Applying Explosiveness Detection to Evaluate Asset Price Movements

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Abstract

This study applies the recent asset price explosiveness testing methodology developed by Boswijk et al. (2024) to identify and evaluate significant episodes of explosive behavior across various asset classes. The test leverages high-frequency asset price data, using realized volatility measures to devolatize log-price increments on daily asset price time series. A supremum-type recursive Dickey-Fuller test is then applied to the devolatized data. To pinpoint the timing of these explosive episodes, we implement a real-time date-stamping strategy. We examine multiple asset types, including stocks, indices from EU and US markets, foreign exchange rates, commodities, and cryptocurrencies, to compare their explosive properties and fundamental price movement patterns. The research concludes with a discussion of the findings, and the implementation code is provided as a reference for reproducibility and further exploration.

1 Motivation

The detection of explosive behaviors in financial markets has gained significant traction, especially in the wake of prominent economic bubbles and their far-reaching consequences. Recent advancements in econometric tools, like the one proposed by Boswijk et al. (2024), offer powerful methods to analyze such phenomena. This project is motivated by the need to evaluate these advanced methodologies in diverse market conditions and across various asset classes, including traditional financial markets and emerging sectors like cryptocurrencies.

Financial bubbles pose severe risks to economic stability, yet they also present opportunities for timely interventions and informed trading strategies. Traditional detection methods often rely on low-frequency data, which may obscure critical, rapidly-evolving market behaviors. By leveraging high-frequency data and devolatizing price series, we aim to overcome these limitations and provide a more nuanced understanding of asset price dynamics.

Furthermore, the unique volatility profiles of cryptocurrencies like Bitcoin (BTC) and Ethereum (ETH) compared to traditional assets like equities and indices offer an intriguing context for comparison. This project seeks to uncover whether the explosiveness tests, particularly the Generalized Supremum Augmented Dickey-Fuller (GSADF) test, can reliably indicate overvaluation and provide actionable insights for investors and policymakers.

2 Introduction and Aim

The aim of this study is to evaluate episodes of explosive price behavior in various financial markets. We implement advanced econometric tools to detect and analyze these behaviors while also assessing practical trading strategies for their implications.

3 Datasets

The explosiveness testing methodology requires high-frequency asset price data to devolatize prices on daily log-price increments. Therefore, each asset price time series could be fetched in high granularity and then aggregated to daily increments when applying the transformations needed for explosiveness testing. Similarly to Boswijk et al. (2024), we used 5-minute pricing data that was fetched from Alpaca and Dukascopy platforms based on the availability of data. This time interval is also consistent with the recommendations to use 4-15 minutes to obtain the realized volatility of liquid assets made by Tsay (2010).

3.1 Assets Used

Category	Asset Name	Data Source
US Stocks	NFLX (Tech), JPM (Banking), XOM (Oil), PFE (Healthcare)	Alpaca
US S&P 500 Index	SPY	Alpaca
EU STOXX 50 Index	EUS	Dukascopy
Hong Kong 40 Index	HKG	Dukascopy
EU Stocks	ASML (Tech), Novo Nordisk NOVOB (Healthcare), Adidas ADS (Consumer), Volkswagen VOW3 (Automotive)	Dukascopy
Commodities	BRENT (Oil), XAU (Gold)	Dukascopy
Forex	EURUSD, USDJPY	Dukascopy
Crypto	BTC, ETH	Alpaca Crypto

Table 1: All tested assets

These datasets were cleaned to remove non-trading periods and contain `datetime` timestamps as well as `o,h,l,c,v` entries. Note that imbalances in the market trading hours are apparent with cryptocurrencies, foreign exchange rate pairs, and commodities trading longer than stocks and indices. This was not problematic but only required the recomputation of the critical values of the explosiveness tests based on different daily time-series sequence lengths.

This initial process resulted in pricing data of separate 5-minute and daily granularities that was then used in the testing process.

4 Methodology

4.1 Devolatization

Devolatization standardizes log-price increments by removing heteroskedasticity caused by time-varying volatility. This process involves estimating the integrated volatility using high-frequency data and then scaling the log-price increments.

The log-price process y_t follows a stochastic process:

$$dy_t = \kappa y_t dt + \sigma_t dW_t,$$

where κ is the persistence parameter, σ_t is the volatility, and W_t is a standard Brownian motion. For discrete time intervals, integrated volatility ω_t is estimated as:

$$\omega_t^2 = \sum_{j=1}^{M} \left(y_{t-1,j} - y_{t-1,j-1}\right)^2,$$

where M is the number of high-frequency observations in a single interval.

The devolatized log-price series is constructed by normalizing log-price increments with realized volatility:

$$x_t = \sum_{i=1}^{t} \frac{\Delta y_i}{\omega_i}.$$

Python Code: Data Stamping Explosive Periods

```
def calculate_realized_volatility(high_freq_prices):

    high_freq_prices['log_price'] = np.log(high_freq_prices['close'])
    high_freq_prices['log_diff'] = high_freq_prices['log_price'].diff() ** 2
    realized_volatility = high_freq_prices.groupby(
        high_freq_prices['timestamp'].dt.date
    )['log_diff'].sum().apply(np.sqrt)
    return realized_volatility

def devolatize_data(low_freq_prices, realized_volatility):

    low_freq_prices['log_price'] = np.log(low_freq_prices['close'])
    low_freq_prices['log_diff'] = low_freq_prices['log_price'].diff()
    low_freq_prices['realized_volatility'] =
    ↪   low_freq_prices['timestamp'].dt.date.map(realized_volatility)
    low_freq_prices['scaled_diff'] = low_freq_prices['log_diff'] /
    ↪   low_freq_prices['realized_volatility']
    low_freq_prices['devol_price'] = low_freq_prices['scaled_diff'].cumsum()
    return low_freq_prices.dropna()
```

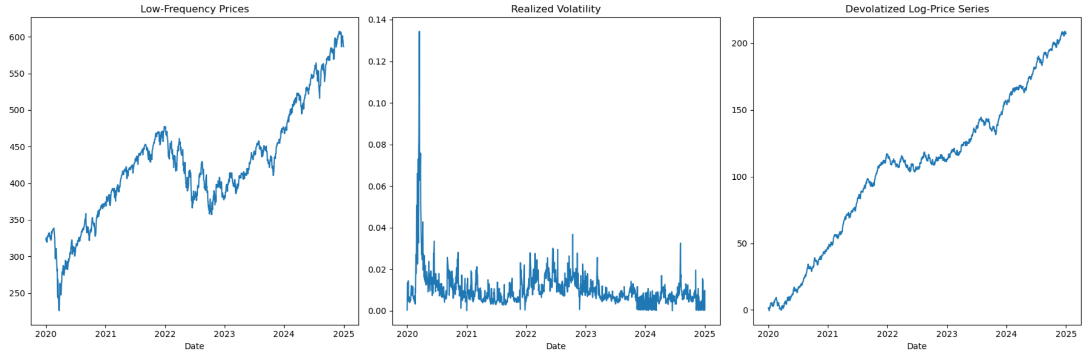

Figure 1: Example of devolatization step

4.2 Recursive Dickey-Fuller Test

The Recursive Dickey-Fuller (RDF) test is used to identify whether the devolatized series exhibits unit root behavior or explosiveness. The test is based on the following autoregressive model:

$$x_t = \phi x_{t-1} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \sigma^2).$$

The null hypothesis tests for a unit root:

$$H_0 : \phi = 1, \quad \text{vs.} \quad H_1 : \phi > 1.$$

The test statistic is computed as:

$$\mathrm{DF}_\tau = \frac{\hat{\phi} - 1}{\mathrm{SE}(\hat{\phi})},$$

where $\hat{\phi}$ is the estimated coefficient, and $\mathrm{SE}(\hat{\phi})$ is its standard error. The RDF test is applied recursively over subsamples to detect episodes of explosiveness.

Python Code: Recurcive Dickey-Fuller Test

```
def recursive_dickey_fuller(devolatized_series, tau0=0.1):
    n = len(devolatized_series)
    min_sample_size = int(tau0 * n)
    sup_stat = -np.inf
    for tau in range(min_sample_size, n + 1):
        sub_sample = devolatized_series.iloc[:tau]
        result = adfuller(sub_sample['devol_price'], maxlag=0,
        ↪   regression='c')
        sup_stat = max(sup_stat, result[0])
    return sup_stat
```

4.3 RVDF Detector and Critical Values

The Recursive Volatility Dickey-Fuller (RVDF) detector identifies explosive behavior in time series by recursively calculating the Dickey-Fuller test statistic over subsamples. The critical values for the RVDF test are estimated using simulations to compare the test statistic against predefined significance levels.

To construct the RVDF statistic, we define:

$$\text{RVDF}\tau = \sup \tau_0 \leq \tau \leq 1\text{DF}_\tau,$$

where DF_τ is the Dickey-Fuller test statistic computed over the subsample ending at fraction τ of the total data. The null hypothesis is:

$$H_0 : \phi = 1 \quad \text{(unit root behavior)}.$$

The critical values are derived through simulations of random walks. For a given series length n, the process generates n-step random walks and computes the supremum of the test statistics:

$$\text{Critical Value} = \sup_{\tau_0 \leq \tau \leq 1} \text{DF}_\tau,$$

where τ_0 ensures sufficient sample size.

Python Code: Estimate Critical Values

```
def estimate_critical_values(series_length, n_simulations=200,
↪   significance_levels=[0.01, 0.05, 0.1]):
    simulated_stats = []

    for _ in range(n_simulations):
        simulated_series = np.random.normal(0, 1, series_length).cumsum()
        df = pd.DataFrame(simulated_series, columns=['devol_price'])
        stat = rolling_dickey_fuller(df)['test_stats'].max()
        simulated_stats.append(stat)

    critical_values = {}
    for alpha in significance_levels:
        critical_values[alpha] = np.percentile(simulated_stats, 100 * (1
        ↪   - alpha))

    return critical_values
```

Python Code: Perform RVDF Test

```
def test_explosiveness_with_rvdf(devolatized_series, tau0=0.1):
    sup_stat = rolling_dickey_fuller(devolatized_series,
    ↪   tau0)['test_stats'].max()
    return sup_stat
```

4.4 Data Stamping

Data stamping identifies the start and end points of explosive episodes within the time series. This process is crucial for determining the precise timing of regime changes, such as transitions into or out of bubbles.

The procedure uses the Recursive Dickey-Fuller (RDF) test to determine the origination and conclusion dates of explosive behavior. The start of the explosive regime ($\hat{r}_e$) is defined as:

$$\hat{r}e = \inf\{\tau : \text{DF}\tau > \text{cv}\},$$

where cv is the critical value. The end of the regime ($\hat{r}_f$) is determined as:

$$\hat{r}f = \inf\{\tau > \hat{r}_e : \mathrm{DF}\tau < \mathrm{cv}\}.$$

This iterative procedure continues until all explosive periods within the series are identified.

Python Code: Data Stamping Explosive Periods

```
def date_stamping_all_periods(devolatized_series, critical_value, tau0=0.1):
    n = len(devolatized_series)
    min_sample_size = int(tau0 * n)
    periods = []
    start = min_sample_size

    while start < n:
        # Find origination date
        origination_date = None
        for i in range(start, n):
            sub_sample = devolatized_series.iloc[:i]
            result = adfuller(sub_sample['devol_price'], maxlag=0,
            ↪ regression='c')
            if result[0] > critical_value:
                origination_date = devolatized_series['timestamp'].iloc[i]
                start = i
                break
        if origination_date is None:
            break
        # Find conclusion date
        conclusion_date = None
        offset = int(np.ceil(np.log(n) / n))
        for i in range(start + offset, n):
            sub_sample = devolatized_series.iloc[:i]
            result = adfuller(sub_sample['devol_price'], maxlag=0,
            ↪ regression='c')
            if result[0] < critical_value:
                conclusion_date = devolatized_series['timestamp'].iloc[i]
                start = i + 1
                break
        if conclusion_date is None:
            conclusion_date = devolatized_series['timestamp'].iloc[-1]
            start = n
        periods.append((origination_date, conclusion_date))
    return periods
```

5 Results

This section covers the results of price explosiveness tests executed for different asset types. The tests were separated by asset groups in order to uncover explosivity co-movements and differentiate between systematic and idiosyncratic explosiveness. The critical values were computed jointly for the whole group if the trading hours and periods were similar, otherwise were computed by each asset individually. Inter-group similarities and differences were then compared to better grasp the global results of the study.

5.1 Indices

Indexes are representative of more systematic market conditions and it can be assumed that global explosiveness could be more rare. However, explosive market bubbles have historically been significant enough to affect the movements of overall indexes. An example of that is the dot-com bubble period where explosive regimes were observed in major US indexes during the period of 1995 - 2001. One reason for that could be the large weights attributed to stocks of particularly aggressively growing large market caps. For example, at the time of writing, Nvidia stock represents 6.75% of total S&P 500 share, therefore together with other highly correlated and large weight tech stocks it can cause large impact movements of the whole S&P 500 index.

While broader market trends are reflected in indices, indices are representative of corresponding regional markets. We tested the explosivity of 3 major global indices: S&P 500, EU STOXX 50, and Hong Kong 40. The critical values for the RWPY test statistic are: 1.94 at 1%, 1.55 at 5%, 1.24 at 10%.

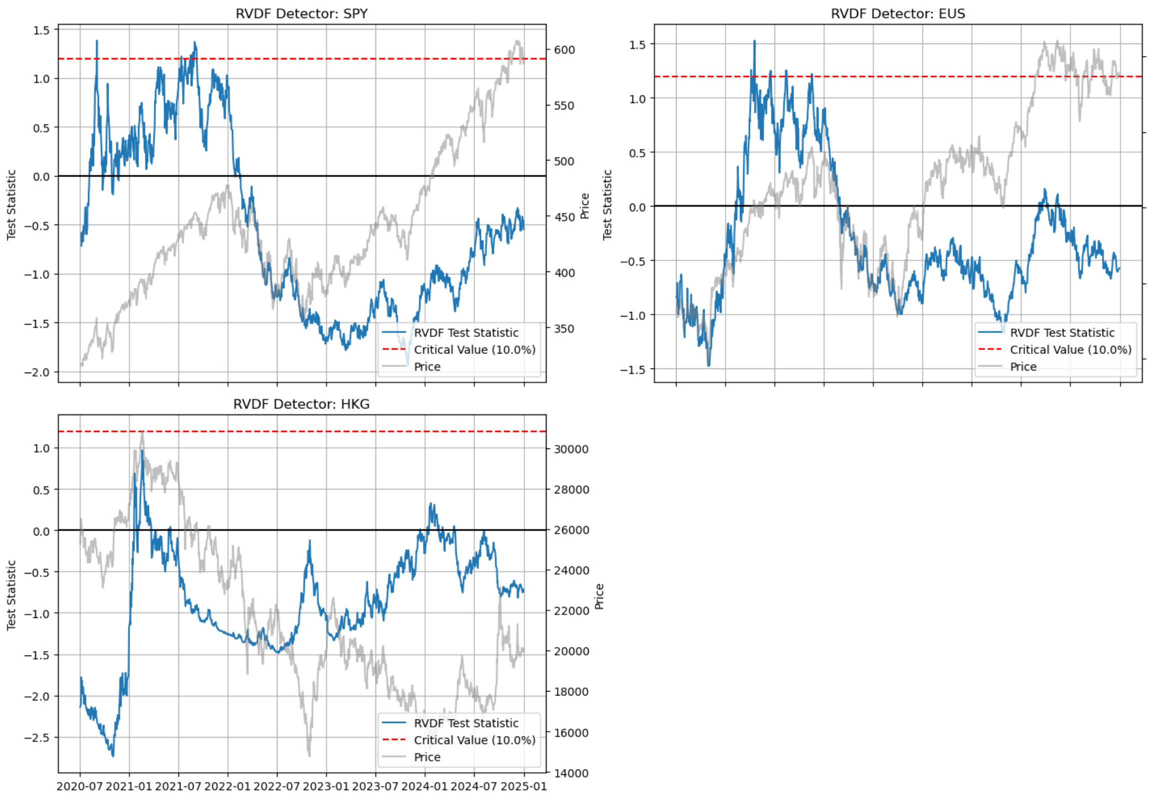

Figure 2: Explosiveness indicators for S&P 500, EU STOXX 50, Hong Kong 40 indices

The results indicate RVPWY test statistics of 1.381 for SPY, 1.53 for EUS, and 0.967. We can therefore reject the unit root regime hypothesis at 10% uniquely for SPY and EUS pricing data (EUS also significant at 5%). The RVDF detector pinpoints the following dates for indications of explosiveness:

Symbol	Start Date	End Date
SPY	2020-09-03	2020-09-04
SPY	2021-07-13	2021-07-14
SPY	2021-08-17	2021-08-18
SPY	2021-08-24	2021-08-27
SPY	2021-08-30	2021-09-08
EUS	2021-04-06	2021-04-07
EUS	2021-04-16	2021-04-21
EUS	2021-06-14	2021-06-21
EUS	2021-08-13	2021-08-17
EUS	2021-11-17	2021-11-18

Table 2: Explosiveness periods for indices

Nonetheless, most of these periods are 1-day fluctuations without high confidence. Indeed, we can see that the ending points of these indicated regimes were marked with sub-10% price crashes. No explosiveness was detected for the Hong Kong 40 index. This is an expected result, since the pricing data suggests downward price trend of this index during our observed period.

5.2 US Stocks

Zooming in on the US market, we have compared stocks of different market sectors. When selecting the stocks, we omitted the largest weight stocks in S&P 500 in order to achieve a better independence of results comparing to previous section where explosiveness of the index price was tested. Overall, we have tested:

1. Netflix (NFLX), a tech sector stock that has been aggressively growing during major part of our observation period.
2. J.P. Morgan (JMP), a bank's stock that was particularly positively affected during the period of Federal Interest Rate raises.
3. Exxon Mobil (XOM), oil sector stock, a period of volatility in 2021-2022.
4. Pfizer (PFE), a health sector stock that had an episode of explosive bubble behavior during mid-2021 to early 2022 due to the COVID-19 vaccine development.

The critical values for the test statistics were the same: 1.94 for 1%, 1.55 for 5%, 1.24 for 10%.

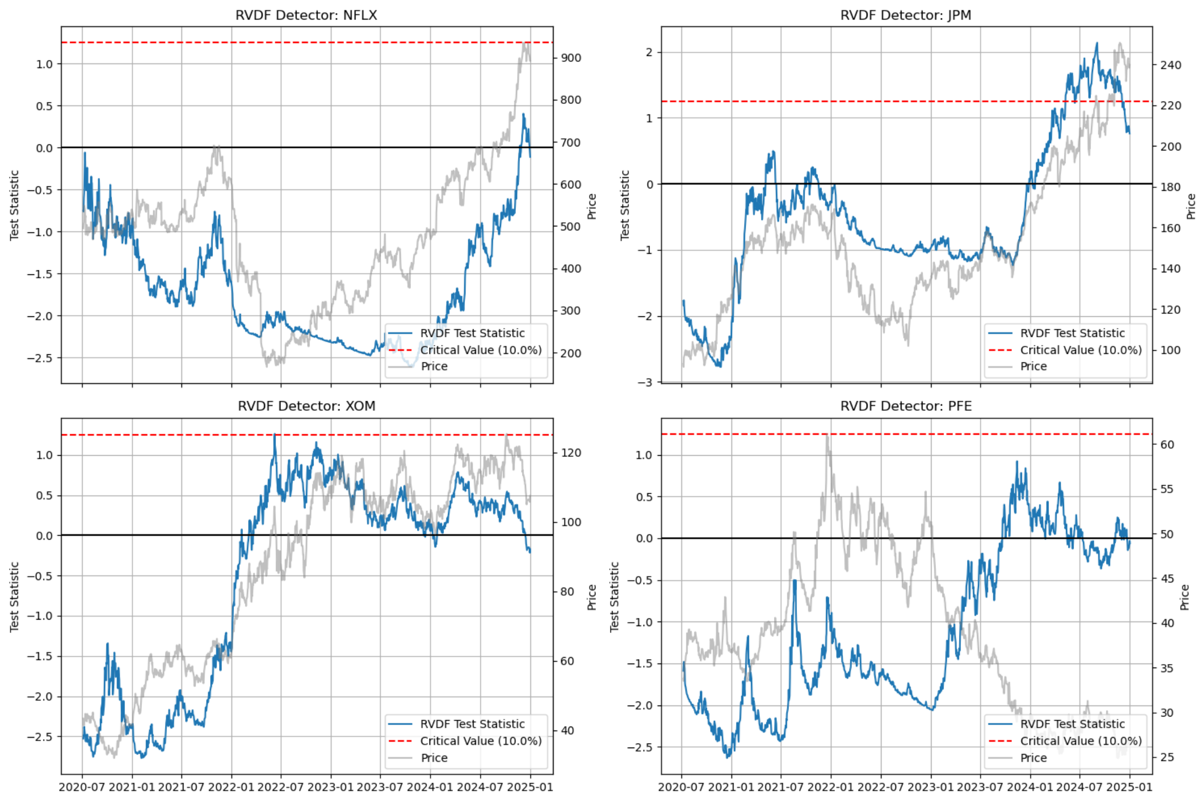

Figure 3: Explosiveness indicators for selected US stocks

The results inidicate an RVPWY test statistics of 0.404 for NFLX, 2.136 for JPM, 1.263 for XOM and 0.922 for PFE. We can therefore reject the unit root regime hypothesis at 10% for XOM and at 1% significance for JPM time series. The RVDF detector marked the following dates for indications of explosiveness:

Symbol	**Start Date**	**End Date**
JPM	2024-05-10	2024-06-13
JPM	2024-06-14	2024-12-04
XOM	2022-06-09	2022-06-10

Table 3: Explosiveness periods for selected US stocks

The overall results and test statistics are differing from the S&P 500 index, even though both NFLX and JPM exhibit correlated price movements. The COVID pricing bubbles for both NFLX and PFE could not be detected even at 10% level, even though both stocks were highly speculated during that timeline. Nonetheless, unit root regime is rejected at 1% for certain instances of recent explosiveness of JPM stock, which is also supported by the high RVPWY statistic. The volatility of the stock price confirms the explosiveness of this stock, however the pricing bubble remains to be confirmed out of the sample.

5.3 EU Stocks

For the EU market, we conducted a similar analysis focusing on prominent stocks from various sectors. As with the US market, we excluded the largest-weight stocks in the region's indices to ensure the independence of results relative to broader index explosiveness tests. Specifically, we tested the following:

1. ASML (ASML), representing the tech sector, a leading semiconductor equipment supplier with strong growth and significant influence on European technology markets.

2. Novo Nordisk (NOVOB), a healthcare stock that experienced notable growth during the observation period due to its advancements in diabetes and weight management treatments.

3. Adidas (ADS), from the consumer discretionary sector, which displayed significant volatility in response to shifting consumer trends and macroeconomic conditions.

4. Volkswagen (VOW3), an automotive stock that was impacted by the transition to electric vehicles and geopolitical events affecting global supply chains.

The critical values for the test statistics were very similar: 1.96 for 1%, 1.53 for 5%, 1.22 for 10%.

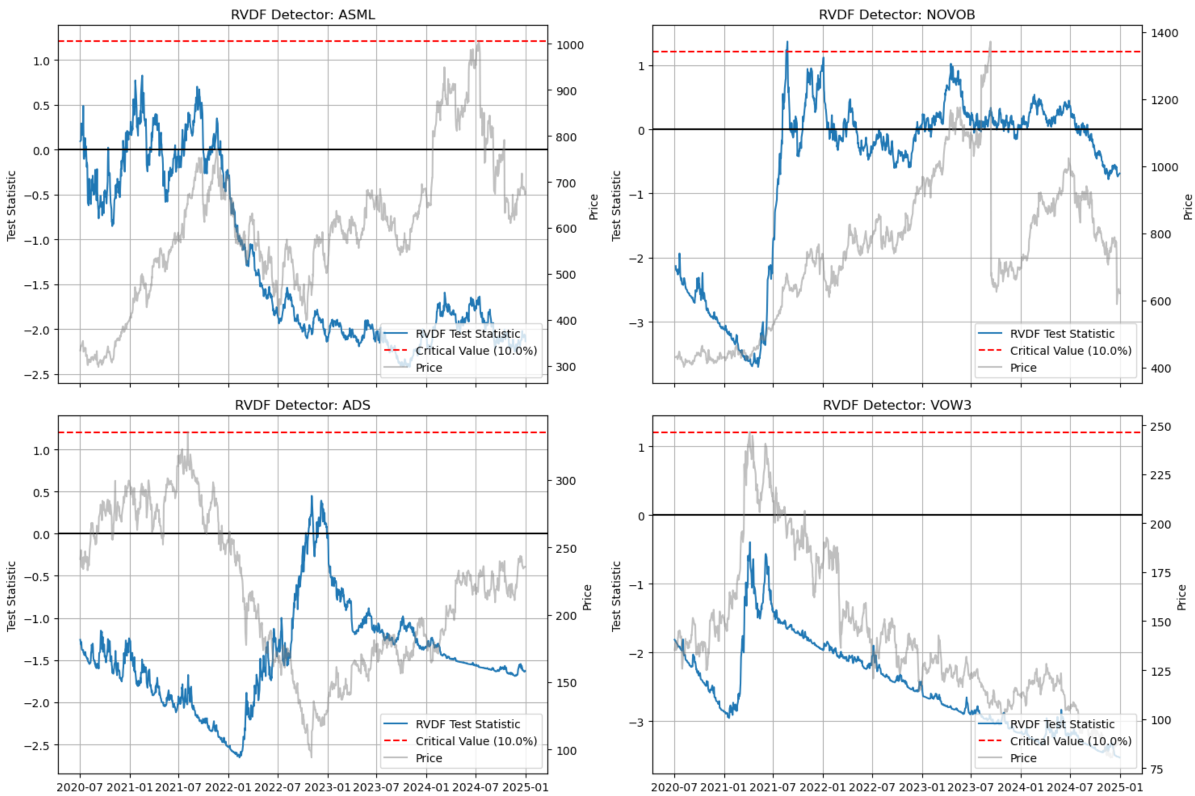

Figure 4: Explosiveness indicators for selected EU stocks

The results indicate an RVPWY test statistics of 0.827 for ASML, 1.369 for NOVOB, 0.445 for ADS and -0.397 for VOW3. We can therefore reject the unit root regime hypothesis for NOVOB only (at 10% level). The RVDF detector marked the following dates for indications of explosiveness:

Symbol	**Start Date**	**End Date**
NOVOB	2021-08-19	2021-08-20
NOVOB	2021-08-23	2021-08-24

Table 4: Explosiveness periods for selected EU stocks

The explosiveness tests fail to detect pricing bubbles in ASML price movements in 2021 and 2024, while intuitively these periods are highly explosive. A similar result is observed for NOVOB where the explosive behavior in 2023 failed to be detected by the date-stamping process. Nonetheless, this result can be motivated by lower volumes in the EU markets where main price movements are very brief and generally happen around periods of the quarterly earnings announcements.

5.4 Commodities

In the commodities market, we analyzed Brent Crude Oil (BRENT) and Gold (XAU). The results for Oil demonstrated expected correlations with the explosiveness statistics of Exxon Mobil, reflecting the close link between energy sector performance and oil price dynamics. Notably, the critical values for the test statistics differed here due to the extended trading hours of commodities and therefore longer time-series sequences: 1.98 for 1%, 1.51 for 5%, 1.27 for 10%.

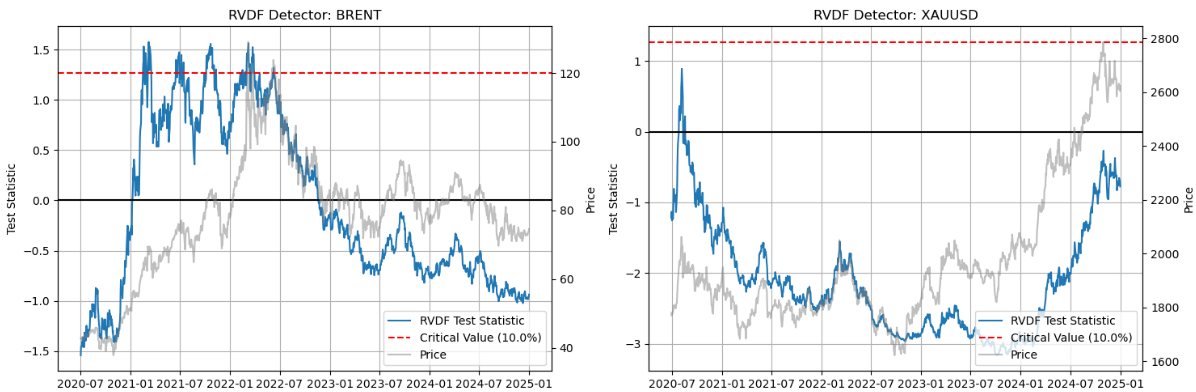

Figure 5: Explosiveness indicators for oil and gold commodities

The RVPWY test statistic for BRENT is significant at 5% level while XAUUSD RVPWY is at insignificant 0.889 value. Multiple periods, some ranging about 15 days are detected by the RVDF date stamping process:

Symbol	Start Date	End Date
BRENT	2021-02-15	2021-03-18
BRENT	2021-06-16	2021-06-29
BRENT	2021-07-02	2021-07-15
BRENT	2021-10-05	2021-11-11
BRENT	2022-02-14	2022-03-31
BRENT	2022-06-09	2022-06-10

Table 5: Explosiveness periods for oil and gold commodities

These results demonstrate consistency with the price movements where oil price fluctuations in the post-COVID recovery period were volatile due to the uncertainty of regenerating demand. The last price shock was observed in early-mid 2022, and is also reflected in the RVDF detections. Nonetheless, the co-explosiveness of previously analyzed XOM oil sector stock and BRENT Oil prices is only apparent throughout this period, with XOM remaining at higher explosiveness levels after this period. In addition, while gold prices have seen gradual increments starting in 2023, the methodology does not detect explosiveness episodes throughout this period.

5.5 Forex rates

In the forex market, we examined the EUR/USD and USD/JPY exchange rates. These pairs were chosen for their global significance and distinct regional influences. The critical values for the test statistics differed slightly due to the 24-hour trading nature of forex markets: 1.91 for 1%, 1.4 for 5%, 1.15 for 10%.

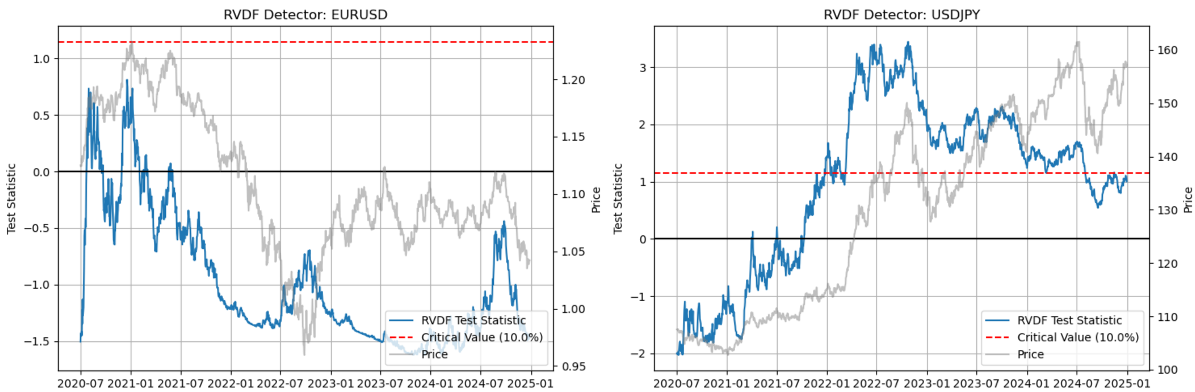

Figure 6: Explosiveness indicators for selected Forex pairs

The tests result in a non-significant RVPWY statistic of 0.812 for EURUSD pair but unusually high statistic of 3.443 for USDJPY which is significant at 1% level. The RVDF method also pinpoints explosiveness periods of large duration:

Symbol	Start Date	End Date
USDJPY	2021-12-24	2022-02-21
USDJPY	2022-03-09	2024-08-02
USDJPY	2024-11-15	2024-11-17

Table 6: Explosiveness periods for selected Forex pairs

This is an unexpected result, especially given relatively low fluctuations in price of the pair (within 20%). However, the most significant RVDF indicator fluctuations in this period were indeed followed by exchange rate corrections. Underlying systematic reasons for this result remain uncovered.

5.6 Cryptocurrencies

In the cryptocurrency market, we focused on Bitcoin (BTC) and Ethereum (ETH). Testing on cryptocurrencies is particularly interesting due to their highly volatile nature. Note that the observation period for the cryptocurrencies differs where the sample is restricted to 01.01.2021 to 01.01.2025 (due to data availability restrictions). The critical values for the test statistics adjusted to account for the 24/7 trading cycle are: 2.02 for 1%, 1.41 for 5%, 1.19 for 10%.

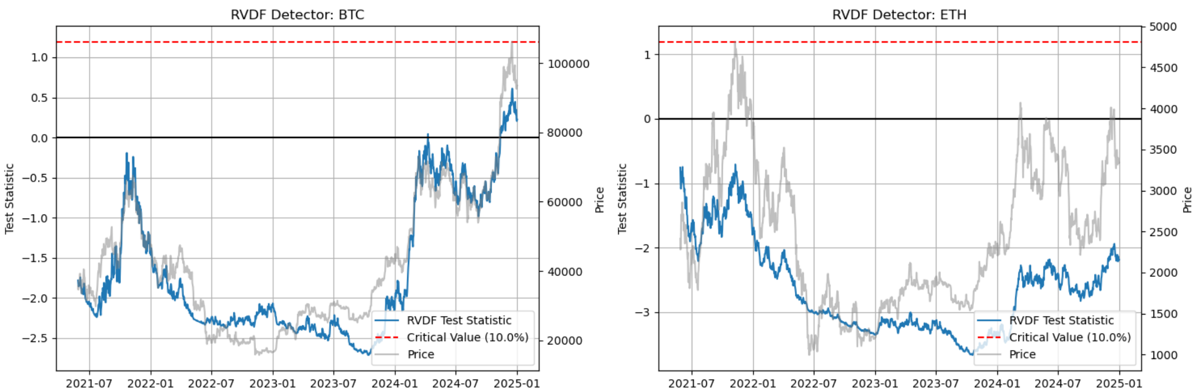

Figure 7: Explosiveness indicators for ETH and BTC cryptocurrencies

Contrary to our initial expectations, the resulting RVPWY statistics are insignificant for both ETH (-0.707) and BTC (0.611). This is a particularly unintuitive result judging BTC price movements throught the year 2024 where BTC price increased 5-fold. Indeed, the price fluctuations of ETH were significant but the overall trend was not completely on the upside. This result, even though covering different market periods, is different from the observations obtained by Boswijk et al. (2024) where episodes of explosivity were detected in ETH temporal price data during the sample period of 2019-2021.

6 Discussion

The results of our price explosiveness tests provide significant insights into the dynamics of different asset classes, highlighting both systematic and idiosyncratic behaviors. For major indices, the findings suggest a nuanced picture. While broader market trends such as the dot-com bubble have historically caused index-wide explosive behaviors, our analysis showed limited evidence of explosiveness during the observed period, with the exception of certain short-lived episodes in the S&P 500 and EU STOXX 50. The absence of detected explosiveness in the Hong Kong 40 index aligns with its downward price trend during this period, emphasizing the importance of underlying market conditions in driving these outcomes.

US stocks presented more pronounced variability in explosiveness across sectors, reflecting idiosyncratic drivers. For example, J.P. Morgan's stock displayed significant explosiveness, consistent with periods of monetary policy tightening, while Exxon Mobil showed evidence of explosiveness during periods of oil price volatility. Conversely, stocks like Netflix and Pfizer, which were anticipated to exhibit explosive behavior during speculative bubbles, did not yield statistically significant results. This divergence underscores the limitations of current testing methodologies in capturing all episodes of perceived market bubbles, particularly in highly dynamic or speculative contexts.

European stocks, on the other hand, revealed more subdued explosive behaviors. Novo Nordisk's results highlighted brief periods of explosiveness linked to earnings announcements and sector-specific growth, while other stocks like ASML and Volkswagen failed to demonstrate expected explosiveness despite intuitive market volatility. These results suggest that lower trading volumes and concentrated price movements in European markets may challenge the ability of standard tests to detect explosiveness, calling for further refinement of methodologies tailored to regional market characteristics.

In commodities, Brent Crude Oil exhibited expected co-explosiveness with the energy sector, particularly Exxon Mobil, during post-COVID recovery and geopolitical disruptions. However, the absence of explosiveness in gold prices during a period of gradual upward trends reflects the complex interplay between asset class characteristics and explosiveness detection. Similarly, forex market results demonstrated a surprising lack of explosiveness in the EUR/USD pair while the USD/JPY pair showed unusually high explosiveness, which warrants further investigation into underlying macroeconomic factors or methodological biases.

Cryptocurrency results diverged significantly from expectations. Neither Bitcoin nor Ethereum exhibited statistically significant explosiveness despite substantial price fluctuations, particularly in Bitcoin during its five-fold price increase in 2024. One possible explanation for this is that the explosiveness test might fail to detect the explosive nature of ETH and BTC because these assets have been in a persistently explosive regime over the observed period. If the sample predominantly captures this ongoing explosiveness, the statistical framework may not register the transitions or phases typically used to identify such dynamics. Furthermore, even in the original research on explosiveness testing, the explosive behavior of ETH and BTC was not as significant as it was for the S&P 500 index, raising questions about the test's applicability to cryptocurrency markets. Future research should consider integrating additional metrics or alternative models to better capture the nuances of cryptocurrency markets, such as volatility clustering, liquidity measures, or trader sentiment indicators to supplement explosiveness testing.

7 Conclusion

Overall, these findings highlight both the potential and the limitations of explosiveness testing across diverse asset classes. While the methodology successfully identified certain episodes of market bubbles and volatility, it also demonstrated gaps in detecting intuitively apparent explosive behaviors, particularly in low-volume markets or during brief, high-volatility episodes. Additionally, the significance level considerations are crucial; most detections occur at the 10% level, with only a few at the more stringent 1% level, questioning the robustness for part of these findings. Future considerations should focus on integrating complementary models, and incorporating region- or asset-specific adjustments to enhance the robustness and accuracy of explosiveness detection.

In conclusion, our study underscores the need for adaptive methodologies. By refining current approaches to explosiveness testing and tailoring them to the unique characteristics of various asset classes, future research can better identify and understand the complex dynamics of market bubbles and volatility.

Appendix

The implementation code is included as a ZIP file with this document. Attached code is documented with respective data fetching, cleaning, and implementation parts separated into their corresponding `ipynb` notebooks. The only pre-requisite for fast reproduction of the results is to download the available intraday pricing data from a dedicated EPFL drive folder. The link to this drive will be provided together with the submission message. In order to run the demo step, you should:

1. Download the data, put it into `data/` folder at the root of the project folder.

2. Run the `clean_intraday.ipynb` notebook to get the cleaned and prepared data files.

3. Run the `implementation.ipynb` notebook to execute a demo run. You can customize which asset(s) to execute on by modifying the `symbols` variable.

References

Boswijk et al. (2024). *Testing for Explosive Behavior in Asset Prices Using High-Frequency Data.*

Tsay, R. S. (2010). *Analysis of Financial Time Series*(3rd ed.)(pp. 162). John Wiley & Sons, Inc.