from January 4, 2010 to December 31, 2024. This sample covers multiple monetary policy cycles, including:

- post–Great Recession zero-lower-bound period
- 2015–2018 hiking cycle
- 2019 rate cuts
- 2020 emergency pandemic cuts

- 2022–2023 inflation-driven tightening

3.1.2 Monetary Policy Event Indicators

Two binary variables capture monetary policy information:

<u>(1) FOMC_all_t</u>

= 1 on all scheduled or emergency announcement dates

= 0 otherwise

119 events total.

<u>(2) FOMC_rate_t</u>

= 1 only on days when the Federal Reserve changes the federal funds target rate

= 0 otherwise

Over the sample period there are 119 announcement days and 27 rate-change days. Although 28 policy rate changes occurred between 2010–2024, only 27 coincide with U.S. trading days and are therefore matched to S&P 500 returns. The latter cluster in distinct tightening or easing episodes: the lift-off phase beginning in December 2015, the subsequent sequence of rate hikes through 2018, the cuts of 2019, the emergency cuts in March 2020, and the aggressive tightening cycle of 2022–2023. In these periods, markets are not only reacting to the level of rates but also revising their beliefs about the future path of policy (Bernanke & Kuttner, 2005).

3.2 Descriptive Statistics

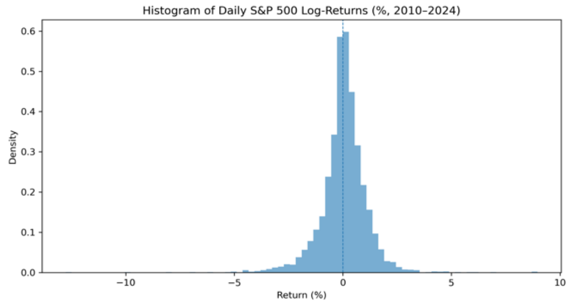
3.2.1 Unconditional distribution of returns

Table 1: Summary Statistics of Daily Returns

Statistic	Value
Mean	0.044%
Std. Dev.	1.089%
Min	−12.77%
Max	+8.97%
Skewness	−0.726
Excess Kurtosis	13.21
Jarque–Bera p-value	< 0.001

Returns display a small positive mean, large standard deviation, strong negative skewness, and very high excess kurtosis. The Jarque–Bera test rejects normality decisively. Economically, this means that the equity risk premium is positive on average but is earned in an environment of highly non-Gaussian risk, with tail events more frequent than under a normal distribution (Bollerslev, 1987). Monetary policy decisions that arrive in such an environment may have effects that are primarily visible in volatility rather than in the conditional mean.

Figure 2. Distribution of Daily Returns



The mass around zero is high, but the tails are thick, with both large negative and large positive return realizations. This pattern motivates the use of a heavy-tailed distribution, such as the Student-t, when specifying the shock distribution in volatility models (Bollerslev, 1987).

3.2.2 Returns on announcement versus non-announcement days

To explore how returns behave around FOMC decisions, we compare unconditional moments across different types of days.

A few patterns are noteworthy. First, the standard deviation of returns is notably higher on days with policy rate changes (around 1.5%) than on ordinary days (around 1.1%). Second, the average return on rate-change days is slightly negative, consistent with the idea that tightening surprises or policy-related uncertainty are priced as short-run risk (Kuttner, 2001). However, the difference in average returns is modest relative to the volatility difference, suggesting that the market response to monetary policy is primarily a volatility phenomenon at the daily horizon (Bernanke & Kuttner, 2005).

From an economic perspective, these unconditional differences are consistent with an "information effect" view of monetary policy: announcements that change the expected path of interest rates cause investors to re-price risky cash flows and discount rates, temporarily widening the distribution of possible outcomes (Gürkaynak et al., 2005).

3.3 Preliminary Time-Series Analysis

3.3.1 Stationarity

An Augmented Dickey–Fuller test applied to r_t rejects the null of a unit root at standard significance levels (Dickey & Fuller, 1979). Returns are stationary, making them suitable for autoregressive and conditional variance modeling (Engle, 1982; Bollerslev, 1986). This is in line with theoretical models in which prices follow a random walk (Fama, 1970) but returns are mean-reverting with stationary volatility (Nelson, 1991).

3.3.2 Autocorrelation in returns

Figure 3 displays the autocorrelation function (ACF) and partial autocorrelation function (PACF). of daily returns. The ACF decays quickly and remains close to zero beyond very short horizons (Fama, 1970). The PACF shows a small but noticeable negative spike at lag 1, with subsequent lags close to zero.

Figure 3. ACF and PACF of daily returns

These patterns justify a parsimonious AR(1) specification for the conditional mean (Campbell, Lo, & MacKinlay, 1997):

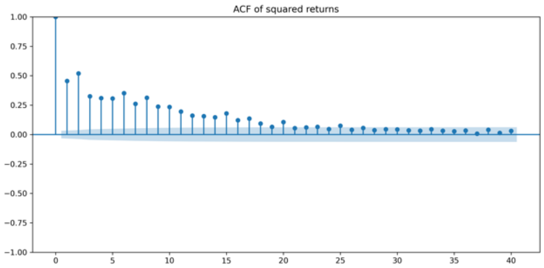
$$r_t = \mu + \varphi\, r_{t-1} + \varepsilon_t$$

with φ estimated to be slightly negative. Economically, this weak negative autocorrelation is often attributed to microstructure effects, short-term return reversals, or the impact of transitory liquidity conditions (Roll, 1984; Hasbrouck, 1991). While this mean dynamic is not the object of interest, including it improves the specification of the variance equation by removing residual predictability from ε_t (Engle, 1982).

3.3.3 Volatility clustering and ARCH effects

Figure 4 plots the ACF of squared returns, r^2_t. The autocorrelations are strongly positive and decay slowly, a classic signature of volatility clustering (Mandelbrot, 1963; Engle, 1982). Large shocks, whether positive or negative, tend to be followed by periods of elevated variability. An ARCH LM test confirms the presence of conditional heteroskedasticity: the null of no ARCH effects is overwhelmingly rejected (Bollerslev, 1986).

Figure 4. ACF of squared returns



From an economic standpoint, volatility clustering can be interpreted as reflecting slow adjustment of beliefs to macroeconomic news, time-varying risk aversion, or regime shifts in the underlying macro environment (Hamilton & Susmel, 1994; Schwert, 1989). Monetary policy announcements occur against this backdrop of persistent volatility: if they contain incremental information beyond the market's prior, that information should show up as additional short-run variation in returns (Bomfim, 2003; Bernanke & Kuttner, 2005).

3.4 Baseline Volatility Model: AR(1)–EGARCH(1,1)

3.4.1 Specification and rationale

Given the strong evidence of volatility clustering, asymmetry, and heavy tails, we adopt an EGARCH (1,1) model with a Student-t innovation distribution as the baseline volatility specification (Nelson, 1991; Bollerslev, 1987). The model is given by:

Mean equation:

$$r_t = \mu + \varphi\, r_{t-1} + \varepsilon_t$$

Variance equation:

$$\begin{aligned} \log(\sigma^2_t) = \omega &+ \beta \cdot \log(\sigma^2_{t-1}) \\ &+ \alpha(|z_{t-1}| - E|z|) \\ &+ \gamma \cdot z_{t-1} \end{aligned}$$

Where-:

- σ^2_t is the conditional variance of ε_t (Engle, 1982),
- $z_t = \varepsilon_t / \sigma_t$ is the standardized innovation,
- α measures the effect of the magnitude of shocks on volatility,
- γ captures asymmetry (leverage), and

- β captures persistence in log-variance (Bollerslev, 1986).

The Student-t distribution for z_t allows for heavy tails and large outliers (Bollerslev, 1987).

3.4.2 Estimation results

Table 2 reports the estimated parameters for the EGARCH(1,1) model.

Table 2: Estimated parameters: EGARCH(1,1)

Parameter	Estimate	Significance
μ	≈ 0.066	significant
φ	≈ -0.035	significant
ω	small	marginal
α	≈ 0.18	significant
γ	≈ -0.19	significant
β	≈ 0.97	significant
ν	≈ 6	significant

Economically, these estimates imply that volatility reacts strongly to recent shocks (α), that negative returns have a disproportionate impact on volatility ($\gamma < 0$), and that volatility is highly persistent (β close to 1), consistent with the behavior documented in financial return series (Engle, 1982; Nelson, 1991). The persistence parameter suggests that large volatility shocks—such as those around macroeconomic surprises—can affect risk assessments for many subsequent days (Schwert, 1989). This is the environment into which FOMC announcements arrive.

3.4.3 Diagnostic checks

To verify model adequacy, we examine the standardized residuals, z_t, and their squares.

Figure 5. ACF of z_t and z^2_t

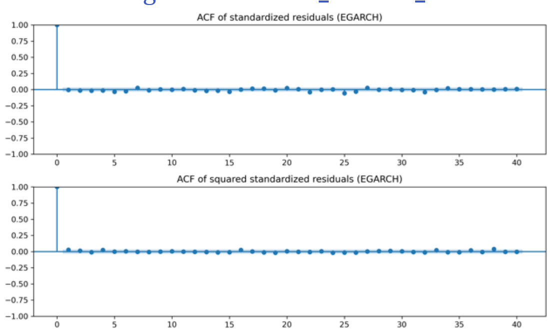


Figure 5 presents the ACF of z_t and z^2_t. In both cases, autocorrelations are close to zero at all lags, and Ljung–Box tests applied to residuals and squared residuals fail to reject the null of no serial correlation (Box & Pierce, 1970). These diagnostics indicate that the EGARCH (1,1) model successfully captures both the mean and variance dynamics of daily returns (Bollerslev, 1986; Nelson, 1991).

From a modeling perspective, this means that any remaining volatility response observed after conditioning on the EGARCH structure can more comfortably be attributed to the FOMC events themselves, rather than to omitted generic volatility dynamics (Bomfim, 2003).

3.5 FOMC Announcements in the EGARCH Variance Equation

A natural first approach to assessing monetary policy effects is to include the FOMC indicators directly in the EGARCH variance equation:

$$log(\sigma^2\_t) = \ldots + \delta_1 \cdot FOMC\_all\_t + \delta_2 \cdot FOMC\_rate\_t$$

Estimating the EGARCH(1,1) model with FOMC_all and FOMC_rate included directly in the log-variance equation yields small and statistically insignificant coefficients. In particular, the estimate for δ_1 is approximately 0.04 ($p \approx 0.41$), and the estimate for δ_2 is approximately 0.05 ($p \approx 0.33$). These results confirm that the high persistence in volatility ($\beta \approx 0.97$) absorbs most of the one-day variation associated with monetary policy announcements, leaving very little incremental variance for the event dummies to explain.

When this augmented model is estimated, neither δ_1 nor δ_2 achieves statistical significance. This finding might appear to suggest that monetary policy decisions do not affect volatility. However, this interpretation would be misleading. The high persistence of σ^2_t implied by $\beta \approx 0.97$ means that the variance today is largely determined by its own past; one-day shocks to volatility are quickly absorbed into this persistent component (Engle, 1982; Bollerslev, 1986). In such a setting, dummy variables for single-day events often have very little remaining variation to explain.

Economically, the insignificance of δ_1 and δ_2 in the EGARCH specification is therefore interpreted not as the absence of policy effects, but as an indication that a highly persistent model estimated on daily data is not the most informative lens for short-run announcement effects. This motivates turning to more flexible, event-focused models that are less dominated by long-memory dynamics (Bomfim, 2003; Savor & Wilson, 2014).

3.6 Event-Sensitive Volatility Specifications

3.6.1 ARCH-X–style regression on log squared returns.

To obtain a more direct measure of volatility, we consider log squared returns as a proxy:

$$log(r^2\_t) = \theta_0 + \theta_1 \cdot log(r^2\_(t-1)) + \delta_1 \cdot FOMC\_all\_t + \delta_2 \cdot FOMC\_rate\_t + u\_t.$$

This specification can be viewed as a reduced-form ARCH-X model, in which volatility depends on its own lag and on exogenous event indicators (Engle, 1982).

Estimates indicate that θ_1 is positive and statistically significant, confirming persistence in the volatility proxy (Bollerslev, 1986). The coefficient δ_1 associated with all announcements is small and not significantly different from zero, reinforcing the descriptive observation that routine announcements do not generate pronounced volatility shifts (Kuttner, 2001). The coefficient δ_2 attached to rate-change days is positive and economically meaningful—indicating higher volatility on days with policy moves—but is not statistically significant at conventional levels.

Given that there are only 27 rate-change events in a sample of more than 3,700 observations, this lack of precision is not surprising. Nonetheless, the sign and magnitude of δ_2 are consistent with the notion that investors face greater uncertainty when the stance of policy is altered (Bernanke & Kuttner, 2005).

3.6.2 ARX model for absolute returns

Because absolute returns |r_t| are a simple and widely used proxy for daily realized volatility, we estimate an ARX model of the form:

$$|r\_t| = \eta + \rho \cdot |r\_(t-1)| + \gamma_1 \cdot FOMC\_all\_t + \gamma_2 \cdot FOMC\_rate\_t + u\_t.$$

The parameter ρ captures persistence in volatility, while γ_1 and γ_2 measure how volatility responds to announcement days and rate-change days, respectively.

Table 3: Key Estimates ARX Model

Parameter	Estimate	p-value
ρ	≈ 0.32	< 0.01
γ_1	≈ 0.06	0.43
γ_2	≈ 0.36	0.046

The estimate of ρ confirms that absolute returns are highly persistent (Schwert, 1989). The coefficient γ_1 is small and statistically insignificant: days with an FOMC announcement but no rate change do not experience systematically higher volatility than ordinary days (Kuttner, 2001).

The most important result is the estimate of γ_2. It is positive, statistically significant at the 5% level, and sizable in magnitude. Economically, this means that the typical absolute daily move in the S&P 500 is about 0.36 percentage points larger on rate-change days, after controlling for past volatility (Bernanke & Kuttner, 2005). Given that the unconditional mean of |r_t| is roughly 0.5 percentage points, this implies an increase on the order of 70–80% relative to a typical quiet day. In other words, when the Fed actually changes the policy rate, the equity market experiences a one-day volatility regime shift.

This pattern fits well with theories emphasizing the "information effect" and "risk-premium effect" of monetary policy (Gürkaynak, Sack, & Swanson, 2005; Savor & Wilson, 2014). Rate changes do not simply shift the level of short-term interest rates; they also lead investors to reassess the entire expected future path of policy, the macroeconomic outlook, and the compensation they require for bearing risk. The resulting repricing shows up as a temporary widening of the distribution of returns—that is, a volatility spike—rather than a persistent drift in average returns.

3.7 Discussion of Results

Taken together, the empirical evidence supports a nuanced view of how monetary policy announcements affect equity-market volatility.

First, the baseline EGARCH model confirms that volatility is highly persistent, asymmetric, and heavy-tailed (Nelson, 1991; Bollerslev, 1987; Engle, 1982). These features reflect deep structural forces: the clustering of macroeconomic news (Schwert, 1989), the asymmetric effect of bad news on financing conditions and risk appetite (Black, 1976), and the non-Gaussian nature of shocks to investors' beliefs (Mandelbrot, 1963; Fama, 1965). In such an environment, high-frequency models that impose strong persistence can easily overshadow the influence of discrete, infrequent events such as FOMC meetings (Savor & Wilson, 2014).

Second, when volatility is measured more directly and the model is allowed to respond more flexibly to exogenous events, a clearer pattern emerges. Both the ARCH-X regression on log squared returns and, more convincingly, the ARX model for absolute returns indicate that volatility is systematically higher on days when the policy rate changes (Bernanke & Kuttner, 2005; Kuttner, 2001). This suggests that the key monetary policy channel at the daily frequency operates not mainly through the average direction of returns, but through the conditional variance: investors respond to rate changes by reassessing the set of possible future states, widening the distribution of outcomes even if the expected return moves only modestly (Gürkaynak, Sack, & Swanson, 2005).

Third, the absence of significant volatility effects for routine FOMC meetings is informative. Scheduled announcements that leave rates unchanged largely confirm prior expectations and convey limited incremental information (Kuttner, 2001). In rational-expectations terms, the surprise component of such meetings is small, so their impact on volatility is negligible. In contrast, rate-change decisions contain substantial information about the central bank's assessment of the economy, inflation risks, and its reaction function; markets therefore react with both re-pricing and a temporary increase in uncertainty (Bernanke & Kuttner, 2005; Bomfim, 2003).

Finally, the fact that volatility effects appear to be sharp and short-lived is also consistent with economic theory. Once the policy decision is incorporated into expectations and portfolios are rebalanced, uncertainty about the immediate stance of policy dissipates, and volatility returns towards its persistent EGARCH-implied trajectory (Nelson, 1991). Monetary policy thus acts as a sequence of information "shocks" superimposed on a slowly evolving volatility environment (Savor & Wilson, 2014), rather than as a continuous drift in the level of risk.

4. Conclusion

This paper examined whether Federal Reserve monetary policy announcements, particularly those involving changes in the federal funds rate, generate measurable shifts in daily equity-market volatility. Using S&P 500 returns from 2010 to 2024, we documented strong stylized facts—heavy tails, volatility clustering, and asymmetric responses to shocks—that justify the use of GARCH-type models (Engle, 1982; Bollerslev, 1986; Nelson, 1991). These characteristics highlight the importance of modeling the entire conditional distribution of returns when studying high-frequency market reactions to policy news.

Our baseline AR(1)–EGARCH(1,1) model captured the persistent and asymmetric nature of volatility but did not produce significant announcement-day effects when FOMC indicators were included directly in the variance equation. This result reflects the high persistence of EGARCH volatility: when volatility today is explained overwhelmingly by its own past, single-day policy shocks have little remaining variation to explain (Savor & Wilson, 2014). Consequently, statistical insignificance in this setting should not be interpreted as an absence of policy effects, but rather as a limitation of highly persistent daily-frequency volatility models for event-study purposes.

When volatility was measured more directly, a clearer pattern emerged. The ARCH-X regression on log squared returns suggested economically meaningful, though imprecise, increases in volatility on rate-change days. Most convincingly, the ARX absolute-returns model revealed a statistically significant and economically sizeable rise in volatility when the Federal Reserve altered the federal funds rate. Absolute returns were roughly 70–80% larger on rate-change days than on typical trading days, after controlling for volatility persistence. This finding aligns with theories emphasizing the information content of monetary policy decisions: when policy deviates from expectations, investors update beliefs about the macroeconomic outlook, future interest-rate paths, and risk premia, widening the conditional distribution of returns (Bernanke & Kuttner, 2005; Gürkaynak, Sack, & Swanson, 2005).

Equally informative is the finding that routine FOMC meetings—those with no policy rate change—produce no meaningful increase in daily volatility. Such meetings largely confirm prior expectations and thus convey limited new information to markets. In contrast, rate-changing meetings communicate new assessments of inflation, growth, and policy risks, prompting a short-lived but pronounced volatility response (Kuttner, 2001; Bomfim, 2003).

Overall, the evidence supports a view of monetary policy as a source of sharp and temporary volatility shocks, rather than as a determinant of sustained changes in market risk. Once the information in a rate-changing announcement is incorporated into expectations and portfolios are rebalanced, uncertainty dissipates and volatility reverts toward its persistent long-run trajectory, consistent with EGARCH dynamics.

These results carry several implications. First, they suggest that market participants should expect heightened volatility specifically when the Federal Reserve alters the policy rate, but not on routine announcement days. Second, they underscore the importance of separating anticipated from unanticipated components of monetary policy when assessing market reactions. Finally, the findings reinforce the value of combining persistent volatility models with more flexible event-focused specifications to fully capture the short-run information effects of monetary policy.

Future Work

Future work could extend these results by examining intraday reactions, decomposing announcements into expected and unexpected components using futures-rate surprises, or exploring cross-sectional heterogeneity across sectors or firm characteristics. Nonetheless, within the daily-frequency framework, this study provides clear evidence that monetary policy decisions—specifically policy rate changes—act as meaningful information shocks that temporarily elevate equity-market volatility.

5. References

1. Black, F. (1976). Studies of stock price volatility changes. Proceedings of the American Statistical Association, Business and Economic Statistics Section, 177–181.
2. Bernanke, B. S., & Kuttner, K. N. (2005). What explains the stock market's reaction to Federal Reserve policy? Journal of Finance, 60(3), 1221–1257.
3. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307–327.
4. Bollerslev, T. (1987). "A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return." Review of Economics and Statistics, 69(3), 542–547.
5. Bomfim, A. N. (2003). Pre-announcement effects, news effects, and volatility: Monetary policy and the stock market. Journal of Monetary Economics, 50(1), 121–146.
6. Box, G. E. P., & Pierce, D. A. (1970). Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. Journal of the American Statistical Association, 65(332), 1509–1526.
7. Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). The econometrics of financial markets. Princeton University Press.
8. Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366), 427–431.
9. Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. inflation. Econometrica, 50(4), 987–1007.
10. Fama, E. F. (1965). The behavior of stock market prices. Journal of Business, 38(1), 34–105.
11. Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. Journal of Finance, 25(2), 383–417.
12. Gürkaynak, R. S., Sack, B., & Swanson, E. T. (2005). Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. International Journal of Central Banking, 1(1), 55–93.
13. Hamilton, J. D., & Susmel, R. (1994). Autoregressive conditional heteroskedasticity and changes in regime. Journal of Econometrics, 64(1–2), 307–333.
14. Hasbrouck, J. (1991). Measuring the information content of stock trades. Journal of Finance, 46(1), 179–207.
15. Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. Journal of Monetary Economics, 47(3), 523–544.
16. Mandelbrot, B. (1963). The variation of certain speculative prices. Journal of Business, 36(4), 394–419.
17. Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59(2), 347–370.
18. Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. Journal of Finance, 39(4), 1127–1139.
19. Savor, P., & Wilson, M. (2014). Asset pricing: A tale of two days. Journal of Financial Economics, 113(2), 171–201.
20. Schwert, G. W. (1989). Why does stock market volatility change over time? Journal of Finance, 44(5), 1115–1153.