Assessing the Efficacy of Intraday Volatility Measures in Response to Unexpected Macroeconomic Announcements

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Abstract

In this study, we investigate the high-frequency impact of macroeconomic announcements on the volatility of key futures contracts. We use three estimators of spot volatility: intraday periodicity, kernel estimation and the intraday GARCH model. Our main objective is to determine which of these estimators best captures the market's reaction to macroeconomic announcements. Our results show that the intraday GARCH model stands out as the most effective in capturing market responses to macroeconomic announcements.

Keywords: commodities, energy, futures, information diffusion, financialization, high-frequency, speculation, sustainable, commercial, institutional, volatility, macro, announcements, surprise, events.

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1 Introduction

In this study, we investigate the high-frequency impact of macroeconomic announcements on the volatility of key futures contracts. We use three estimators of spot volatility: intraday periodicity, kernel estimation and the intraday GARCH model. Our main objective is to determine which of these estimators best captures the market's reaction to macroeconomic announcements. Our results show that the intraday GARCH model stands out as the most effective in capturing market responses to macroeconomic announcements.

By combining non-parametric kernel estimation with intraday periodicity and GARCH approaches, we deepen our understanding of the complex and often non-linear reactions of financial markets to economic news. This methodology enriches our analysis, offering a more flexible and comprehensive perspective than traditional parametric techniques.

The significant and immediate impact of macroeconomic announcements on futures volatility is clearly demonstrated, with variations depending on the type of contract and the nature of the announcement. Our study shows that, among the methods evaluated, the intraday GARCH model is the best able to capture these nuances.

This work contributes to a better understanding of market dynamics and offers valuable insights for traders, investors and policymakers. By highlighting the rapid reactivity of markets to economic information, we establish a basis for more informed trading strategies and more accurate anticipation of market movements following major macroeconomic announcements.

2 Literatture Review

2.1 Intraday spot volatility

Intraday spot volatility estimation is a crucial aspect of financial market analysis, particularly in understanding the dynamic nature of volatility within a trading day. The availability of high-frequency intraday data has enabled the development of various estimators to capture the intraday variations of volatility. Researchers have explored different methods such as realized volatility, Fourier spot volatility estimator, and stochastic volatility models to study the stochastic properties of returns and to forecast intraday volatility Barndorff-Nielsen and Shephard (2002); Mancino and Recchioni (2015); Xin (2013). It has been observed that intraday volatility exhibits complex, periodic patterns driven by the global migration of trading, macroeconomic announcements, and market microstructure noise Stroud and Johannes (2014); Hansen and Lunde (2006); McGroarty et al. (2005). Additionally, studies have highlighted the importance of adjusting for intraday periodicities to accurately model and forecast intraday volatility Chakrabarti and Rajvanshi (2017); Martens et al. (2002).

The intraday spot volatility patterns have been found to have significant implications for trading mechanisms, price volatility, and market microstructure noise Park (1993); Wang and Zou (2014). Furthermore, the relationship between spot volatility and trading volume has been a subject of empirical investigation, providing insights into the intraday dynamics of volatility Illueca and Lafuente (2003); Luengo (2009). It is evident that intraday volatility estimation is essential for various applications, including volatility forecasting, jump detection, and examining the impact of calendar events on volatility dynamics Agarwalla and Pandey (2012); Boudt et al. (2011); Wang and Wang (2010).

To measure spot volatility in high-frequency financial data, various methods have been developed and applied. These methods include the estimation of spot volatility using high-frequency data, such as realized variance and integrated variance, as well as the use of option prices and nonparametric approaches. For instance, the use of realized variance estimates from high-frequency data has been reported for assets like futures contracts and indices Gatheral et al. (2018). Additionally, alternate spot volatility measurement methods based on option prices have been utilized, confirming the roughness of volatility Livieri et al. (2017). Furthermore, nonparametric estimation techniques have been developed for spot volatility, considering the presence of market microstructure noise Dahlhaus and Neddermeyer (2013), and the use of short-dated options for measuring and forecasting volatility has been explored, leading to increased precision in estimating spot diffusive volatility Todorov and Zhang (2021).

Moreover, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) approach has been employed to measure volatility in both spot and futures markets, analyzing the relationships between their volatilities Khan (2006). Additionally, the use of GARCH methodology has been reported for estimating spot volatility in the stock index market Illueca and Lafuente (2003). Furthermore, the estimation of spot volatility using the GARCH model has been applied in the analysis of the spin financial market Takaishi (2013).

In summary, the leading methods for measuring spot volatility in high-frequency financial data encompass various approaches, including the use of realized variance, integrated variance, option prices, nonparametric techniques, and GARCH methodology. These methods offer diverse perspectives on spot volatility estimation, considering different financial instruments and market dynamics.

2.2 Impact of macro news announcements on high-frequency spot volatility

The impact of macro news announcements on high-frequency spot volatility has been extensively researched in financial economics. Füss et al. (2011) focused on the impact of macroeconomic announcements on implied volatility, emphasizing the scarcity of studies that concentrate on the effect of these announcements on option implied volatilities Füss et al. (2011). Maserumule Alagidede (2017) evaluated the impact of scheduled macroeconomic news announcements on the volatility of the South African rand and US dollar exchange rate using high-frequency data Maserumule and Alagidede (2017). Lee Ryu (2019) aimed to comprehensively examine the effect of macroeconomic news announcements on the dynamics of various implied volatilities and identify the factors that change these implied volatilities in response to such announcements Lee and Ryu (2019). Evans Speight (2010) found that macroeconomic news announcements from the US caused the vast majority of the statistically significant responses in volatility, with US monetary policy and real activity announcements causing the largest reactions of volatility across the three rates Evans and Speight (2010). Bollerslev et al. (2018) based their results on high-frequency intraday data and new econometric techniques to infer the relationship between trading intensity and spot volatility around public news announcements Bollerslev et al. (2018). Huang (2015) studied financial market volatility and jump responses to macroeconomic news announcements, while Chatrath et al. (2014) investigated the impact of macro news on currency jumps and cojumps Huang (2015); Chatrath et al. (2014).

3 Econometric Framework

In the domain of financial econometrics, accurately estimating intraday spot volatility is pivotal for various applications, including risk management, derivative pricing, and market microstructure analysis. Three sophisticated approaches have been instrumental in advancing our understanding and computation of this measure.

Firstly, the method proposed by Beltratti and Morana (2001) introduces a novel perspective by incorporating a stochastic periodicity factor into the volatility model. This approach decomposes the spot volatility estimation into four distinct components: a random walk, an autoregressive process, a stochastic cyclical process, and a deterministic cyclical process. The intricate dynamics of these components are adeptly captured and estimated using a quasi-maximum likelihood method that is facilitated by the Kalman Filter. This framework allows for the stochastic elements of periodicity to be modeled, thereby enriching the volatility estimation with a layer of realism that acknowledges the inherent unpredictability of financial markets.

Next, the nonparametric method developed by Kristensen (2010) offers an alternative route for filtering spot volatility. This technique leverages kernel weights applied to the standard realized volatility estimator, thus allowing for a flexible and nuanced capture of the volatility process. By employing various kernels and bandwidths, this method can be tailored to highlight specific features of the volatility dynamics, such as jumps or continuous components. The kernel approach is particularly notable for its adaptability, as it can be fine-tuned to the idiosyncrasies of the dataset at hand.

Lastly, the seminal work of Andersen and ANDERSEN1997115 has contributed a foundational GARCH-based model that incorporates intraday seasonality. This model is a testament to the multifaceted nature of volatility, recognizing that it is not only a phenomenon evolving through time but also one that exhibits a systematic pattern within the trading day. The GARCH framework, with its ability to model volatility clustering and mean reversion, is enriched by the inclusion of a seasonal component that reflects the predictable intraday variations in market activity.

3.1 Stochastic periodicity method

The Beltratti and Morana approach is grounded in the assumption that volatility exhibits stochastic periodicity. This assumption is pivotal as it accommodates the variability of volatility patterns observed in intraday data. The method decomposes spot volatility into four distinct components, each representing a different aspect of volatility behavior:

1. A non-stationary component modeled as a random walk, capturing the long-term trends in volatility. This component evolves as $\mu_{t,n} = \mu_{t,n-1} + \xi_{t,n}$, where $\xi_{t,n}$ are independent and normally distributed with a mean of zero and variance σ^2_ξ.

2. A stationary acyclical component following an autoregressive process. This aspect, denoted as $h_{t,n} = \phi h_{t,n-1} + \nu_{t,n}$, reflects short-term fluctuations, with $\nu_{t,n}$ being normally distributed with mean zero and variance σ_η^2, and ϕ being the autoregressive coefficient.

3. A stochastic cyclical component, introducing a periodic behavior to the model. It is defined using a state-space form, allowing the model to capture cyclical patterns in volatility.

4. A deterministic cyclical process, providing a structured periodic component to the volatility.

Estimation of this model is achieved through a quasi-maximum likelihood method leveraging the Kalman Filter, specifically implemented using the FKF package. This method is adept at handling the complexity and non-linearity inherent in the model's structure.

The model for the intraday change in the return series is given by

$$r_{t,n} = \sigma_{t,n}\varepsilon_{t,n}, \quad t = 1, \dots, T; \quad n = 1, \dots, N,$$

where $\sigma_{t,n}$ is the conditional standard deviation of the n-th interval of day t and $\varepsilon_{t,n}$ is a i.i.d. mean-zero unit-variance process. The conditional standard deviations are modeled as

$$\sigma_{t,n} = \sigma \exp\left(\frac{\mu_{t,n} + h_{t,n} + c_{t,n}}{2}\right)$$

with σ being a scaling factor and $\mu_{t,n}$ is the non-stationary volatility component

$$\mu_{t,n} = \mu_{t,n-1} + \xi_{t,n}$$

with independent $\xi_{t,n} \sim \mathcal{N}(0, \sigma_\xi^2)$. $h_{t,n}$ is the stochastic stationary acyclical volatility component

$$h_{t,n} = \phi h_{t,n-1} + \nu_{t,n}$$

with independent $\eta_{t,n} \sim \mathcal{N}(0, \sigma_\eta^2)$ and $|\phi| \leq 1$. The cyclical component is separated into two components:

$$c_{t,n} = c_{1,t,n} + c_{2,t,n}$$

The first component is written in state-space form,

$$\begin{pmatrix} c_{1,t,n} \\ c_{1,t,n}^* \end{pmatrix} = \rho \begin{pmatrix} \cos\lambda & \sin\lambda \\ -\sin\lambda & \cos\lambda \end{pmatrix} \begin{pmatrix} c_{1,t,n-1} \\ c_{1,t,n-1}^* \end{pmatrix} + \begin{pmatrix} \kappa_{1,t,n} \\ \kappa_{1,t,n}^* \end{pmatrix}$$

with $0 \leq \rho \leq 1$ and $\kappa_{1,t,n}, \kappa_{1,t,n}^*$ are mutually independent zero-mean normal random variables with variance σ_κ^2.

The second component is given by

$$c_{2,t,n} = \mu_1 n_1 + \mu_2 n_2 + \sum_{p=2}^{P} (\delta_{cp} \cos(p\lambda) + \delta_{sp} \sin(p\lambda n))$$

with $n_1 = 2n/(N+1)$ and $n_2 = 6n^2/(N+1)/(N+2)$.

Beltratti and Morana (2001) model decomposes intraday volatility into various components, each characterized by specific parameters that offer insights into the nature and dynamics of financial market volatility. The following parameters are analyzed:

- σ_ξ^2: Represents the variance of the error term $\xi_{t,n}$ in the non-stationary volatility component $\mu_{t,n}$. This parameter measures the degree of variability in the non-stationary component of volatility, reflecting longer-term volatility trends.

- ϕ: The autoregressive coefficient in the stationary acyclical volatility component $h_{t,n}$. It indicates the extent to which current volatility is influenced by its immediate past values, capturing short-term volatility persistence.

- σ_η^2: Denotes the variance of the error term $\eta_{t,n}$ in the stationary acyclical component. This parameter measures the degree of random fluctuations in the short-term volatility component.
- ρ **and** λ: Parameters defining the stochastic cyclical component of volatility. ρ captures the degree of attenuation in the cyclical pattern, indicating the persistence of cycles, while λ determines the frequency of these cycles.
- σ_κ^2: The variance of the error terms in the stochastic cyclical component ($\kappa_{1,t,n}$ and $\kappa_{1,t,n}^*$). It quantifies the random fluctuations within the cyclical pattern of volatility.
- σ: A scaling factor for the conditional standard deviation $\sigma_{t,n}$. This factor provides a baseline level of volatility against which the impact of other components is measured.

Each of these parameters plays a crucial role in modeling the intricate patterns of intraday volatility. Together, they provide a comprehensive framework for understanding both the magnitude and the dynamics of volatility fluctuations, particularly in high-frequency trading contexts.

3.2 GARCH models with intraday seasonality

In this model, daily returns r_t based on intraday observations $r_{i,t}$, $i = 1, \ldots, N$ are modeled as

$$r_t = \sum_{i=1}^{N} r_{i,t} = \sigma_t \frac{1}{\sqrt{N}} \sum_{i=1}^{N} s_i Z_{i,t}.$$

with $\sigma_t > 0$, intraday seasonality $s_i > 0$, and $Z_{i,t}$ being a zero-mean unit-variance error term.

$x_{i,n} = 2\log|R_{i,n} - E[R_{i,n}]| - \log \sigma_t^2 + \log N = \log s_{i,n}^2 + \log Z_{i,n}^2.$

Our modeling approach is then based on a non-linear regression in the intraday time interval, n, and the daily volatility factor, σ_t,

$$x_{i,n} = f(\theta; \sigma_t, n) + u_{i,n},$$

where the error, $u_{i,n} = \log Z_{i,n}^2 - E(\log Z_{i,n}^2)$, is i.i.d. mean zero. In the actual implementation the non-linear regression function is approximated by the following parametric expression,

$$f(\theta; \sigma_t, n) = \sum_{j=0}^{J} \sigma_t^j \left[\mu_{0,j} + \mu_{1,j}\frac{n}{N_1} + \mu_{2,j}\frac{n^2}{N_2} + \sum_{i=1}^{D} \lambda_{i,j} I_{n=d_i} \right] \tag{1}$$

$$+ \sum_{i=1}^{P} \left[\gamma_{i,j} \cos\left(\frac{pn2\pi}{N}\right) + \delta_{i,j} \sin\left(\frac{pn2\pi}{N}\right) \right], \tag{2}$$

where $N_1 = N^{-1}\sum_{i=1}^{N} i = (N+1)/2$ and $N_2 = N^{-1}\sum_{i=1}^{N} i^2 = (N+1)(N+2)/6$ are normalizing constants. For $J = 0$ and $D = 0$, Eq. (A.3) reduces to the standard flexible Fourier functional form proposed by Gallant (1981, 1982). Allowing for $J \geq 1$ and thus a possible interaction effect between σ_t^j and the shape of the periodic pattern might be important in some markets, however. Each of the corresponding J flexible Fourier forms are parameterized by a quadratic component (terms with μ-coefficients) and a number of sinusoids (the γ- and δ-coefficients). Moreover, it may be advantageous to also include time-specific dummies for applications in which some intraday intervals do not fit well within the overall regular periodic pattern (the A-coefficients)

3.3 Kernel estimation

The spot volatility $\sigma(t)$ at intraday time t can be estimated using kernel regression as follows:

$$\hat{\sigma}(t) = \frac{\sum_{i=1}^{n} K_h(t - t_i) Y_i}{\sum_{i=1}^{n} K_h(t - t_i)}, \tag{3}$$

where:

- Y_i represents the observed quantity related to volatility at time t_i (e.g., squared returns).
- $K_h(\cdot)$ is the kernel function with bandwidth h.
- n is the number of intraday observations.

Cross-validation can be used to select the optimal bandwidth h by minimizing the prediction error:

$$CV(h) = \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{\sigma}_{-i}(t_i) \right)^2, \tag{4}$$

where $\hat{\sigma}_{-i}(t_i)$ is the volatility estimate at time t_i obtained by leaving out the i-th observation from the dataset.

4 Results

4.1 Analysis of Stochastic Periodicity Method Results

The analysis of the presented results in the table, summarizing the estimates of the stochastic periodicity model for various financial instruments, requires an in-depth understanding of the meaning of each parameter. Here is an interpretation of these results:

1. **Parameter σ (Scaling Factor):**

   - Relatively low values for fixed income securities (ZN, ZF, ZT) indicate low volatility.

- Higher values for commodities (CL, GC, SI) and VIX suggest higher volatility.

2. **Parameter σ_μ (Volatility of Non-Stationary Component):**

   - Higher values for commodities and VIX suggest greater variation in long-term volatility trends for these instruments.

3. **Parameter σ_h (Volatility of Stationary Acyclical Component):**

   - Similar values across all instruments, indicating homogeneity in short-term volatility fluctuations.

4. **Parameter σ_k (Volatility of Stochastic Cyclical Component):**

   - Highly variable values, with particularly high values for Gold (GC) and Silver (SI), suggesting strong variability in the cyclical component of these markets.

5. **Parameter ϕ (Autoregressive Coefficient):**

   - Values close to 0.2 for all instruments, suggesting low persistence in the stationary acyclical component.

6. **Parameter ρ (Cyclical Persistence Coefficient):**

   - High values for most instruments, indicating strong persistence in the cyclical components.

7. **Parameters μ_1 and μ_2:**

   - Represent linear influences on the deterministic cyclical component, with variable values across instruments.

8. **Parameters δ_c and δ_s:**

   - These parameters describe the specific shape of cycles in the deterministic cyclical component.

- Positive and negative values reflect different amplitudes and phases of cycles for each instrument.

The analysis of these results shows distinct volatility behaviors among the different financial instruments. Fixed income securities exhibit overall lower volatility, while commodities and VIX show higher volatility and more significant variations in their cyclical components. This analysis can be useful for understanding the behavior of these markets and for managing the associated risk with each type of instrument.

5 Tables

Table 1: Overview of the different futures contracts used

Futures	Exchange	Ticker	Start date	End date
10-Year Treasury Note	CBOT	ZN	2008-01-01	2023-11-24
5-Year Treasury Note	CBOT	ZF	2008-01-01	2023-11-24
2-Year Treasury Note	CBOT	ZT	2008-01-01	2023-11-24
Crude Oil	NYMEX	CL	2008-01-01	2023-11-25
Gold	CME	GC	2008-01-31	2023-11-26
Silver	CME	SI	2008-01-01	2023-12-01
VIX	CBEO	VX	2008-08-05	2023-12-06

Table 2: Estimated of the Stochastic periodicity method

Parameter	10-Year (ZN)	5-Year (ZF)	2-Year (ZT)	Crude Oil (CL)	Gold (GC)	Silver (SI)	VIX (VX)
σ	0.0007798063	0.0006970592	0.0003831521	0.003609821	0.002194310	0.002497049	0.004204958
$\sigma_m u$	0.0074651745	0.0087302788	0.0044128791	0.024709518	0.018046040	0.018884839	0.015048596
σ_h	0.0068043180	0.0067887030	0.0068189611	0.005981323	0.006835663	0.006805529	0.006701747
σ_k	0.0028014130	0.0019895893	0.0003272993	0.008194699	0.054697479	0.027004559	0.006714377
ϕ	0.1938920040	0.1938905996	0.1938874343	0.193857511	0.193968896	0.193936302	0.193838676
ρ	0.9562948558	0.9523310680	0.8726654062	0.969417257	0.986767229	0.991546512	0.973038093
μ_1	1.1730150012	1.1594010076	1.0784093763	-1.788421840	1.174868846	1.217981639	1.171144056
μ_2	-0.7863329446	-0.8022814473	-0.7828573809	1.569855203	-0.558031910	-0.608767805	-0.604324099
δ_{c1}	-0.0213379850	0.0081848028	-0.0687763251	0.099941415	0.025465942	0.031180505	0.038217524
δ_{c2}	-0.7555120401	-0.7862469418	-0.9453732488	3.266989020	-0.200094629	-0.247336105	-0.162979296
δ_{c3}	0.0087724739	-0.0001522230	-0.0338684167	0.850598602	0.328741484	0.275714345	0.252979557
δ_{c4}	-0.0692692591	-0.0716717200	-0.1869340711	-7.045867146	-0.260893463	-0.168208610	-0.007446514
δ_{c5}	0.2433047624	0.2567757119	0.2125435752	1.907514201	0.409926081	0.322779546	-0.123227053
δ_{s1}	-1.3810970557	-1.3736932697	-1.4107420690	-1.212740128	-1.335638055	-1.318813308	-1.308125093
δ_{s2}	-0.9961629874	-1.0146000328	-1.1763732653	-5.145213592	-1.000736196	-0.922395566	-0.999093448
δ_{s3}	-0.0348958486	-0.0394850863	-0.0785816874	0.874984457	0.217705417	0.152956511	-0.210117368
δ_{s4}	0.3935814500	0.4038916086	0.4636070306	-3.322064273	0.386573922	0.368976465	-0.047834082
δ_{s5}	-0.0820568323	-0.0779318095	-0.0614524988	3.748309404	-0.203923729	-0.236236653	-0.11450617

Table 3: Estimated of GARCH models with intraday seasonality

	CL	GC	SI	ZN	ZF	ZT
AR(1)	0.228527***	0.369002***	0.292615***	0.297409***	0.233653***	0.310631***
MA(1)	-0.387254***	-0.134914***	-0.503499***	-0.611484***	-0.518379***	-0.656613***
ω	-0.469154	-1.243200	-0.602242	-0.748839	-1.041791	-1.374559
α_1	-0.012683***	-0.021867***	-0.010686***	-0.015199***	-0.006010***	0.001021***
β_1	0.930894***	0.932689***	0.939041***	0.936414***	0.936934***	0.926418
$\gamma_{1,j}$	0.266306***	0.348065**	0.330069**	0.235870	0.284407	0.065040***
$\gamma_{2,j}$	0.226487**	0.248930***	0.284787	0.212309	0.248374	0.080662**
$\gamma_{3,j}$	0.193413	0.191948***	0.191419	0.168649*	0.196120	0.074046
$\gamma_{4,j}$	0.171753	0.171587	0.204207	0.186726	0.174662	0.097744
$\gamma_{5,j}$	0.085865	0.121915*	0.162004	0.111526	0.084575*	0.066334
$\gamma_{6,j}$	-0.974082	-0.019573	-0.398336	-0.536993**	0.164330**	-0.015285
$\delta_{1,j}$	1.119530	0.612025**	0.546928	0.444635	-0.035154	0.014803
$\delta_{2,j}$	0.031016	0.243889	-0.121361	-0.192585*	-0.245696**	-0.054523*
$\delta_{3,j}$	-0.075754	0.014260	-0.184993	-0.163320	-0.189988*	-0.016591*
$\delta_{4,j}$	-0.141155	-0.058707	-0.154684	-0.126136	-0.116845	-0.008229*
$\delta_{5,j}$	-0.219489	-0.085708	-0.135379	-0.139784	-0.140285	-0.021034**
$\delta_{6,j}$	-0.215962	-0.136164**	-0.166092	-0.114614**	-0.118252***	-0.013501**

6 Figures

FIG1_PRICE.png

FIG2_PRICE.png

VX_PI.png

ZN_PI.png

ZT_PI.png

ZF_PI.png

GC_PI.png

CL_PI.png

SI_PI.png

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CL_PERIOI.png

Figure 10: Typical intraday spot volatility for Crude Oil

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GC_PERIO.png

Figure 11: Typical intraday spot volatility for Gold

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SI_PERIO.png

Figure 12: Typical intraday spot volatility for Silver

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Figure 13: Typical intraday spot volatility for 10-year treasury

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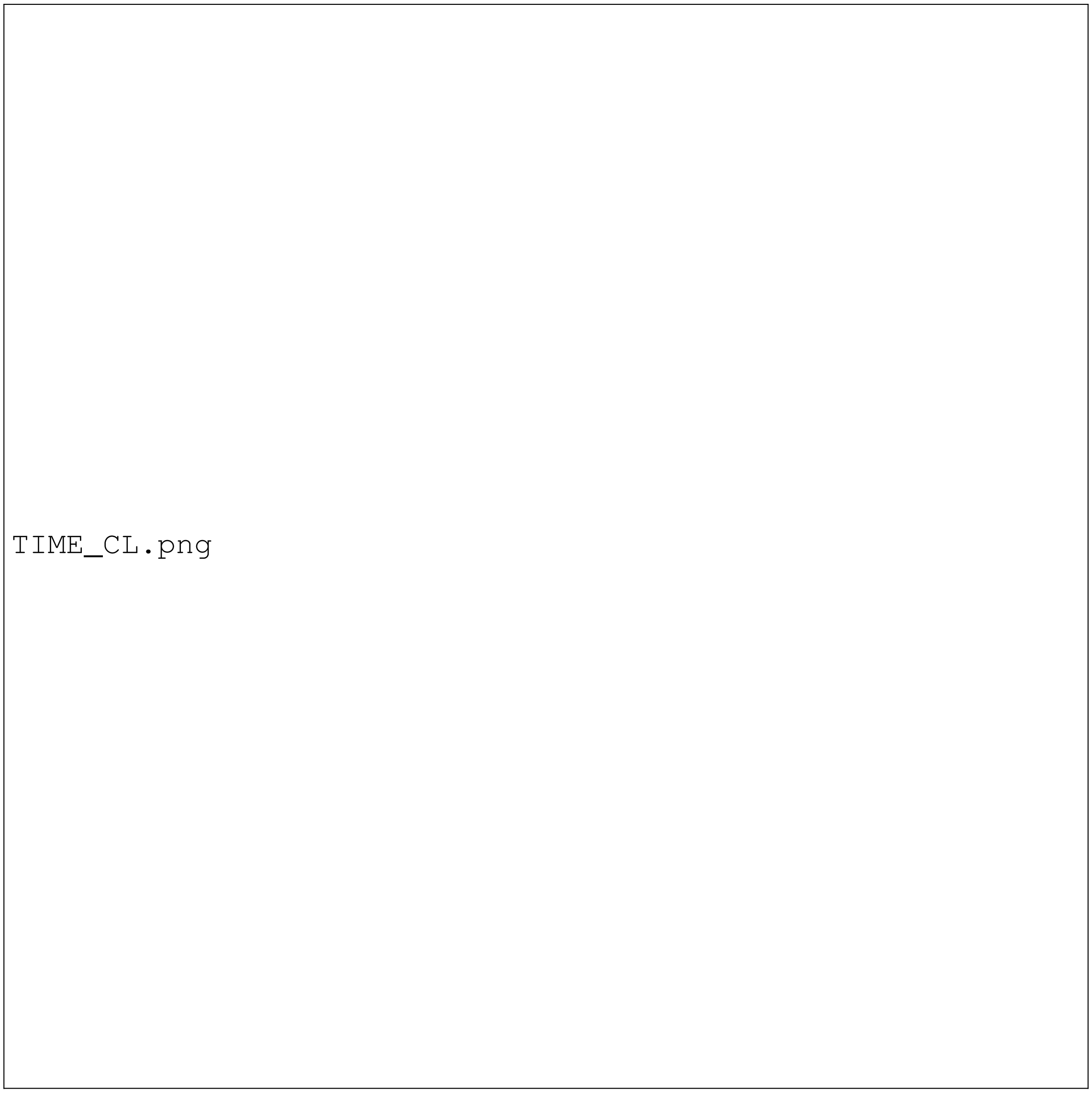

Figure 14: Time Series of spot volatility for Crude Oil

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Figure 15: Time Series of spot volatility for Gold

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Figure 16: Time Series of spot volatility for Silver

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Figure 17: Time Series of spot volatility for 10-year treasury