A Comparison of Realized Covariances in Examining Gold's Properties Against Leading Eurozone Stocks

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Abstract

This paper examines whether gold can act as a safe haven and/or a hedge against the eurozone stock market by identifying periods of negative or zero integrated covariance (ICOV), estimated from high-frequency prices for each trading day. There is no consensus on a unique ICOV estimator due to the sensitivity of realized counterparts to market imperfections. Hence, this research employs an appropriate synchronization scheme, an optimal sampling frequency, and a top-ranked robust price-jump estimator. Unlike existing studies that rely on daily prices or simulated intraday prices, this paper contributes by determining which realized covariance provides an unbiased and consistent ICOV estimate between the EUROSTOXX50 index and gold using one-minute transaction data. The robust version of the realized two-times scaled covariance (RRTSCOV) is appointed as the benchmark against which other estimators are compared and ranked by mean squared error, quasi-likelihood loss functions, and the Diebold-Mariano test. The realized outlyingness-weighted covariance (ROWCOV) at a sampling frequency of 22 minutes confirms that gold served as a safe haven during the first wave of the COVID-19 pandemic and the onset of the war in Ukraine. Thus, in the short run, gold exhibits strong safe-haven properties, but in the long run, the realized covariance indicates a weak hedge for leading eurozone stocks.

Keywords: eurozone stock market, gold properties, intraday prices, realized covariance

JEL classification: C55, C58, G11, G15

1 Introduction

In recent literature, realized covariance measures (RCOV) have been increasingly used for the optimal allocation of various assets within modern portfolio management (Bollerslev et al., 2018). RCOV enables the estimation of the unobservable integrated covariance (ICOV), whereas alternative ex-post approaches, such as historical models based on lower-frequency data or GARCH (generalized autoregressive conditional heteroskedasticity) models, lack this capability. However, RCOV imposes the use of high-frequency data, recorded at equally spaced, non-empty, and disjoint short time intervals, thereby preserving intraday information (Barndorff-Nielsen & Shephard, 2004a). Intraday transaction data make RCOV a more efficient estimator of integrated covariance compared to traditional methods. While this is its primary advantage, it also introduces several challenges due to discrete price observations, microstructure noise, price jumps, and asynchronous and irregularly spaced sampling intervals (Barndorff-Nielsen et al., 2011; Boudt et al., 2022). For the same reasons, it is not straightforward to obtain an unbiased and consistent estimate of integrated covariance. To address these issues, various realized covariance measures have been proposed (Barndorff-Nielsen & Shephard, 2004b; Hayashi & Yoshida, 2005; Boudt et al., 2011; Zhang, 2011; Boudt & Zhang, 2015), each of them exhibiting specific properties. However, empirical studies have not identified a universally accepted ICOV estimator. Synchronization schemes and optimal sampling frequency selection are crucial for obtaining an unbiased ICOV estimate, effectively mitigating two primary sources of bias: (a) microstructure noise and (b) the so-called Epps effect. Nonetheless, additional challenges persist, as not all proposed estimators are robust to price jumps, nor do they ensure positive semidefiniteness or affine equivariance of the realized variance-covariance matrix. These challenges become even more complex as the number of assets increases.

As this study aims to identify the most suitable estimator for examining gold's properties against leading eurozone stocks, aggregated into the single EUROSTOXX50 index, while also offering recommendations on the use of realized covariance under different market conditions, it represents a significant contribution to the existing literature. Accordingly, six estimators are employed, with one serving as the benchmark against which the other five, each computed at its own optimal sampling frequency, are compared and ranked using loss functions such as mean squared error (MSE) and quasi-likelihood (QLIKE), along with the Diebold-Mariano (DM) test. The DM test indicates whether significant differences exist in integrated covariance estimates between pairs of competing realized measures relative to the benchmark. The benchmark is selected as the estimator exhibiting the most preferable properties, which are thoroughly elaborated in Section 3. The fact that an asset serves as a safe haven does not necessarily imply that it also functions as a hedge. Therefore, realized covariance will be further utilized to reexamine the hedge property over the long term, providing an additional contribution of this study. Moreover, the findings on gold's performance as a safe investment against the EUROSTOXX50 index during recent crises help bridge a gap in the existing literature, which often neglects high-frequency data. The EUROSTOXX50 index was chosen as a representative of the eurozone stock market, as it comprises the 50 most liquid stocks of leading companies across 11 eurozone countries. The dataset, retrieved from Bloomberg, encompasses 1-minute price observations of the EUROSTOXX50 index (denominated in euros) and gold (denominated in US dollars) over the period from January 31, 2020, to January 31, 2023.

Apart from the introduction, the remainder of the paper is structured as follows. Section 2 delivers the theoretical background on gold as a safe haven and hedge, critically reviewing relevant literature. Section 3 elaborates the methodological framework of realized covariance, with particular attention to the challenges addressed in its application. The fourth section presents the empirical results and discussion. The final, fifth section provides concluding remarks with implications, limitations of the study, and potential research paths.

2 Review of Previous Studies

Global stock markets have faced high volatility and significant losses, causing great concerns among investors and analysts, particularly in the last few years. For example, the Dow Jones Industrial Average (DJIA) and S&P 500 indices lost over 30 percent of their value in the first few months of 2020 due to the COVID-19 pandemic. Likewise, stocks on European markets recorded a 10 percent decline when Russia invaded Ukraine in February 2022. The negative sentiment at the beginning of 2023, driven by inflation expectations and uncertainty with respect to the energy supply crisis, also exerted additional pressure on European stock markets. As concerns and uncertainty increased, so did the interest in safe assets, whose values either remain steady or even increase during periods of significant turmoil. Such assets are referred to as safe havens and provide investors with the opportunity to protect a portion of their wealth from losses. Baur and Lucey (2010) first introduced the safe-haven concept, which explicitly distinguishes itself from a hedge and/or diversifier. Assets used for hedging and diversification are either uncorrelated or negatively correlated with other assets or the entire portfolio over the long term. These assets are not specifically intended for offsetting losses during crisis periods, as they may be positively correlated with other assets during crises and negatively correlated in non-crises periods. Conversely, a safe-haven asset does not need to be negatively correlated with other assets or the entire portfolio on average; instead, this correlation should be negative or at least zero during stressful periods, meaning that it can be positively correlated in normal conditions.

Several types of assets are conventionally considered safe havens, such as precious metals, government bonds, foreign currencies, and even cryptocurrencies (Dimitriou et al., 2020; Ji et al., 2020; Disli et al., 2021). Since gold is the most well-known safe haven, its price typically increases during periods of financial and other crises. For instance, the price of gold rose during the oil crisis from 1973 to 1975, the energy crisis triggered by the Iranian revolution in 1979, and the 2007 financial crisis, when the absolute price of gold increased by as much as 78.9 percent, while other assets recorded significant losses (Baur & McDermott, 2010). In August 2020, the absolute price of gold reached its historical maximum at 2,074.88 USD per ounce, marking an increase of approximately 18 percent from the beginning of 2020. The recent upward trend in gold prices, starting in November 2022, was driven by the less aggressive stance of the US Federal Reserve regarding interest rate hikes, as well as the reopening of the Chinese economy, leading to higher demand for gold (Čupić, 2025). Treasury bills and government bonds with high credit ratings are also considered safe havens due to their extremely low risk and volatility. Bitcoin, as the most prominent cryptocurrency, is fundamentally uncorrelated with financial assets due to the specific way its price is determined and its independence from monetary policy (Hasan et al., 2021). However, given the high risk associated with investing in cryptocurrencies, as well as the ongoing debate among researchers regarding their role as a safe haven, further investigation is required.

Numerous studies have analyzed the performance of gold over different time periods and across various markets. Using an asymmetric GARCH model on a sample of daily closing prices from 1995 to 2005, Baur and Lucey (2010) concluded that gold played the role of a safe haven against the stock markets in the USA, the United Kingdom, and Germany, but not in relation to the bond markets of the same countries. The results of the rolling window regression applied by Baur and McDermott (2010) to daily, weekly, and monthly returns from 1979 to 2009 suggest that gold functions as both a hedge and a safe haven relative to major European stock markets and the USA, but not in relation to Australia, Canada, Japan, or the large emerging markets of the BRIC countries (Brazil, Russia, India, and China). This research is extended by Beckmann et al. (2015), who considered a longer period from 1970 to 2012 and included additional countries that are significant producers and consumers of gold (Indonesia, Turkey, Thailand, Egypt, Korea, and South Africa). They implemented two switching regimes: the first related to periods of average returns to test gold's role as a hedge, and the second focused on periods of extreme market returns and high volatility to test its role as a safe haven. Using monthly data, they documented that gold generally serves as both a hedge and a safe haven, although this depends on the country-specific economic environment. On the other hand, Hood and Malik (2013) found that gold is a good hedge but a weak safe haven with respect to the US stock market. Tronzano (2022) used multivariate GARCH model DCC (dynamic conditional correlation) and monthly gold prices, the Swiss franc currency (nominal exchange rate of the Swiss franc against a basket of currencies), and the prices of four leading global stock indices (USA, Europe, Japan, and emerging countries). He demonstrated that from 1999 to 2021, the Swiss franc was a significantly stronger safe haven than gold for portfolios composed of leading global stock indices. Ciner et al. (2013) used daily data from 1990 to 2010 for the USA and UK to examine dynamic correlations between stocks, bonds, currencies, gold, and oil. Their results show that gold can be considered a hedge against exchange rates in both countries, confirming its role as a monetary asset. Baur and Glover (2012) took a different perspective and showed that excessive speculative investment in gold can diminish the effectiveness and duration of its safe-haven properties during crises, which may have adverse implications for financial stability.

The crisis triggered by the COVID-19 pandemic cast doubt on the effectiveness of traditional safe-haven assets. Disli et al. (2021) analyzed daily closing prices for three stock indices and three potential safe havens from 2016 to 2021 using wavelet coherence and spillover analysis. Their findings suggest that gold, crude oil, and Bitcoin exhibited low coherence with all three stock indices (traditional, sustainable, and Islamic) across all time horizons before the pandemic. However, once the crisis began, spillover effects increased, and strong correlations emerged across all pairs of indices and safe havens. Nevertheless, decomposition of time-varying co-movements showed that the significant correlations were primarily driven by short-term fluctuations (up to four days), implying that the safe-haven properties of gold, crude oil, and Bitcoin were compromised only in the short term.

In addition to the COVID-19 crisis, Choudhury et al. (2022) examined the safe-haven properties of gold and US and Japanese government bonds relative to the S&P 500 and MSCI Emerging Markets indices during viral epidemics such as SARS, Ebola, and the swine flu. Using a DCC-MGARCH model, they found that gold was a weak safe haven, while US government bonds were consistently safer, followed by Japanese government bonds. Ji et al. (2020) used a sequential tracking approach to detect changes in the left tail of stock return distributions for the MSCI US, MSCI EU, and MSCI China indices and evaluated whether these could be mitigated by adding safe-haven assets (gold, Bitcoin, EUR/USD and CNY/USD exchange rates, oil, soybeans, and US Treasury bills). They showed that gold and soybean futures had the strongest safe-haven properties during the pandemic, with soybeans benefiting from increased demand. Hasan et al. (2021) also confirmed the time-varying nature of safe-haven assets using 12 candidates against the S&P 500 index from 2002 to 2020 and found that Islamic stocks and the cryptocurrency Tether exhibited the strongest safe-haven properties during COVID-19, while gold and the US dollar acted as strong hedges.

The conclusions drawn from the reviewed studies on gold's performance vary depending on the time span, sampling frequency, crisis conditions, countries examined, the assets against which safe-haven and hedge properties are tested, and the predominantly parametric methods used. Studies investigating gold as a safe haven against leading eurozone stocks using high-frequency data remain scarce, with almost no research employing a non-parametric approach based on realized covariance or realized correlation while addressing the challenges associated with estimating integrated covariance. Therefore, this study contributes to the literature by examining gold's role as a safe haven and hedge using high-frequency data during the COVID-19 pandemic and the war in Ukraine.

3 Transaction Data and Realized Covariance Measures

The increasing availability of high-frequency intraday data has sparked interest in realized variance (RV) and realized covariance (RCOV) as non-parametric estimators of integrated variance (IV) and integrated covariance (ICOV). Numerous studies highlight the advantages of high-frequency-based RCOV estimators over lower-frequency alternatives. Bollerslev and Zhang (2003) showed improved systemic risk measurement and multi-factor asset pricing with high-frequency data. Similarly, Fleming et al. (2003), Pooter et al. (2008), and Jin and Maheu (2013) conclude that realized variance-covariance matrices enhance portfolio risk management. It should be noted that the basic RCOV estimator and its variants are non-parametric ex-post estimators, collectively referred to as "realized measures", since they incorporate all available transaction data (tick-by-tick) or at least the data available at the highest frequency. Dealing with such data imposes several challenges. The first is the tremendous number of observations, which can reach millions per day for a single financial asset (Boudt et al., 2011). The second challenge is the asynchronous nature of trading across different securities, where transactions are often irregularly spaced (Griffin & Oomen, 2011). Zhang (2011) documented that asynchronicity leads to the downward bias of realized covariance measures, a phenomenon known as the Epps effect, which becomes more pronounced as sampling frequency increases, especially for less liquid assets. Additionally, high-frequency data are contaminated by market microstructure noise, which also distorts realized covariance estimates (Aït-Sahalia et al., 2010). From a market perspective, microstructure noise represents deviations of asset prices from their fundamental values, caused by several factors such as wide bid-ask spreads, discrete price observations, price rounding, or information asymmetry. From an econometric standpoint, microstructure noise generates errors that render realized covariance estimators biased and inconsistent (Boudt et al., 2022), and leads to systematic underestimation of realized covariance (Pooter et al., 2008). Another key issue is the presence of price jumps, which make it difficult to distinguish between genuine changes in intrinsic asset value and short-term market anomalies. This also introduces bias in realized covariance estimates (Vander-Elst & Veredas, 2017). Price jumps are particularly prevalent in high-frequency data, as short-term anomalies tend to occur within the trading day itself. A prominent example is the Flash Crash, during which the DJIA plummeted nearly 9 percent before recovering within 36 minutes.

As a consequence of the aforementioned issues, numerous alternative estimators have been developed to enhance the basic RCOV estimator. In the bivariate case, the realized covariance (RCOV) for each trading day is computed as the sum of the products of synchronized and equally spaced intraday returns sampled at the K-th frequency. As the sampling frequency increases (the sampling interval shortens), RCOV converges to the integrated covariance (ICOV), assuming no microstructure noise in synchronized returns (Barndorff-Nielsen & Shephard, 2004a). However, in practice, microstructure noise causes the diagonal elements of the covariance matrix to be biased upward and the off-diagonal elements to be biased downward as sampling frequency increases, leading to significantly distorted realized correlations. In the case of non-synchronous returns, an additional bias in realized correlation arises due to the Epps effect, further reducing the absolute value of off-diagonal elements. Thus, the sampling frequency K should neither be too low (due to inefficiency) nor too high (due to bias). Andersen et al. (2003) demonstrate that a 30-minute sampling frequency is optimal, as it yields more accurate realized forecasts compared to GARCH-based predictions. Using synchronized data, Fleming et al. (2003) and Bollerslev and Zhang (2003) found that five-minute frequencies enhance investment forecasts. Meanwhile, Pooter et al. (2008) argued that selecting the optimal sampling frequency is crucial, concluding that, for portfolio performance, an optimal frequency is closer to one hour rather than the commonly used intervals of 5 to 30 minutes, even for the 100 most liquid S&P 500 constituents.

Reducing the sampling frequency comes at the cost of efficiency, as some information is discarded. In an effort to design an estimator that retains all available data while remaining robust to microstructure noise, Zhang et al. (2005) proposed the realized two-times scaled covariance (RTSCOV) estimator, balancing between efficiency and bias. This estimator preserves all available data and is robust to microstructure noise but remains sensitive to price jumps. To address this limitation, Boudt and Zhang (2015) introduced an improved version of RTSCOV, named robust realized two-times scaled covariance (RRTSCOV), which is robust not only to microstructure noise and price jumps but also to asynchronous trading, as it employs the refresh-time synchronization scheme (previous tick method) proposed by Harris et al. (1995). Unlike the ROWCOV (realized outlyingness-weighted covariance), but similarly to the RTHRESCOV (realized threshold covariance), it uses a jump detection rule to truncate the effect of jumps at a slow time scale. Unfortunately, the RRTSCOV is not always positive semidefinite, and in those cases, the negative eigenvalues of the covariance matrix are replaced with zeros.

On the other hand, RTHRESCOV and ROWCOV estimators are robust to price jumps but not to microstructure noise. This category of estimators also includes the realized bipower covariance (RBPCOV), which was developed by Barndorff-Nielsen and Shephard (2004a) as a generalization of the realized bipower variance (RBPV). It does not use a truncation technique with an indicator function but subtracts the product of the absolute differences of adjacent returns for the two assets from the product of the absolute sums of their adjacent returns. This approach mitigates the impact of jumps, even at high sampling frequencies. Boudt et al. (2011) highlighted that ROWCOV is less sensitive to price jumps than RBPCOV, and additional simulations confirm its high efficiency under the BSMFAJ process (Brownian semimartingale with finite activity jumps).

In essence, ROWCOV is a weighted version of the RCOV estimator, where the weights depend on the squared Mahalanobis distance based on the minimum covariance determinant (MCD).

A major breakthrough in developing jump-robust estimators was made by Hayashi and Yoshida (2005). A realized Hayashi-Yoshida covariance (RHYCOV) does not require any prior synchronization of the data, and it is unbiased and consistent in the absence of microstructure noise.

Many authors have adopted various approaches to address the issues of asynchronization, market microstructure noise, and price jumps to obtain an unbiased and asymptotically consistent estimate of integrated covariance. In this regard, Table 1 summarizes the properties of six estimators used in this study, as the most established and commonly applied in empirical research, although numerous variants of integrated covariance estimators have been proposed in the literature (Barndorff-Nielsen et al., 2011; Christensen et al., 2010; Vander-Elst & Veredas, 2017). The majority of them (RBPCOV, RTHRESCOV, ROWCOV, and RRTSCOV) are robust to price jumps, and only two of them can use tick-by-tick data. The only advantage of RHYCOV is that it does not require any synchronization scheme, whereas RRTSCOV uses refresh-time synchronization. Estimators that are not robust to microstructure noise can become robust if a sufficiently low (optimal) sampling frequency is selected. This applies to all estimators except RRTSCOV, which is the only one that does not lose data under sparse sampling, as its fast time scale J is fixed at the highest possible frequency, while the selection of optimal sampling frequency is restricted to the low time scale K (Arnerić et al., 2019). Based on Table 1, the RRTSCOV estimator is identified as the one with the most desirable properties, justifying its use as a benchmark for this research.

Table 1: *Properties of Integrated Covariance Estimators*

Estimator	Jump robust	Microstructure noise robust	Irregularly spaced data and asynchronized	Positive semidefinite	Affine equivariance
RCOV				✓	✓
RBPCOV	✓				
RTHRESCOV	✓			✓	
ROWCOV	✓			✓	✓
RHYCOV			✓		
RRTSCOV	✓	✓	✓	✓	✓

Source: Authors' construction.

Furthermore, most of the research relies on simulations, while significantly fewer studies only use real data (Aït-Sahalia et al., 2010; Jin & Maheu, 2013; Bollerslev et al., 2018). Empirically determining which estimator is most appropriate when the integrated covariance is unknown represents a major challenge. This leads to the main contribution of this paper, which aims to reexamine gold as a safe haven and hedge. Empirical determination of the most suitable estimator requires a comparison against benchmark estimators. For this purpose, loss functions such as MSE and QLIKE were primarily used, followed by the Diebold-Mariano test (Diebold & Mariano, 1995). MSE measures the average squared difference between realized correlations obtained from the competing estimator and realized (reference) correlations obtained from the benchmark estimator. Unlike MSE, the quasi-likelihood loss function (QLIKE) is less sensitive to extreme deviations (Patton, 2011). By incorporating a log term, QLIKE captures the relative accuracy between competing and benchmark realized correlations, which is adequate when the scales of the two estimators differ. Finally, the Diebold-Mariano (DM) test is conducted, which statistically tests the significance of the difference in the mean squared errors of pairs of competing estimators against the benchmark. A positive sign of the DM statistic indicates that the first competing estimator produces overestimated realized correlations, and thus a preference is given to the second competing estimator, and vice versa.

4 Empirical Findings and Discussion

The one-minute spot prices of the EUROSTOXX50 index, expressed in euros, and the one-minute spot prices of an ounce of gold, expressed in US dollars, were observed over the period from January 31, 2020, to January 31, 2023, with one minute being the highest frequency available from Bloomberg. The EUROSTOXX50 instruments officially traded from 09:00 to 17:30 on every business day on the Eurex platform, while gold was traded continuously on the Forex platform, except on weekends. Therefore, only transactions within the official 8.5 trading hours were considered, covering 773 trading days (Čupić, 2025). On average, there were 479.2 one-minute transactions per day for the stock index, and 510.88 one-minute transactions per day for gold (Table 2).

Figure 1: *One-Minute Prices and Returns of the EUROSTOXX50 Index and Gold From January 31, 2020, to January 31, 2023*

Source: Authors' construction using RStudio and data provided by Bloomberg.

The sharp decline in the EUROSTOXX50 index in February 2020 was due to the outbreak of the coronavirus and widespread panic. After recovering from the initial shock, the EUROSTOXX50 recorded a positive trend until February 2022, when the start of the war in Ukraine caused another drop. Interestingly, the price of an ounce of gold followed a positive trend until the middle of summer 2020, and unlike the EUROSTOXX50 index, it began to rise with the onset of the war in Ukraine (upper panel of Figure 1). The intraday returns for both assets are presented in the lower panel of Figure 1, while their properties are elaborated using the key indicators provided in Table 2.

Both return series exhibit volatility clustering, as well as high volatility periods aligned with crisis periods in which prices moved in opposite directions (Figure 1). Moreover, the scale of intraday returns is much higher for the EUROSTOXX50 (from -0.0213 to 0.0218) than for gold. The significance of kurtosis strongly demonstrates heavy-tail phenomena for both return series, while significant skewness reflects a deviation from normality (Table 2).

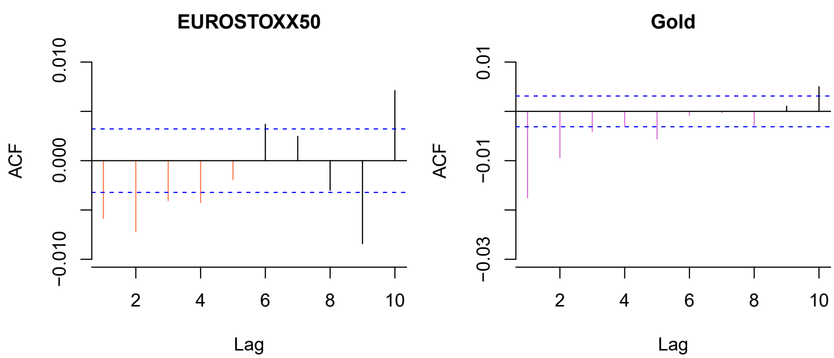
Table 2: *Descriptive Statistics of Transaction Data and Pre-Estimation Diagnostics of Intraday Returns (Aligned for 1 Minute) of EUROSTOXX50 and Gold*

	Statistic	EUROSTOXX50	Gold
Daily transactions within official trading hours	Min.	221	449
	Max.	511	511
	Mean	479.19	510.88
	Total	370,900	395,934
Intraday returns	Min.	-0.021276	-0.009056
	Max.	0.021845	0.012797
	Mean	0.000000	0.000000
	Std. deviation	0.000540	0.000364
	Skewness	-0.0475***	-0.1893***
	Kurtosis	45.4361***	30.3286***
	Ljung-Box(5)	46.14***	346.43***
	ADF unit root test	-435.03***	-456.24***
	AJ jump test	10.99%	6.86%
	Jump activity index	0.0927	0.0586

Note: *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

Source: Authors' construction using RStudio and data provided by Bloomberg.

Figure 2: *Autocorrelation Functions of the EUROSTOXX50 and Gold One-Minute Returns*

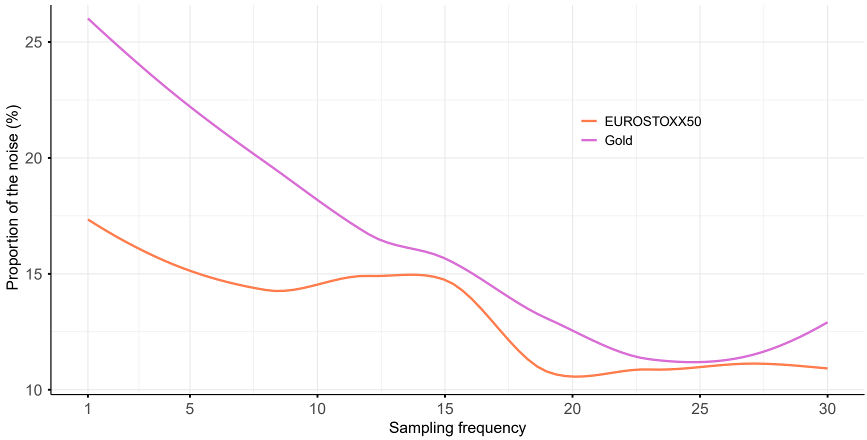


Source: Authors' construction using RStudio and data provided by Bloomberg.

According to Figure 2, microstructure noise is present in the one-minute returns of both assets, with negative ACFs exhibited for the first five lags in the case of the EUROSTOXX50 index and for eight lags in the case of gold. Negative first-order autocorrelation is an indicator of microstructure noise, which is typically driven by bid-ask bounce as a key source of market friction (Christensen et al., 2010). Moreover, gold's intraday returns are more contaminated by this noise compared to the EUROSTOXX50 index, due to the greater magnitude of negative autocorrelation. The Ljung-Box test up to 5 lags confirms the significance of negative autocorrelation for both intraday returns (Table 2). Furthermore, the presence of jumps can be detected formally by employing the AJ jump test according to Aït-Sahalia and Jacod (2009). It uses the standardized ratio of realized power variation sampled from a fast time scale and a slower time scale. Thus, for each trading day, a standardized statistic is computed, and whenever the null hypothesis of the AJ test (no jumps) is rejected at a 5 percent significance level, evidence of a significant jump is found. By overall repetition of the AJ jump test, significant price jumps in EUROSTOXX50 returns are detected in 85 trading days (32 jumps are negative and 53 positive), while a lower number of significant jumps are identified in gold returns, i.e., out of the total 53 significant jumps, 16 are negative and 37 positive. These results are reported in Table 2 as percentages of total trading days. Interestingly, on days when significant jumps occurred in one asset, they typically did not occur in the other, suggesting a lack of co-movements in price jumps.

Despite the existence of various realized measures, they all share a fundamental assumption of the data-generating process, i.e., the assumption of a continuous-time Itô semimartingale of the latent price dynamics with finite activity jumps. Accordingly, diagnostic tests are performed in the pre-estimation phase to empirically demonstrate whether the observed prices, sampled every minute, accommodate this precondition for each asset (1-minute prices were the highest frequencies accessible to us from Bloomberg). Therefore, Table 2 reports the results of two additional diagnostic tests: the augmented Dickey-Fuller unit root test (ADF), to check the stationarity of intraday returns, and the jump activity index, to check the existence of sparse large jumps (finite activity) instead of many small jumps (infinite activity), in accordance with Aït-Sahalia and Jacod (2009). The ADF test statistic, applied to 1-minute returns, is far below the 1 percent critical value for both assets (Table 2), confirming that returns (increments) are stationary and, consequently, price processes are consistent with an Itô semimartingale due to the unit root in the price levels. The ADF unit root test was computed without deterministic components because intraday returns exhibit a zero mean and no trend, while the BIC was used to select the optimal lag length with a stronger penalty than AIC. In addition to the AJ jump test, which demonstrated that significant jumps are rare (they occur approximately 10 percent of the time or less), the jump activity index proposed by the same authors was estimated for each trading day and then averaged for each asset (Table 2). The resulting averages are close to zero, indicating a finite number of jumps, i.e., jumps are rare but potentially large. Although the presence of microstructure noise is found in both assets due to negative first-order autocorrelation of 1-minute returns, the portion of microstructure noise-induced returns variance is plotted against sampling frequencies to visualize its extent (Figure 3).

Figure 3: *Portion of the Returns Variance Attributed to the Noise for Both Assets*



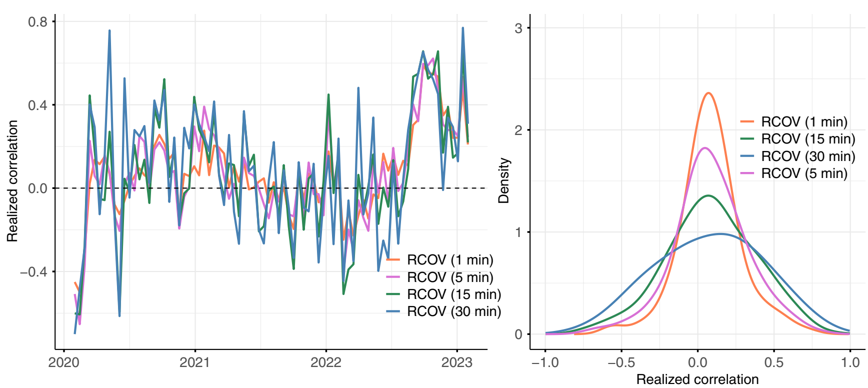
Source: Authors' construction using RStudio and data provided by Bloomberg.

As expected, a larger portion of the return variance is driven by microstructure noise at higher sampling frequencies, while at lower sampling frequencies the proportion of noise-induced variance declines (equivalently, the bias in the realized measure is reduced). At the highest sampling frequency of 1-minute, gold exhibits a higher degree of microstructure noise (26 percent) compared to the equity index (approximately 17 percent). However, in both assets, the microstructure noise does not dominate the return variance.

The first step in further analysis is the synchronization of high-frequency data. In this study, the "refresh-time" synchronization scheme introduced by Harris et al. (1995) was used, in which only those time intervals during which each asset was traded at least once relative to the last time point (previous tick) are considered. This synchronization scheme is suitable when actual, but not common, transaction times are very close to being regular, which is the case in this study. Once the data have been synchronized, the realized covariance and realized correlations can be computed at the optimal frequency at which the realized covariance is unbiased, i.e., the one where the mean squared error (MSE) of the estimator is the smallest, while keeping in mind that this still does not resolve the issue of price jumps. The refresh-time scheme synchronizes prices across assets, although the resulting timestamps are not necessarily regular. This is not an issue, as sampling at an appropriate sparse frequency produces a consistent grid without structural gaps. The more relevant issue is the Epps effect, which is likewise mitigated by selecting the optimal (sufficiently sparse) sampling frequency after synchronization.

From 773 realized correlation matrices, off-diagonal elements were isolated for the purpose of illustrating the smoothed realized correlations between the EUROSTOXX50 returns and gold returns at selected sampling frequencies of 1, 5, 15, and 30 minutes (left panel of Figure 4).

Figure 4: *Smoothed Realized Correlations Between EUROSTOXX50 and Gold Based on RCOV Estimator at Different Sampling Frequencies and Their Empirical Density Functions*



Source: Authors' construction using RStudio and data provided by Bloomberg.

In order to better highlight differences in realized correlations, their empirical density functions were compared (right panel of Figure 4). From Figure 4 (left panel), it is evident that at higher sampling frequencies (i.e., shorter time intervals), the realized correlations exhibit weaker intensity because a significant portion of the signal is masked by microstructure noise, which reduces the observable magnitude of the true correlation. Haugom et al. (2014) noted that with higher sampling frequencies, the probability decreases that a simultaneous price (return) change of two or more financial assets caused by the same event will actually be realized within a very short time interval. This is why negative realized correlations are less likely at higher sampling frequencies, as their corresponding empirical density functions are more narrow around zero (right panel of Figure 4). As the sampling frequency decreases, the realized correlation increases up to a certain point (which represents the optimal frequency), after which it stops increasing and remains stable. Following this principle, after refresh-time synchronization, the optimal sampling frequency for each estimator was determined by minimizing its MSE. According to Table 3, the RBPCOV estimator records the minimum MSE value at a frequency of 7 minutes, the RHYCOV estimator at 12 minutes, the RCOV and RTHRESCOV estimators at 17 minutes, and the ROWCOV estimator at 22 minutes. To rank the estimators relative to the benchmark estimator (RRTSCOV), the next step involves calculating the QLIKE loss measure along with the MSE (at the optimal frequency previously determined for each estimator individually). The QLIKE loss function calculates penalties resulting from inaccurate estimates, which are defined as a function of the difference between the estimated and reference values. Table 3 shows the ranked estimators based on MSE and QLIKE, as well as the proportion of matching signs as additional information. The estimator with the lowest MSE compared to the benchmark estimator is the realized covariance estimator with weighted outliers at a frequency of 22 minutes, while the estimator with the highest average squared error is the realized bipower covariance estimator at a frequency of 7 minutes.

Table 3: *Estimator Ranking Against the RRTSCOV Benchmark With Respect to the MSE and QLIKE Measures and Proportion of Matching Signs*

Estimator	Frequency	MSE	Rank	QLIKE	Rank	Match	Rank
ROWCOV	22	0.0254	1	436.92	2	0.903	1
RTHRESCOV	17	0.0257	2	1793.13	3	0.828	4
RCOV	17	0.0292	3	21,371,610	5	0.832	3
RHYCOV	12	0.0335	4	358.60	1	0.833	2
RBPCOV	7	0.0411	5	6707.19	4	0.797	5

Source: Authors' construction using RStudio and data provided by Bloomberg.

The highest QLIKE loss was recorded for the RCOV estimator, which means that it performs the worst relative to the benchmark estimator. In contrast, according to the QLIKE criterion, RHYCOV performs the best relative to the benchmark estimator. However, the fact that in 90.3 percent of cases the signs of the realized correlations between the ROWCOV estimator and the benchmark match cannot be ignored places ROWCOV in first place again. Finally, the DM test was conducted for all pairs of estimators relative to the benchmark estimator (Table 4). The results clearly show that the RCOV estimator performs better against the benchmark estimator than the RBPCOV and RHYCOV estimators. The RTHRESCOV and ROWCOV estimators are shown to be more precise compared to the RCOV, RBPCOV, and RHYCOV estimators. The RHYCOV estimator is more accurate only in relation to RBPCOV, which was found to be the least precise of all the estimators. No statistically significant difference was found between the RTHRESCOV and ROWCOV estimators (Table 4).

Table 4: *Results of the DM Test Between Pairs of Competing Estimators*

Estimator	RBPCOV	RTHRESCOV	ROWCOV	RHYCOV
RCOV	-5.4811***	2.2572**	1.9357**	-2.2528**
RBPCOV		7.0028***	7.0397***	3.6521***
RTHRESCOV			11.044***	-3.5842***
ROWCOV				-3.5102***

Note: *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.
Source: Authors' construction using RStudio and data provided by Bloomberg.

After the estimators were ranked based on MSE, QLIKE, proportions of matching signs, and the DM test, it can be concluded that the ROWCOV estimator consistently ranks at the top. In contrast, the RBPCOV estimator consistently ranks at the bottom, which is not surprising since it is highly sensitive to zero returns, does not ensure positive semidefiniteness, and can result in a realized correlation that is absolutely greater than one.

As already mentioned, the substantial issue in realized correlation measures is the Epps effect, caused by two sources of bias, which is mitigated by selecting the optimal (sufficiently sparse) sampling frequency after refresh-time synchronization. For this reason, all ICOV estimators are ranked based on their own optimal sampling frequency, rather than using an arbitrary fixed sampling frequency for all of them. An optimal frequency for one estimator is not necessarily optimal for another, i.e., not all estimators are unbiased and asymptotically consistent or stable under the same sampling scheme. Consequently, the ranking of estimators based on their own optimal frequency is an important methodological contribution of this study in terms of safe-haven and hedge evidence. Nevertheless, a robustness analysis is conducted in which estimators are ranked across several alternative sampling frequencies with respect to MSE and QLIKE (Table 5).

Table 5: *Estimator Ranking With Respect to Alternative Sampling Intervals*

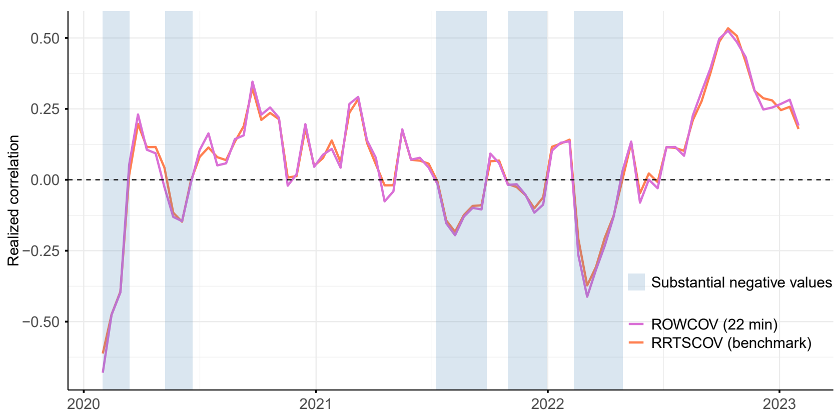
	Ranking by MSE					Ranking by QLIKE				
Estimator	**5**	**10**	**15**	**20**	**25**	**5**	**10**	**15**	**20**	**25**
ROWCOV	1	1	1	1	1	1	1	2	2	1
RTHRESCOV	2	2	2	2	2	3	3	4	3	4
RCOV	3	3	3	3	4	5	4	1	5	2
RHYCOV	5	4	4	4	5	2	5	3	1	5
RBPCOV	4	5	5	5	3	4	2	5	4	3

Source: Authors' construction using RStudio and data provided by Bloomberg.

The ordering remains stable, confirming the robustness of the main results reported in Table 3. As the optimal sampling interval across different ICOV estimators lies between 7 and 22 minutes, it was reasonable to reevaluate their rankings at alternative intervals of 5, 10, 15, 20, and 25 minutes. Under both loss functions, ROWCOV consistently ranks at the top, while RBPCOV and RHYCOV exhibit the poorest performance. Stable rankings across sampling intervals are not evidence that the estimators are invariant to sampling frequency, but rather that their relative performance is preserved with respect to the benchmark.

The results of the most appropriate estimator (ROWCOV) and the benchmark estimator (RRTSCOV) are shown in Figure 5.

Figure 5: *Smoothed Realized Correlations of ROWCOV Estimator and Benchmark Estimator*



Source: Authors' construction using RStudio and data provided by Bloomberg.

Figure 5 reveals two periods of severe negative realized correlation (the first quarter of 2020 and February to April 2022) and three periods of milder negative correlation (May and June 2020, summer 2021, and the last two months of 2021). These five periods stem from a series of unprecedented events that heightened risk and uncertainty in European stock markets. The COVID-19 pandemic in the first quarter of 2020 caused one of the most severe shocks, with strict lockdowns, disrupted supply chains, business closures, and halted economic activity leading to steep declines in the EUROSTOXX50. By May and June 2020, European markets faced renewed uncertainty about recovery, with fears of second infection waves, inconsistent fiscal responses among EU members, and external pressures from US-China tensions increasing risk aversion. In summer 2021, the Delta variant reignited concerns of prolonged disruption, spiking infection rates and triggering new restrictions that particularly impacted tourism and travel during the critical summer season. Late 2021 saw surging energy prices and record-high inflation across Europe, raising fears of stagflation and creating policy uncertainty as the European Central Bank (ECB) struggled to balance inflation control with economic support. From February to April 2022, Russia's invasion of Ukraine dealt another severe blow to European markets, with disruptions in oil and gas supplies exacerbating inflationary pressures as commodity prices, particularly for energy and agriculture, surged. This crisis intensified stagflation fears, led to sharp equity sell-offs, and drove investors toward safe-haven assets, exposing Europe's vulnerability to geopolitical instability and energy dependency. Finally, the long-term realized correlation at approximately zero (0.065 according to ROWCOV, which is almost equal to 0.068 obtained by the RRTSCOV benchmark) indicates a weak hedge property of gold against EUROSTOXX50.

The five episodes of negative realized correlation correspond to major economic, health, and geopolitical shocks, indicating that gold's safe-haven properties against EUROSTOXX50 are strongly state-dependent and emerge primarily during periods of severe systemic stress, such as the COVID-19 outbreak and the Russia-Ukraine conflict. Milder negative realized correlations are observed during inflation surges and energy-market disruptions, while in the long run, zero correlation confirms that gold functions as a weak hedge. The evidence therefore supports that gold behaves as a crisis-specific safe haven rather than an effective long-term hedge. These findings also suggest that policymakers should limit volatility spillovers to reduce vulnerabilities arising from Europe's energy dependence and inflation uncertainty.

5 Conclusion

Searching for a reliable safe-haven asset has occupied both practitioners and academics for many years and continues to be a relevant topic amid increasing global uncertainty. While traditionally used in jewelry making, gold's implementation has expanded significantly since the gold standard was abandoned in the 1970s.

This study confirms that gold acts as a strong safe haven but a weak hedge against leading eurozone stocks. These findings contrast with the conclusions of Hood and Malik (2013), Disli et al. (2021), and Choudhury et al. (2022), while partially supporting the results of Baur and McDermott (2010) and Tronzano (2022). Empirical results imply that investors can rely on gold during crises, but they may need alternative hedging instruments to mitigate day-to-day risk. This means that gold should be used strategically rather than as a constant hedge, with investors increasing exposure during periods of uncertainty. Additionally, policymakers and institutional investors may turn to gold in times of financial instability.

The methodological approach in this paper differs from previous papers by employing the concept of realized covariance (RCOV) to estimate integrated covariance, a framework not widely adopted in the existing literature. Namely, there is no consensus on a unique non-parametric estimator for integrated covariance (ICOV), as proposed methods, relying on high-frequency transaction data, are attractive for their efficiency compared to low-frequency counterparts. However, they are not always unbiased or consistent. It is challenging to work with high-frequency data due to irregularly spaced intervals, asynchronicity across multiple assets, microstructure noise, and price jumps. This study systematically addresses these issues by examining the properties of one-minute prices and selecting appropriate synchronization schemes, optimal sampling frequencies to reduce microstructure noise, and an estimator that is robust to price jumps. These selections ensure a balance between estimator efficiency and bias while keeping as much data as possible. The choice of RRTSCOV as the benchmark estimator, against which other estimators are compared and ranked, underscores the rigor of this approach. Using the ROWCOV estimator at a sampling frequency of

22 minutes, the study confirms that gold acted as a safe haven during key periods of market stress, such as the first wave of the COVID-19 pandemic and the early stages of the war in Ukraine in 2022. A key contribution of this research lies in finding an estimator of integrated covariance with the best performance and applying it to real high-frequency data to examine gold's role as a safe haven and hedge, unlike prior studies that often relied on low-frequency (daily) data or simulation data. Therefore, it offers a more nuanced understanding of gold's performance relative to the EUROSTOXX50 index, a benchmark comprising the 50 most liquid stocks from 11 eurozone countries. Additionally, this research systematically presents the theoretical background of the realized covariance approach and addresses challenges posed by the use of high-frequency data.

Using one-minute prices rather than higher-frequency data, such as one-second prices or tick-by-tick prices, is a limitation of the research, but it does not diminish the value of the findings. Future studies should consider examining other assets as potential safe havens or hedges while integrating additional criteria for ranking competing estimators. Such efforts could lead to stronger conclusions about the most appropriate estimators and expand the understanding of safe-haven dynamics across diverse financial markets. Once the realized (ex-post) measure is computed using an appropriate estimator, it can be combined with existing forecasting models, e.g., quantile regression can serve as a complementary method to enhance the predictive accuracy of tail-risk models when applied to high-frequency data (Kawakami, 2023). However, the focus of this paper is not on single-asset realized volatility forecasting (such as the HAR model, realized GARCH, or HEAVY model), but on realized co-volatility and, consequently, the daily realized correlation between gold and the EUROSTOXX50 index. The paper also does not compare whether daily realized measures of ICOV can be predicted as accurately as, for instance, multivariate GARCH models (which traditionally rely on lower-frequency data but can be adapted to incorporate high-frequency data), which represents yet another direction for future research.

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