Climate Risks and Predictability of the Trading Volume of Gold: Evidence from an INGARCH Model

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Abstract

We investigate the ability of textual analysis-based metrics of physical or transition risks associated with climate change in forecasting the daily volume of trade contracts of gold. Given the count-valued nature of gold volume data, our econometric framework is a log-linear Poisson integer-valued generalized autoregressive conditional heteroskedasticity (INGARCH) model with a particular climate change-related covariate. We detect a significant predictive power for gold volume at 5- and 22-day-ahead horizons when we extend our model using physical risks. Given the underlying positively evolving impact of such risks on the trading volume of gold, as derived from a full-sample analysis using a time-varying INGARCH model, we can say that gold acts as a hedge against physical risks at medium- and long-horizons. Such a characteristic is also detected for platinum, and to a lesser extent, for palladium, but not silver. Our results have important investment implications.

JEL Classification: C22; C53; Q02; Q54.

Keywords: Climate Risks; Precious Metals; Forecasting; Trading Volumes; Count Data; INGARCH.

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1. Introduction

Climate change is associated with two types of risks namely, physical and transition. The former involves risks due to rising temperatures, higher sea levels, more destructive storms, and floods or wildfires. The latter is associated with a gradual switchover to a low-carbon economy and includes risks due to climate policy changes, emergence of competitive green technologies, and shifts in consumer preferences. Naturally, though the level and form of the underlying uncertainty may vary, every scenario in the future includes climate-related financial risks. Hence, climate-related risks have been shown to adversely affect a large number of asset classes, including equities, fixed-income securities, real estate, and even financial institutions (Battiston et al., 2021; Giglio et al., 2021). In the process, climate risks tend to raise the stress of the entire financial system (Flori et al., 2021).

Due to heightened distress in the financial system arising out of climate risks, gold, which is historically a well-established "safe haven" (Boubaker et al. (2020), Bouri et al. (2022)), becomes highly important. This is because gold serves as an investment vehicle that offers portfolio diversification and/or hedging benefits during periods of financial turmoil, originating from climate-related events. In such instances of "bad news", due to the information-seeking actions of traders, it is expected that gold returns and its volatility should increase due to higher trading volumes, capturing information flows, emanating from its higher demand (Wang and Yau, 2000; Lucey and Batten, 2010; Baur, 2012). Evidence of a positive relationship between gold returns and its volatility with climate risks has been recently provided by Cepni et al. (2022) and Gupta and Pierdzioch (2022), respectively.

In light of the underlying intuition that climate risks can be associated with higher returns and volatility of gold prices due to increased trading volumes, we aim to analyze the direct effect of climate risks on the volume of traded contracts of gold. In this regard, instead of an in-sample predictability analysis, we resort to an out-of-sample forecasting exercise over the daily period of 3rd January, 2005 to 29th October, 2021. The latter is essential for two reasons: Statistically, forecasting is considered to be a more robust test of predictability in terms of both models and predictors (Campbell, 2008). Secondly, accurate real-time forecasting of volumes (based on the information content of climate risks), which is known to lead returns and volatility, should be of much more value to traders and investors in the gold market, relative to in-sample evidence, in the timely pricing of related derivative securities and for devising portfolio-allocation strategies.

Realizing the count-valued nature of the time series data on the trading volume of gold, our econometric framework is a log-linear Poisson integer-valued generalized autoregressive conditional heteroskedasticity (INGARCH) model with predictors, which in turn are textual analysis-based metrics of physical or transition risks associated with climate. While the focus is on gold, given that recent studies have also depicted the possible safe haven characteristic for palladium, platinum, and silver (Lucey and Li, 2015; Salisu et al., forthcoming), we also consider the role of climate risks as predictors of the trading volumes of these three different precious metals, over the same period as gold. To the best of our knowledge, this is the first paper to use count data-based models to forecast daily volumes of precious metals by relying on the information contained in physical and/or transition climate risks to provide a direct test of the safe haven characteristic of this important asset-class. The remainder of the paper is organized as follows: Section 2 presents the methodology, while Section 3 discusses the data, and Section 4 is devoted to the empirical findings. Finally, Section 5 concludes the paper.

2. Methodology

We implement the following autoregressive model for count time-series, inspired from the GARCH model of Bollerslev (1986), which in turn is called an INGARCH model, and has become a state-of-the-art framework (Davis et al., 2021) for analyzing count data:

$$
\begin{aligned}
y_t | y_{t-1}, y_{t-2}, \cdots &\sim Poi(\lambda_t) \\
\lambda_t &= \alpha_0 + \alpha_1 y_{t-1} + \beta_1 \lambda_{t-1}
\end{aligned}
\tag{2.1}
$$

However, the parameter space for these models is restricted due to positivity, and this gives rise to the following log-linear INGARCH model, making the parameter space relatively more unrestricted:

$$y_t|y_{t-1}, y_{t-2}, \cdots \sim Poi(\lambda_t) \tag{2.2}$$
$$\lambda_t = \alpha_0 + \alpha_1 y_{t-1} + \beta_1 \lambda_{t-1}$$

Bringing in covariates or predictors, we obtain the following log-linear Poisson INGARCH(1,1) model:

$$y_t|y_{t-1}, y_{t-2}, \cdots \sim Poi(\lambda_t) \tag{2.3}$$
$$\log(\lambda_t) = \alpha_0 + \alpha_1 \log(1 + y_{t-1}) + \beta_1 \log(\lambda_{t-1}) + \eta^T X_t$$

where X_t is the matrix of covariates and y_t denotes a count time series. To ensure stationarity it is necessary to assume that: $0 < \alpha_1 + \beta_1 < 1$.

We use the prediction routine in the `tscount` package in R (Liboschik et al. (2017)) to produce forecasts. Briefly put, this method chooses a roll-over forecasting scheme. To predict y_{n+1} based on $y_1, \cdots y_n$, the simple conditional expectation is used, and for y_{n+2} one uses the same conditional expectation, but this time replacing the unknown y_{n+1} by $\hat{y}_{n+1}$ based on the previous computation.

We judge the quality of future $h-$step aggregated forecast, i.e. $y_{n+1} + \cdots + y_{n+h}$ for different values of h through a pseudo-out-of-sample evaluation metric. More specifically, we follow the following steps:

- Predict $FWC_{i,h} = \hat{y}_{i+m} + \cdots + \hat{y}_{i+m+h-1}$ using the log-linear INGARCH tsglm predict routine with covariate(s) based on pairs (y_j, X_j) $j = i, \cdots, i+m-1$;

- $FWOC_{i,h} = \hat{y}_{i+m} + \cdots + \hat{y}_{i+m+h-1}$ using the log-linear INGARCH tsglm predict routine without covariates based on pairs (y_j) $j = i, \cdots, i+m-1$;

- Next we compare the two forecasted series $FWC_{\{\},h}$ and $FWOC_{\{\},h}$ by the means of Clark and West (CW; 2007) test.

3. Data

Our climate risks data are sourced from Bua et al. (2022) and consist of a daily Physical Risk Index (PRI) and Transition Risk Index (TRI). These two novel climate risk indicators are the result of a text-based approach which combines the term frequency-inverse document frequency and the cosine-similarity techniques expanding on the work of Engle et al. (2020). Specifically, the authors first group various scientific texts on climate change by topic, either involving physical or transition risk, to obtain two documents that, if digested, provide a comprehensive understanding of the physical and transition climate risks. The authors then use these climate risks-related documents to feed their text-based algorithms, and search the same structured information within a corpus of (European) news sourced by Reuters News. As output, they obtain two distinct time series, so-called "concerns", roughly representing the news media attention towards physical and transition risks, which we indicate as: $\text{CONCERN}_{\text{PR}}$ and $\text{CONCERN}_{\text{TR}}$, respectively. As a final step, the authors model the climate risks series, PRI and TRI, as autoregressive order one (AR(1)) residuals of the concerns series in order to capture shocks and innovations in physical and transition risks.

We use these measures of climate risks because the proposed measures, which originated from advanced climate vocabularies, exhibit several advantages with respect to previous studies. They, for instance, embed multiple dimensions of the risks without discarding relevant aspects resulting in complete climate risks indicators, which can enhance studies on the financial implications of climate risks. The PRI includes both acute and chronic physical risks like floods, extreme weather events, permafrost thawing, and sea level rise, as well as issues about climate adaptation actions, and other physical risk-averse effects like the loss in biodiversity. The TRI, on the other hand, includes news on regulations and measures to curb greenhouse gas (GHG) emissions, news concerning the costs associated with the transition to a greener economy, and news discussing the advances of technological innovation and renewable energies to reach, for example, net-zero emissions targets. Bua et al. (2022) also perform commonality tests to assess the actual degree of overlap of the two indicators and conclude that both PRI and TRI carry relevant individual information.

We collect daily data on the volume of traded contracts of the top four precious metals: gold, palladium, platinum and silver, with the series downloaded from Bloomberg. Our analysis covers the period of 3rd January, 2005 to 29th October, 2021, i.e., 4245 daily observations. Note that, the start and end dates of our samples are driven purely by the availability of data on the climate risks predictors. All the variables of interest have been plotted in Figure 1.

4. Empirical results

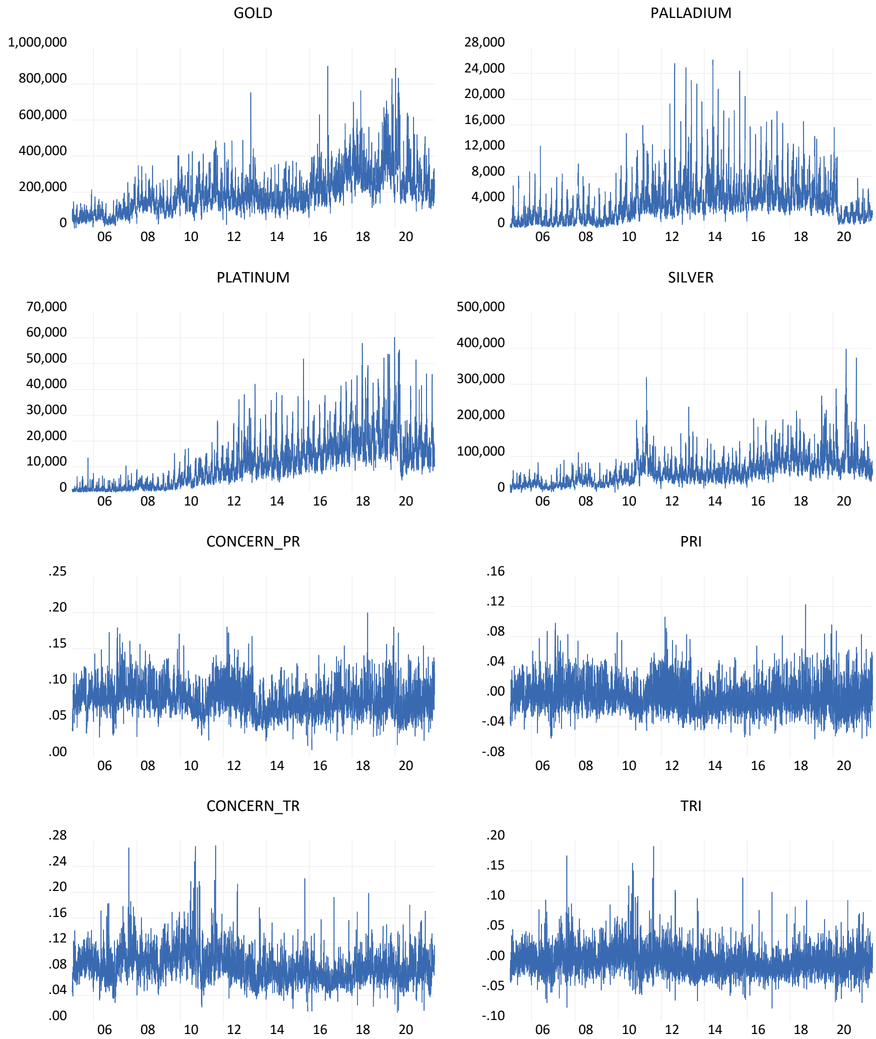
4.1. Preliminary analysis of the relationship between trading volumes and climate risks

Before we proceed to the formal forecasting exercise, we wanted to check if indeed climate risks positively impact the trading volume of gold, as is expected in light of gold's ability to hedge climate risks being a safe haven. For this purpose, we utilize a time-varying analogue of Eq. (2.3).[5] As can be seen from Panel A of Figure 2, whereby we report the time-varying t-statistic involving the effect of $\text{CONCERN}_{\text{PR}}$ and $\text{CONCERN}_{\text{TR}}$ on the trading volume of gold, the effect is generally positive in a statistically significant manner under physical risks, i.e., CONC_{PR}, while this is not necessarily the case under CONC_{TR} capturing transition risks of climate.[6] Qualitatively similar observations were also drawn for palladium and platinum in particular, and to a lesser degree for silver, as shown in Panels B, C and D, respectively of Figure 2. This finding is expected to a certain degree, given the underlying nature of these two risks, with the effects of physical risks likely to be felt immediately on the stress of the financial system. In light of this evidence related to the sign of the effect of climate risks, we would want to put relatively more reliance on the forecasting accuracy of gold volumes

[5]The time-varying log-linear Poisson INGARCH(1,1) model can be described as: $y_t|y_{t-1}, y_{t-2}, \cdots \sim Poi(\lambda_t)$, with $\log(\lambda_t) = \alpha_0(t/n) + \alpha_1(t/n)\log(1 + y_{t-1}) + \beta_1(t/n)\log(\lambda_{t-1}) + \eta(\mathbf{t}/\mathbf{n})^T X_t$. For the estimation of the parameter functions $(\alpha_0(\cdot), \alpha_1(\cdot), \beta_1(\cdot), \eta)$, we employ a kernel-based technique padded on quasi-maximum likelihood estimation as in Karmakar et al. (2022). In this regard, we use the rectangular kernel $K(x) = I(-1 \leq x \leq 1)$ and bandwidth $b_n = m/n$ to remain consistent with our forecasting set-up, which in turn assumes stationarity of the last m observations.

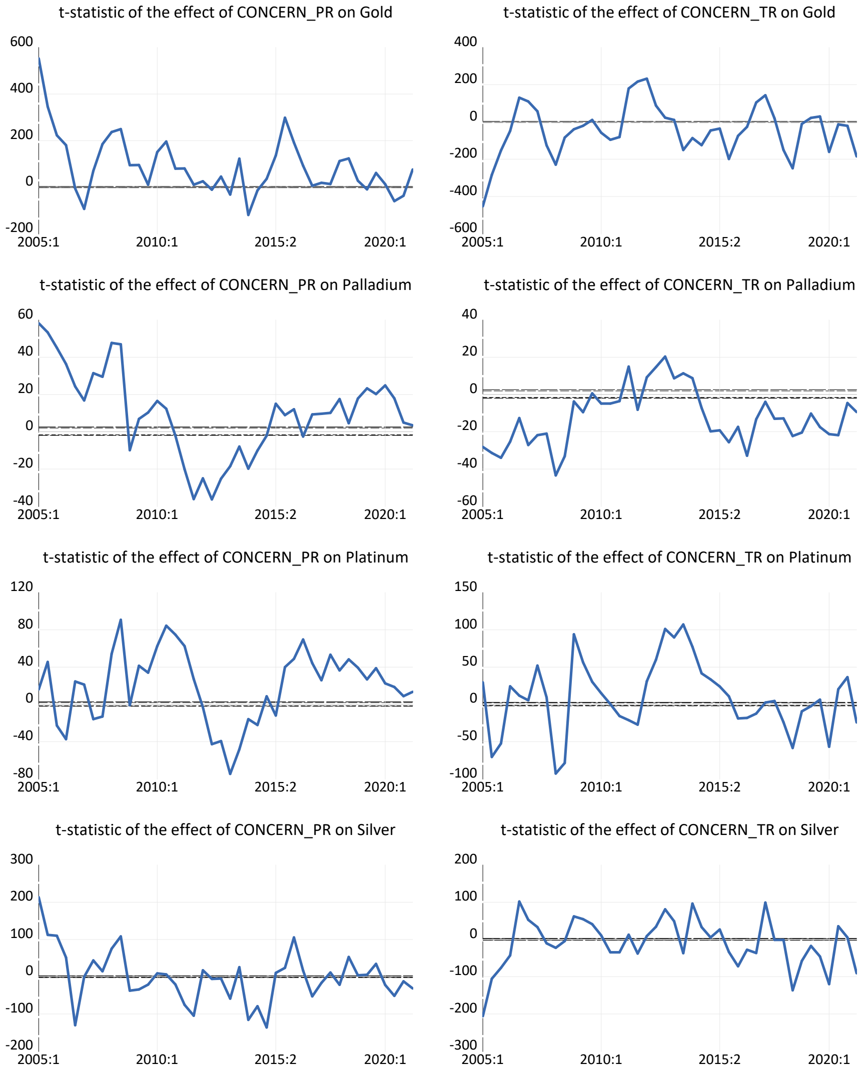
[6]Using PRI and TRIs instead of $\text{CONCERN}_{\text{PR}}$ and $\text{CONCERN}_{\text{TR}}$, yielded, not surprisingly, similar observations, with the results available upon request from the authors.

Fig. 1: Time series plot of climate risk measures and count data variables



emanating from physical rather than transition risks in the process of validating the safe haven nature of gold (and palladium and platinum).

Fig. 2: Time-varying effect of climate risks on the volume of contracts traded for the precious metals



Note: The dotted lines correspond to t-values at the significance levels of 1% (+/−2.575), 5% (+/−1.96) and 10% (+/−1.645).

4.2. *Climate risks and forecasting results of trading volumes of precious metals*

In Table 1, we present the p-values of the CW test, derived based on a rolling-window estimation of $m = 500$, i.e., approximately two years of data points, which in turn ensures that the out-of-sample basically starts from the tumultuous period associated with the beginning of the global financial crisis. The forecasts were conducted for three horizons of $h = 1$, 5, and 22, corresponding to a one-day-, one-week-, and one-month-ahead. We find that $\text{CONCERN}_{\text{PR}}$ produces statistically superior forecasting gains relative to the benchmark model at $h = 5$ and 22 for the trading volume of gold, which in turn are also reflected in the PRI for these corresponding forecasting horizons. TRI is also found to produce statistical forecasting gains for gold trading volumes at $h = 5$, but the corresponding PRI produces a much lower p-value, which is indicative of a stronger predictive ability of the same. In sum, while we do not find evidence of forecastability of gold volume a-day-ahead, we do so at a week- and month-ahead, and that too from the physical risks component of climate change. Given the positive time-varying impact of such risks on the trading volume of gold (as shown in Figure 2), we can say that gold acts as a hedge against physical risks at medium- and long-horizons.

Turning now to the other three precious metals, we find that statistically superior forecasting gains for palladium emanating from both physical and transition risks are obtained at $h = 1$, while this holds for both $h = 5$ and $h = 22$ for platinum. As far as silver is concerned, accurate forecasting is derived from the climate risks-related metrics for all three horizons, with a stronger effect obtained under transition risks compared to physical ones, especially when one compares the p- values associated with TRI and PRI. In light of the underlying time-varying relationship between the trading volumes of palladium, platinum, and silver with climate risks, we tend to conclude that while the former two, especially platinum, can hedge climate risks, silver, with its volume being negatively impacted, is not necessarily well-suited to play the role of a safe haven relative to physical and transition risks.[7]

[7] As part of additional analysis, we collected 5-minute interval intraday price data of these four precious

Table 1: CW p-values for forecasts of trading volumes of precious metals based on metrics of climate risks

		Gold	Palladium	Platinum	Silver
$h = 1$	$\text{CONCERN}_{\text{PR}}$	0.1516	0.0338	0.5155	0.0185
	$\text{CONCERN}_{\text{TR}}$	0.7873	0.0080	0.9380	0.5576
	PRI	0.3311	0.0115	0.4822	0.0054
	TRI	0.3779	0.0977	0.5424	0.0860
$h = 5$	$\text{CONCERN}_{\text{PR}}$	0.0036	0.8603	0.0985	0.6815
	$\text{CONCERN}_{\text{TR}}$	0.3347	0.2218	0.5316	0.3738
	PRI	0.0037	0.5924	0.0024	0.0078
	TRI	0.0338	0.1357	0.0373	0.0000
$h = 22$	$\text{CONCERN}_{\text{PR}}$	0.0071	0.8689	0.0139	0.5256
	$\text{CONCERN}_{\text{TR}}$	0.8585	0.8147	0.3902	0.1232
	PRI	0.0146	0.5540	0.0037	0.0062
	TRI	0.5376	0.6736	0.2331	0.0001

5. Conclusion

In this paper, we forecast the daily volume of trade contracts of gold based on the information contained in textual analysis-based metrics of physical or transition risks associated with climate change. In light of the count-valued nature of the time series data of gold volume, we utilize a log-linear Poisson integer-valued generalized autoregressive conditional heteroskedasticity (INGARCH) model involving a specific-type of climate change-related predictor. Based on daily data covering the period of 3rd January, 2005 to 29th October, 2021, emanating from physical risks, we detect statistically superior forecasting gains for gold volume at week- and month-ahead horizons, but not for one-day-ahead. Given the underlying positively evolving impact of such risks on the trading volume of gold, obtained from a full-sample analysis using a time-varying INGARCH model, we conclude that gold

metals from Bloomberg, and computed daily counts of positive and negative log-returns. The idea in this instance is that if gold and the other three metals are indeed safe haven, then climate risks should be able to predict relatively more accurately the positive rather than the negative counts, as an indication of being a hedge against such risks. For this exercise, we consider the period of 1st May, 2018 to 29th October, 2021, with the start date concentrated around the peak date (19th September, 2018) of the physical risk metrics, with which gold trading volumes were shown to be, in general, positively related. As shown in Table A1 of the Appendix, gold is the only case, compared to the three other precious metals, whereby not only physical, but also transition risks, tend to accurately forecast positive returns only at $h = 1$- and 5-day ahead. Note that, in light of the small sample size of 973 observations, we use a rolling-window of 125 days to obtain our results. These findings, in turn, confirm that gold is indeed best-suited among precious metals to hedge climate risks.

acts as a hedge against physical risks of climate change at medium- and long-horizons. Such an observation could also be detected for platinum, and to a lesser extent, for palladium, but not silver. Considering that trading volume is known to lead to gold returns and volatility, our results have important investment implications in terms of the design of optimal portfolios. In particular, we find that gold can be included in a portfolio to hedge against the physical aspect of climate risks, which is known to negatively impact the risk of financial assets.

A similar future analysis could be devoted to forecasting the trading volume of "green" and "environmental, social, and governance (ESG)" assets.

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Appendix

Table A1: CW p-values for forecasts of count of negative and positive log-returns of precious metals based on metrics of climate risks. Palla, Plati and Silv stand for Palladium, Platinum and Silver respectively

		Gold(−)	Gold(+)	Palla(−)	Palla(+)	Plati(−)	Plati(+)	Silv(−)	Silv(+)
h =1	$\text{CONCERN}_{\text{PR}}$	0.5133	0.1752	0.4537	0.3530	0.2563	0.3806	0.5666	0.1382
	$\text{CONCERN}_{\text{TR}}$	0.5863	0.0974	0.0005	0.2325	0.3271	0.2477	0.1800	0.4095
	PRI	0.5582	0.3376	0.0911	0.1454	0.5451	0.1769	0.4141	0.0584
	TRI	0.2448	0.0101	0.0000	0.0001	0.0979	0.0295	0.0055	0.0599
h = 5	$\text{CONCERN}_{\text{PR}}$	0.8809	0.0614	0.6413	0.1020	0.8995	0.0616	0.6656	0.0231
	$\text{CONCERN}_{\text{TR}}$	0.8519	0.1150	0.6939	0.0674	0.5921	0.4680	0.9058	0.2494
	PRI	0.4390	0.1400	0.4699	0.0724	0.8710	0.0501	0.3262	0.0173
	TRI	0.6106	0.0978	0.1539	0.0061	0.4548	0.2239	0.7337	0.1364
h = 22	$\text{CONCERN}_{\text{PR}}$	0.9741	0.4987	0.3309	0.6267	0.7895	0.5719	0.9915	0.1660
	$\text{CONCERN}_{\text{TR}}$	0.8692	0.5397	0.8881	0.1097	0.7086	0.8413	0.9736	0.6213
	PRI	0.8479	0.8827	0.8744	0.7016	0.9113	0.6123	0.8696	0.1650
	TRI	0.8745	0.7585	0.8180	0.0985	0.6247	0.9366	0.9059	0.5890

Note: − or + corresponding to the name of a precious metal indicates the case of negative or positive count of log-returns.