

Energy Market Dynamics and the ESG–Conventional Equity Spread: Evidence from Quantile Regression

Liviu-Mihai Bogdan¹, Gabriel Saiu², Carmen Munteanu³ and Iulian Gabriel Ionescu⁴

¹⁾²⁾⁴⁾ *Bucharest University of Economic Studies, Bucharest, Romania.*

³⁾ *Independent Researcher, Bucharest, Romania.*

E-mail: bogdanliviu20@stud.ase.ro; E-mail: saiugabriel20@stud.ase.ro;

E-mail: carmen.munteanu14@gmail.com; E-mail: ionescuiulian22@stud.ase.ro

Please cite this paper as:

Bogdan, L., Saiu, G., Munteanu, C., & Ionescu, I. (2026). Energy Market Dynamics and the ESG–Conventional Equity Spread: Evidence from Quantile Regression. In C. Vasiliu, D.-C. Dabija, A. Tziner, D. Pleșea, & V. Dinu (Eds.), *Proceedings of BASIQ International Conference on New Trends in Sustainable Business and Consumption, 12th Edition* (pp. 64–71). Editura ASE.
DOI 10.24818/BASIQ/2026/12/056

Abstract

This study investigates what drives the daily return differential between the STOXX 600 ESG-X sustainability-screened index and the conventional STOXX 600 benchmark—referred to as the ESG spread—and whether those drivers operate differently across market states and macro-energy regimes. Using more than a decade of European daily data (March 2012–February 2026), we apply Koenker–Bassett quantile regression at five quantile levels, with Brent crude oil, TTF gas, EU Emissions Allowances, European equity volatility (V-STOXX) and German Bund yields as regressors. Inference is based on a moving-block bootstrap, and the model is re-estimated over three economically distinct sub-periods. The central finding is that Brent oil returns consistently compress the ESG spread—the clearest empirical signature of an energy-exclusion wedge—while equity volatility matters mainly around median market conditions. Full-sample slope effects are broadly proportional across the distribution, but the factor structure shifts substantially across regimes: financial conditions dominate the pre-crisis decade, commodity shocks dominate during the energy crisis, and tail-specific effects persist thereafter. These results imply that ESG screening embeds a time-varying, regime-contingent exposure to energy commodity cycles that can amplify tracking error during stress episodes, with direct implications for ESG benchmark design, investor disclosure under SFDR and the EU Taxonomy, and transition-finance instruments.

Keywords

STOXX 600 ESG-X; return spread; quantile regression; energy markets; ESG investing; V-STOXX; EU ETS

DOI: 10.24818/BASIQ/2026/12/056

Introduction

The mainstreaming of ESG mandates has renewed the question of whether sustainability-screened portfolios behave differently from conventional benchmarks, especially when the excluded sector is also the market's best performer. The 2021–2022 energy shock made this tension visible in Europe, where ESG screens removed much of the fossil-fuel exposure that supported conventional benchmark returns (Pástor et al., 2022). For SFDR- and Taxonomy-oriented investors, the central issue is therefore not a universal ESG premium, but the regime-dependent cost of exclusion screening.

What remains under-studied is the distributional dimension of that cost. Mean-regression evidence is informative about average performance (Broadstock et al., 2021; Demers et al., 2021), but it does not show whether the ESG-conventional spread reacts differently in weak, normal or strong market states, nor whether those responses change across macro-energy regimes.

This paper therefore examines which shocks explain the daily ESG spread and whether their effects vary across conditional quantiles and across three macro-energy regimes. The contribution is to analyse the

spread as a stand-alone object, interpret it as an energy-exclusion wedge, and combine quantile regression, moving-block-bootstrap inference and regime decomposition in one European daily-data setting.

The remainder of the paper is organised as follows. Section 1 reviews the ESG-performance, energy-finance and quantile-methods literature. Section 2 describes the data, variable construction and econometric design. Section 3 presents the full-sample and sub-period evidence. The final section discusses implications, limitations and future research directions.

1. Literature review

The ESG-performance literature does not support a single, stable ESG premium once portfolio construction, rating disagreement and changing investor preferences are considered. Meta-evidence is broadly favourable to ESG (Friede et al., 2015), but empirical results remain sensitive to ESG data providers, regional coverage and sample periods (Halbritter & Dorfleitner, 2015; Gibson Brandon et al., 2021). Recent European index evidence reinforces this conditional view: Kossentini et al. (2024) show that ESG benchmarks can perform comparably to conventional indices, but that alpha and beta are time-varying and depend on market states. This is consistent with Pástor et al. (2022), who argue that realised green returns can reverse when energy producers outperform sharply.

A second issue is that ESG indices are not neutral containers of firm-level sustainability information. They translate screening rules into sector weights, exclusions and implicit factor exposures. For broad European benchmarks, this distinction is central because an ESG screen can reduce exposure to fossil-fuel producers while leaving most non-energy constituents similar to the parent index. The resulting performance differential is therefore partly a sustainability signal and partly a benchmark-construction outcome.

A related strand focuses on crisis resilience. Broadstock et al. (2021) document stronger COVID-19 resilience among high-ESG Chinese firms, whereas Demers et al. (2021) find that intangible assets, rather than ESG scores alone, explained US crisis performance. These mixed findings matter for ESG index research because exclusion-based benchmarks combine sustainability preferences with active sector tilts. The financial outcome is therefore not only an ESG effect, but also a composition effect that becomes visible when the excluded sector experiences a large shock.

Energy-finance studies provide the mechanism through which such composition effects may arise. Koch et al. (2014) show that EU ETS prices respond to energy-market fundamentals, Reboredo (2018) documents stronger green-bond co-movement during stress, Ferrer et al. (2018) identify time- and frequency-varying links between renewable-energy equities and oil, and Broadstock and Cheng (2019) report that macro-financial conditions shape the green-versus-black bond differential. These studies imply that energy prices, carbon prices and risk sentiment can jointly affect the relative valuation of green and conventional assets.

Recent evidence makes the energy channel more directly relevant for Europe. Karkowska and Urjasz (2023) show that the Russia-Ukrainian war changed connectedness between clean and dirty energy markets and global equity indices, while Ahad et al. (2024) analyse European ESG indices, Brent oil futures and natural gas during the same geopolitical shock. Both studies support the idea that ESG-related assets are not insulated from fossil-energy shocks; rather, their responses depend on the prevailing stress regime and the direction of energy-market spillovers.

Quantile methods are well suited to this setting because they recover slope behaviour across the conditional distribution rather than only at the mean. Beyond the classic contribution of Taylor (1999), sustainable-finance applications use quantile and connectedness frameworks to uncover tail-sensitive green-asset linkages (Chatziantoniou et al., 2022; Mensi et al., 2024; Pham, 2021; Ziadat et al., 2024). Mar'I et al. (2024) further show that green and conventional bonds and stocks react differently to financial stress and uncertainty across quantiles, supporting the need to model market-state dependence explicitly.

The remaining gap is that most existing studies analyse ESG levels, green assets, clean-energy equities or connectedness systems rather than the daily return spread between a broad European ESG-screened benchmark and its conventional parent index. This paper addresses that gap by treating the STOXX 600 ESG-X minus STOXX 600 return differential as the empirical object of interest, interpreting it as an energy-exclusion wedge and combining quantile regression, block-bootstrap inference and explicit regime decomposition. The approach also has disclosure relevance, because tracking error should be interpreted through regime-specific exposure to energy shocks, not only through average returns.

2. Research methodology

Daily closing data for the STOXX 600 ESG-X, STOXX 600, V-STOXX, German Bund 10-year yield, TTF gas, Brent crude and EUA spot prices are collected for 19 March 2012-2 February 2026, yielding 3,526

usable observations after differencing. The dependent variable is the daily ESG spread, defined as the log-return on the ESG-X minus the log-return on the STOXX 600; regressors are log-returns for Brent, TTF and EUA, plus first differences in V-STOXX and Bund yields.

Sub-periods are set to 2012-2019, 2020-2022 and 2023-2026 to capture, respectively, Figure no. 1, the pre-crisis environment, the COVID-19/energy-crisis shock and the post-crisis repricing phase. These breaks are economically motivated rather than estimated structural break dates, and the rolling-window outputs indicate gradual rather than knife-edge transitions around them.



Figure no. 1. STOXX 600 ESG-X vs. STOXX 600 (rebased to 100, 19 March 2012 = 100). Shaded regions denote the three sub-periods

A natural quantitative anchor for the energy-exclusion wedge is the sector-weight gap between the two benchmarks. In the STOXX factsheets dated 31 March 2025, Energy accounts for about 5.5% of the STOXX Europe 600 but only about 0.7% of the STOXX Europe 600 ESG-X, implying an underweight of roughly 4.8 percentage points in the ESG-screened index.

The dependent variable is the ESG spread, defined as follows.

$$Spread_t = \ln\left(\frac{ESG_t}{ESG_{t-1}}\right) - \ln\left(\frac{MKT_t}{MKT_{t-1}}\right) \quad (1)$$

The explanatory variables are defined as follows.

$$\Delta VSTOXX_t = VSTOXX_t - VSTOXX_{t-1}; \quad \Delta Bund_t = Bund_t - Bund_{t-1} \quad (2)$$

$$r_{TTF,t} = \ln\left(\frac{TTF_t}{TTF_{t-1}}\right), \quad r_{Brent,t} = \ln\left(\frac{Brent_t}{Brent_{t-1}}\right), \quad r_{EUA,t} = \ln\left(\frac{EUA_t}{EUA_{t-1}}\right) \quad (3)$$

Tables no. 1 and no. 2 report the descriptive statistics and unit-root diagnostics used in the subsequent estimations.

Table no. 1. Descriptive Statistics (n = 3,526 daily observations, 19 March 2012 – 2 February 2026)

Variable	Mean	Std. Dev.	Min	Q25	Median	Max
ESG Spread	-0.000002	0.000394	-0.002766	-0.000202	-0.000000	0.003251
ΔV -STOXX	0.000394	1.697329	-11.8979	-0.765525	-0.095500	17.7581
$\Delta Bund$ (10Y)	0.000226	0.043947	-0.290000	-0.024000	-0.001000	0.298000
r(TTF gas)	0.000087	0.040253	-0.352421	-0.015231	-0.000489	0.412784
r(Brent oil)	-0.000182	0.022937	-0.279761	-0.010266	0.000757	0.190774
r(EUA carbon)	0.000671	0.030645	-0.432421	-0.013935	0.000837	0.239230

Table no. 2. Augmented Dickey–Fuller and Phillips–Perron Unit Root Tests

Series	ADF Stat.	ADF p-value	PP Stat.	PP p-value	Order	Lag
ESG Spread	−13.268	< 0.001***	−58.176	< 0.001***	I(0)	26
$\Delta V\text{-STOXX}$	−14.498	< 0.001***	−66.363	< 0.001***	I(0)	27
$\Delta \text{Bund (10Y)}$	−59.810	< 0.001***	−59.884	< 0.001***	I(0)	0
$r(\text{TTF gas})$	−10.542	< 0.001***	−57.178	< 0.001***	I(0)	24
$r(\text{Brent})$	−58.156	< 0.001***	−58.182	< 0.001***	I(0)	0
$r(\text{EUA})$	−11.131	< 0.001***	−61.613	< 0.001***	I(0)	28

Note: ADF lag selected by AIC; reported lag lengths are 26, 27, 0, 24, 0 and 28, respectively. PP bandwidth = 30 (Newey–West). *** $p < 0.001$

VIF values below 1.11 indicate no material multicollinearity. The core specification is a Koenker–Bassett quantile regression estimated at $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$:

$$Q_\tau(\text{Spread}_t | X_t) = \alpha(\tau) + \beta_1(\tau) \Delta V\text{STOXX}_t + \beta_2(\tau) \Delta \text{Bund}_t + \beta_3(\tau) r_{\text{TTF},t} + \beta_4(\tau) r_{\text{Brent},t} + \beta_5(\tau) r_{\text{EUA},t} \quad (4)$$

where $Q_\tau(\text{Spread}_t | X_t)$ denotes the τ -th conditional quantile.

$$\rho_\tau(u) = u(\tau - 1\{u < 0\}) \quad (5)$$

Because the series display non-normality, heteroscedasticity and serial dependence, inference relies on a moving-block bootstrap with 22-trading-day blocks and $B = 1,000$ replications (Koenker, 2005). Bootstrap quantile-difference tests compare the coefficient pairs (0.10, 0.50), (0.10, 0.90) and (0.50, 0.90) following Koenker and Machado (1999).

Rolling 252- and 504-day quantile estimates were also generated as a stability check and support the qualitative regime ranking reported below; detailed paths are available on request.

3. Results and discussion

Table no. 1 shows that the ESG spread is centred near zero (mean = −0.000002), confirming tight daily co-movement between the two indices, while Table no. 2 rejects the unit-root null for every series at the 0.001 level. Residual diagnostics further justify bootstrap inference: Jarque–Bera statistics are significant at all quantiles, ARCH-LM tests indicate strong volatility clustering, and Ljung–Box p-values stay below 0.002. The 2020 and 2023 cut-offs should therefore be read as approximate regime markers; rolling 252- and 504-day estimates indicate gradual transitions, and the qualitative ranking of the main drivers is unchanged by nearby (+/- 3 month) boundary shifts.

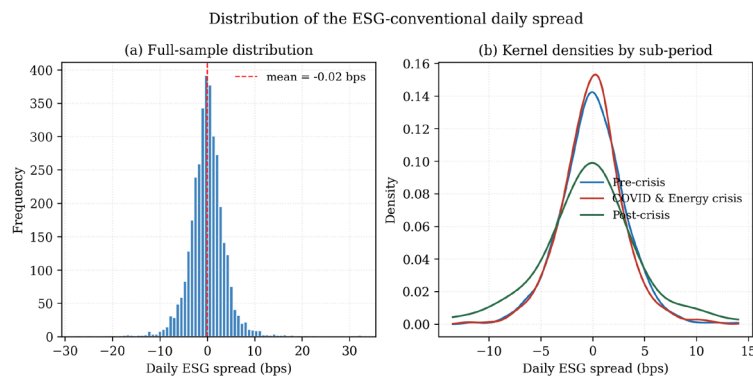


Figure no. 2. Distribution of the daily ESG-conventional spread: full-sample histogram (a) and kernel densities by sub-period (b)

For interpretation, one-sigma daily shocks from Table 1 equal 1.697 V-STOXX points, 0.043947 percentage points in the Bund yield, 4.03% in TTF gas, 2.29% in Brent oil and 3.06% in EUA prices. The quantile coefficients can therefore be read against realistic daily shock sizes rather than only one-unit moves.

Table no. 3 shows that Brent is the only full-sample driver that is negative throughout the distribution and statistically significant from $\tau = 0.25$ to $\tau = 0.90$; the coefficient ranges from -0.000567 at $\tau = 0.10$ to -0.001728 at $\tau = 0.90$. This is the clearest empirical signature of the energy-exclusion wedge: when oil prices rise, the conventional benchmark retains gains from energy producers that the ESG-X excludes.

Table no. 3. Quantile Regression Results — Dependent Variable: Daily ESG Spread

Variable	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
Constant	-0.000414*** [-0.000453, -0.000378]	-0.000200*** [-0.000216, -0.000182]	-0.000001 [-0.000010, 0.000008]	0.000193*** [0.000178, 0.000206]	0.000405*** [0.000373, 0.000429]
ΔV -STOXX	-0.000016 [-0.000035, 0.000000]	-0.000018* [-0.000033, -0.000002]	-0.000014* [-0.000027, -0.000001]	-0.000007 [-0.000020, 0.000003]	-0.000005 [-0.000024, 0.000012]
ΔBund (10Y)	0.000238 [-0.000307, 0.000791]	0.000334 [-0.000120, 0.000808]	0.000280 [-0.000115, 0.000641]	0.000401* [0.000046, 0.000745]	0.000299 [-0.000221, 0.000761]
$r(\text{TTF gas})$	0.000169 [-0.000487, 0.000641]	-0.000092 [-0.000514, 0.000314]	-0.000196 [-0.000466, 0.000104]	-0.000245 [-0.000745, 0.000077]	-0.000453 [-0.001156, 0.000033]
$r(\text{Brent oil})$	-0.000567* [-0.002567, 0.000707]	-0.000946** [-0.001669, -0.000037]	-0.000793** [-0.001458, -0.000161]	-0.001257** [-0.002014, -0.000260]	-0.001728** [-0.002576, -0.000046]
$r(\text{EUA carbon})$	0.000639 [-0.000614, 0.001271]	0.000354 [-0.000397, 0.000914]	0.000010 [-0.000429, 0.000465]	0.000025 [-0.000428, 0.000530]	0.000084 [-0.000459, 0.000915]
Pseudo R^2	0.0052	0.0057	0.0052	0.0052	0.0063

Note: Coefficients from quantile regression. 95% block-bootstrap confidence intervals ($B = 1,000$; block length = 22 days) shown in brackets. *** $p < 0.001$; ** $p < 0.05$; * $p < 0.10$. $n = 3,526$

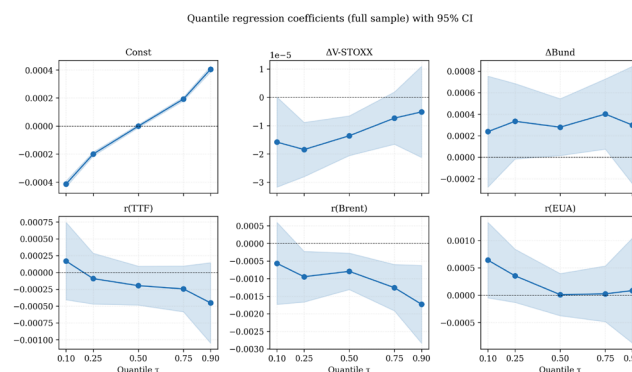


Figure no. 3. Quantile regression coefficient paths with 95% bootstrap confidence intervals. The intercept location shift and the broadly stable Brent slope indicate a proportional rather than asymmetric distributional effect

ΔV -STOXX is significantly negative at $\tau = 0.25$ and $\tau = 0.50$, implying a moderate-stress channel rather than a pure tail-risk effect, while Bund yield changes are only weakly positive at $\tau = 0.75$. TTF gas and EUA returns are not stable full-sample determinants once Brent is included.

Pseudo- R^2 values range from 0.52% to 0.63%, which is consistent with the fact that the dependent variable is a small daily spread between highly overlapping portfolios. This magnitude is also in line with published daily green-versus-conventional spread work, where macro-financial covariates explain only a limited fraction of day-to-day differentials outside stress episodes (Broadstock & Cheng, 2019).

Bootstrap quantile-difference tests reject equality of intercepts but not equality of slopes. The full-sample evidence is therefore best described as a location shift in the conditional distribution, with genuine slope heterogeneity emerging only once the sample is split into macro-energy regimes.

Table no. 4 condenses the sub-period evidence. The broad pattern is clear: financial conditions dominate before 2020, Brent/Bund/EUA shocks dominate in 2020-2022, and post-2023 effects become tail-specific rather than pervasive.

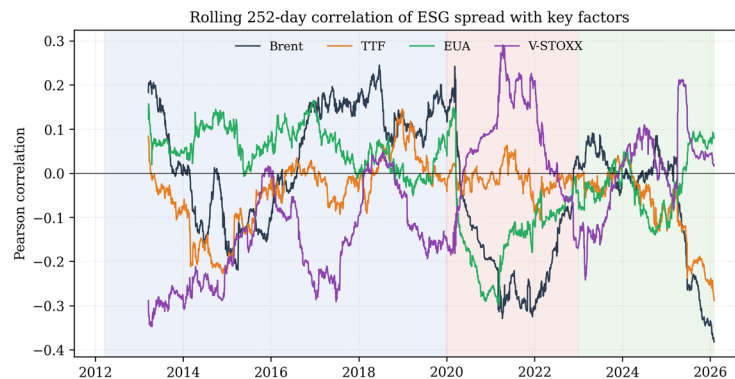


Figure no. 4. Sub-period quantile coefficient paths with 95% bootstrap confidence intervals

Table no. 4. Comparative Synthesis of Sub-period Quantile Results

Regime	Significant drivers	Quantiles	Comparative reading
2012-2019	$\Delta V\text{-STOXX}$ (-), ΔBund (+), EUA (+), TTF (- at median); Brent not significant	V-STOXX and Bund: all five quantiles; EUA: $\tau = 0.10\text{-}0.50$; TTF: $\tau = 0.50$	Pre-crisis spread behaviour is dominated by financial conditions and risk sentiment rather than commodity shocks.
2020-2022	Brent (-), ΔBund (-), EUA (-); V-STOXX and TTF not significant	Brent: $\tau = 0.25\text{-}0.90$; ΔBund and EUA: $\tau = 0.25\text{-}0.75$	During the energy crisis, the energy-exclusion wedge becomes explicit and overwhelms the earlier sentiment channel.
2023-2026	Brent (-), TTF (-), EUA (+), ΔBund (lower-tail only)	Brent: $\tau = 0.10$ and 0.90 ; TTF: $\tau = 0.75$; EUA: $\tau = 0.90$; ΔBund : $\tau = 0.10$	Post-crisis effects narrow to the tails, indicating partial normalisation but persistent vulnerability to extreme energy shocks.

The comparative table replaces lengthy regime-by-regime narration without changing the substantive conclusion: the financial consequences of ESG screening are regime dependent, and they intensify when fossil-fuel pricing becomes the dominant market shock.

Conclusions

This paper applied quantile regression with moving-block-bootstrap inference to the daily return spread between the STOXX 600 ESG-X and STOXX 600 indices over 19 March 2012 to 2 February 2026. Three factual conclusions emerge. First, in the full sample, Brent crude oil returns are negative across all quantiles and significant from $\tau = 0.25$ to $\tau = 0.90$; the 95% bootstrap CI at $\tau = 0.10$ includes zero. Second, V-STOXX changes exert a significant negative effect at intermediate quantiles ($\tau = 0.25$ and 0.50) but not in the tails, while TTF, EUA and Bund effects are not stable in the full sample. Third, quantile-difference tests indicate that the full-sample heterogeneity operates mainly as a location shift in the intercept rather than as asymmetry in slopes; genuine heterogeneity surfaces across the three sub-periods, where the factor structure of the spread changes qualitatively between the pre-crisis, crisis and post-crisis regimes.

The implications for practice follow directly. For investors, ESG screening should be understood to introduce an implicit, time-varying exposure to the energy commodity cycle; during commodity-stress

regimes this exposure manifests as a measurable tracking-error cost relative to the conventional benchmark. For benchmark design and governance, the structural instability documented across sub-periods suggests that static exclusion rules interact with the prevailing energy regime in ways that standard factor-model disclosures do not capture, and that supplementary regime-conditional risk metrics—at a minimum, an explicit sector-weight differential and a rolling energy- β —would strengthen transparency. For risk communication under frameworks such as SFDR and the EU Taxonomy, the commodity-cycle exposure embedded in ESG screening is a material feature that warrants explicit disclosure rather than being presented solely as a long-horizon transition story.

Taken together, the findings support a view of ESG screening as a strategy whose financial performance is shaped less by a stable ESG premium and more by a regime-contingent energy-exclusion wedge. This reframing complements rather than contradicts the existing literature: ESG portfolios can still be valuable on sustainability grounds, but their return profile should be communicated to beneficiaries as cycle-dependent rather than uniformly comparable to conventional benchmarks.

Several limitations qualify the analysis. First, the study uses daily index-level data, which cannot capture constituent-level heterogeneity in energy exposure within either index—the energy-exclusion wedge is identified only on average, not firm-by-firm. Second, potentially relevant drivers are omitted by construction, notably ESG fund flows, regulatory and policy announcements (EU ETS reforms, SFDR-related re-labelling), and sector-level rating revisions. Third, the low pseudo- R^2 values (0.52–0.63% in the full sample) are not unusual for daily spread regressions but confirm that a substantial share of daily ESG-spread variation remains unexplained by the specified energy and macro-financial factors and should be interpreted as noise rather than systematic signal.

Future research can extend the present framework along three directions that follow directly from these results. First, an explicit time-varying sector-weight differential between the ESG-X and its parent index would allow the energy-exclusion wedge to be quantified structurally rather than inferred. Second, Brent shocks could be interacted with an energy-share measure to test whether the commodity effect scales with the instantaneous composition gap. Third, event-window analyses centred on major EU ETS reforms and key energy-policy episodes would isolate the policy-driven component of the ESG spread from its commodity-price component, sharpening the identification of the transmission mechanism.

Generative Artificial Intelligence (GenAI) usage statement:

Claude (Anthropic, claude-sonnet-4.6) and ChatGPT (OpenAI, GPT-5.5) were responsibly used for language improvement and structural editing during the preparation of this manuscript. After this process, the authors reviewed and edited the content as needed and take full responsibility for the content of the present article.

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