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Research Article

Persistent cointegration and regime-sensitive market leadership: Evidence from international tobacco stocks

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ABSTRACT

This paper develops a data-driven framework combining fractional cointegration and structural break detection to examine long-run interdependence and market leadership among international tobacco equities. Using weekly data from May 2008 to October 2024 for Philip Morris International, Altria, British American Tobacco, Imperial Brands, and Japan Tobacco, the study applies the Fractionally Cointegrated Vector Autoregressive (FCVAR) model of Johansen and Nielsen (2012) integrated with the Bai–Perron multiple-break methodology. The empirical analysis supports the presence of a single fractionally cointegrated equilibrium relationship characterized by long memory and regime-dependent persistence. Three model-implied regime shifts, which align closely in timing with major regulatory and ESG-related events, such as the 2012 WHO-FCTC harmonization, the 2015 expansion of FDA regulation, and the 2021 post-COVID ESG rotation—mark distinct equilibrium regimes in the global tobacco market. Within these regimes, adjustment dynamics indicate recurrent long-run leadership by Japan Tobacco, more heterogeneous leadership patterns for Altria, and a clearly regime-dependent role for Philip Morris International. The integration of fractional modeling and break detection provides a robust data-science approach to disentangling persistence from structural change, offering new insights into leadership cycles, systemic risk, and sectoral resilience. These findings underscore how regulated and ESG-sensitive industries evolve through adaptive equilibrium processes, contributing to the broader literature on long-memory econometrics and data-driven financial analytics.

1. Introduction

Understanding the long-term co-movements among asset prices across financial markets has become a central concern in empirical finance, particularly in the context of global structural shifts, market segmentation, and investor heterogeneity. In this regard, cointegration techniques have provided a powerful empirical framework to explore long-run equilibrium relationships among nonstationary time series, especially in systems affected by persistent shocks, regime changes, and partial market integration (Bekaert and Harvey, 1995; Engle and Granger, 1987; Johansen, 1991). More recently, the development of the Fractionally Cointegrated Vector

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Autoregressive (FCVAR) model has allowed researchers to capture not only the cointegrating structure of asset prices but also the degree of fractional integration, thus accommodating long memory and mean-reverting dynamics (Johansen and Nielsen, 2012).

Parallel to these methodological advances, a growing body of research has sought to apply cointegration tools to assess asset behavior during periods of structural instability. Empirical evidence has demonstrated that ignoring regime shifts or structural breaks may lead to biased estimations and incorrect inference about equilibrium relationships (Gregory and Hansen, 1996; Bai and Perron, 2003). Against this backdrop, this study incorporates the Bai-Perron methodology for detecting multiple structural breaks into the FCVAR framework, offering a regime-sensitive approach to understanding interdependencies among financial assets.

This analytical strategy is particularly relevant in the case of tobacco stocks, which have received increasing attention for their unique risk-return profile and potential role as defensive assets. Despite widespread environmental, social, and governance (ESG) concerns and growing regulatory pressure, several tobacco firms have shown strong market performance, low beta behavior, and relatively stable dividends. For instance, Bauer (2018) highlights how exclusionary screening of tobacco equities in ESG portfolios may come at the cost of diversification and returns. Blitz and Swinkels (2020) argues that the defensive characteristics of tobacco stocks make them attractive during market downturns. Meanwhile, Fitchet (2018) emphasizes that tobacco stocks tend to exhibit stable fundamentals and can provide hedging benefits in crisis periods. More recent contributions, such as Côdea (2024) and Yunita and Barkah (2024), examine the cointegration and volatility patterns of tobacco equities in emerging and developed markets, respectively, underscoring the importance of long-run modeling frameworks in these contexts.

Building on these findings, this paper aims to assess the dynamic cointegration structure of five major tobacco firms—Philip Morris International (PMI), Altria (MO), British American Tobacco (BATS), Imperial Brands (IMB), and Japan Tobacco (JTI)—across structurally segmented regimes. By applying the FCVAR model with endogenous break detection, we not only investigate the long-run relationships among these firms' stock prices but also evaluate their relative roles in terms of market leadership (via adjustment coefficients) and hedging potential (via memory parameters and cointegrating vectors). This dual focus allows for a nuanced classification of assets into systemic leaders and followers, a distinction with direct implications for portfolio optimization and macro-financial supervision.

Finally, this paper contributes to the literature in several ways. First, it extends the empirical use of FCVAR models by integrating structural break detection into the estimation process, allowing for regime-specific parameterization. Second, it offers an asset classification scheme grounded in long memory theory and error correction dynamics, particularly suitable for industries subject to external shocks and regulatory interventions. Third, it bridges financial econometrics with sectoral finance by applying high-dimensional time series tools to the tobacco industry, thereby enriching the discussion on how controversial yet resilient sectors behave under structural uncertainty. This approach aligns with the increasing demand for robust methods in the study of financial risk, systemic resilience, and asset pricing under nonstationarity.

1.1. Literature review

Research on fractional integration and cointegration has profoundly reshaped the understanding of persistence and long-run dependence in financial and macroeconomic time series. Traditional econometric frameworks based on the dichotomy between stationary I(0) and non-stationary I(1) processes often fail to capture the gradual decay of shocks and the slow mean reversion observed in real-world data. The seminal contribution of Baillie and Bollerslev (1994) introduced the concept of fractional integration into financial econometrics, demonstrating that asset returns and volatility processes frequently exhibit long memory, where the effects of innovations diminish hyperbolically rather than exponentially. Their findings revealed that the persistence of volatility in exchange rates and other financial variables cannot be adequately described by short-memory ARMA models or standard GARCH structures. Instead, fractional processes provide a more realistic description of the temporal dependence inherent to financial dynamics. This notion of fractional integration laid the groundwork for a vast empirical literature emphasizing the intermediate degree of persistence between full integration and stationarity, thereby motivating the subsequent development of fractionally cointegrated models.

Building on this foundation, Lien and Tse (1999) investigated long-run relationships among futures and spot prices using fractional cointegration techniques. Their analysis showed that market efficiency and the law of one price can coexist with fractional adjustment, implying that deviations from equilibrium persist for extended periods before reverting to the mean. This finding was important because it revealed that financial markets may remain efficient even when convergence is gradual rather than instantaneous. Similarly, Aloy et al. (2013) applied fractional cointegration methods to examine interest rate parity in emerging economies and found that long-memory adjustment mechanisms were consistent with partial market integration. These early applications collectively established that fractional cointegration is not merely a theoretical generalization but a necessary empirical tool to describe real financial linkages in the presence of persistence.

Subsequent methodological advances deepened the empirical toolkit for modeling such relationships. Gil-Alana et al. (2012) extended fractional cointegration to multivariate systems, showing that fractionally integrated errors can arise even when the underlying variables differ in their order of integration. This flexibility allowed for more nuanced modeling of financial linkages, especially in markets subject to heterogeneous trading behaviors and information frictions. Gil-Alana and Yaya (2014) further demonstrated that fractional models outperform traditional cointegration tests in the presence of long-memory volatility and regime shifts, highlighting the importance of fractional differencing in both mean and variance equations. Their results provided compelling evidence that persistence in financial data often originates from institutional inertia, transaction costs, and structural rigidities rather than from simple random walks. Subsequent work by Yaya et al. (2021a, 2021b) reinforced these insights by exploring fractional cointegration within nonlinear and regime-switching frameworks, revealing that memory properties can vary across different volatility states or economic regimes.

A major strand of literature has linked fractional cointegration to the broader theory of market efficiency. Caporale et al. (2016) examined stock price comovements among major international indices using fractional cointegration and found evidence of persistent but mean-reverting relationships, consistent with partial efficiency. Their results challenged the notion that market integration necessarily implies immediate adjustment and instead suggested that shocks propagate gradually through global financial networks. Caporale et al. (2022) extended this analysis by applying the Fractionally Cointegrated VAR (FCVAR) model proposed by Johansen and Nielsen to capture both long-run equilibrium and fractional adjustment dynamics simultaneously. They demonstrated that the FCVAR framework can accommodate long memory in both the cointegrating residuals and short-run dynamics, yielding more robust inference than conventional vector error-correction models. In a more recent contribution, Caporale et al. (2024) used fractional cointegration to analyze energy and ESG-related markets, showing that fractional persistence is particularly pronounced in sectors exposed to regulatory uncertainty and sustainability transitions. Their results confirmed that long-memory cointegration captures not only financial inertia but also structural adaptation to institutional change—a feature highly relevant for regulated industries such as tobacco.

Parallel developments have expanded the empirical scope of fractional models beyond equity markets. Gil-Alana et al. (2018) explored fractional dynamics in commodity prices and found that long-memory behavior is pervasive across energy and agricultural sectors, reinforcing the idea that persistence arises from storage constraints and speculative trading. Wu et al. (2021) applied similar methods to examine linkages between renewable and non-renewable energy assets, concluding that fractional cointegration reveals deeper and more stable equilibrium relationships than traditional cointegration models. Saha et al. (2023) analyzed volatility spillovers under fractional dependence and found that market integration intensifies during episodes of global financial stress, where persistence in volatility increases. These results collectively underscore the empirical relevance of fractional modeling in capturing both the persistence and the nonlinearity inherent to complex markets.

The integration of fractional cointegration with structural break analysis represents a crucial methodological evolution in this literature. While fractional models capture persistence, structural break techniques identify temporal heterogeneity—changes in the parameters or equilibrium relationships that reflect shifts in underlying economic regimes. Afzal and Sibbertsen (2021) proposed an approach combining fractional integration with structural breaks, demonstrating that neglecting breaks can bias the estimated degree of persistence upward, leading to spurious long-memory detection. Their study emphasized the importance of distinguishing between genuine long memory and apparent persistence arising from regime changes. Bejaoui et al. (2022) similarly noted that ignoring structural instability can distort inference about cointegrating relationships, especially in markets subject to evolving regulatory or geopolitical conditions. Coskun et al. (2023) extended this framework by employing fractional cointegration with time-varying parameters, showing that both persistence and equilibrium relationships evolve gradually rather than discontinuously. Together, these studies highlight the necessity of integrating fractional and structural methodologies to capture the full dynamics of financial systems.

The methodological convergence between the FCVAR model and the Bai–Perron multiple-break approach has provided an effective empirical strategy to analyze both persistence and instability in financial time series. Dettoni et al. (2024) combined fractional cointegration with break detection in the context of ESG and sustainable finance, illustrating that persistence often changes across regulatory cycles. They found that the inclusion of breakpoints improves model fit and enhances the interpretability of fractional parameters by distinguishing between periods of regulatory turbulence and stability. Similar conclusions were drawn by Caporale et al. (2024), who showed that the FCVAR–Bai–Perron integration can disentangle genuine long-run comovement from spurious cointegration caused by regime changes. These methodological refinements have made fractional frameworks more flexible and empirically credible, allowing researchers to capture both smooth long-memory dynamics and discrete structural transitions within a unified model.

Applications of fractional cointegration and long-memory analysis have also expanded to sectors beyond traditional equities, offering new perspectives on how persistence interacts with institutional and macro-financial forces. Gil-Alana et al. (2023) analyzed fractional comovement in cryptocurrency markets and found that long-memory properties persist even under high-frequency trading and speculative environments. This finding implies that long-range dependence is not confined to mature markets but extends to emerging digital assets where information diffusion remains incomplete. Adekoya (2021) investigated fractional integration in African equity markets, revealing that long memory coexists with structural fragility, and that fractional models are particularly suited to capturing persistence in markets undergoing financial liberalization. These studies demonstrate the versatility of fractional cointegration as a framework capable of encompassing a wide variety of asset classes and institutional settings.

The relationship between fractional cointegration and price discovery mechanisms has received growing attention in recent years. Caporale et al. (2022) and Yaya et al. (2021a, 2021b) emphasized that fractional adjustment parameters can be interpreted as indicators of informational leadership: assets that do not significantly adjust to disequilibria are those that lead in price discovery. This interpretation bridges the gap between econometric modeling and financial microstructure, linking persistence to the speed of information assimilation. The notion that long memory and leadership may be two sides of the same process—where dominant assets anchor equilibrium while others adjust—has opened new avenues for analyzing market hierarchies. It also provides the conceptual foundation for applying fractional cointegration to the study of market leadership under structural breaks, as developed in the present paper.

The incorporation of structural breaks into the analysis of fractional cointegration has significant implications for understanding the stability of long-run relationships in the face of policy and macroeconomic shocks. Several studies have shown that the degree of fractional integration can change following regulatory interventions, crises, or technological transitions. For example, Afzal and Sibbertsen (2021) and Bejaoui et al. (2022) documented how ignoring such breaks exaggerates the persistence of shocks, leading to overestimation of the fractional differencing parameter. Similarly, Gil-Alana et al. (2018) and Caporale et al. (2024) found that persistence tends to decline in the aftermath of major policy harmonization efforts, suggesting that coordinated regulation can enhance market efficiency by reducing long-run dependence. These results imply that fractional integration is not a static property but an evolving characteristic shaped by institutional and financial developments. The combination of FCVAR and Bai–Perron methodologies, therefore, represents a methodological synthesis capable of modeling both the continuity and the discontinuity of market dynamics.

Empirical applications of this integrated approach have generated several robust insights. Studies employing fractional cointegration with structural breaks consistently find that the long-run relationships between assets persist but adjust in their strength and composition across regimes. For instance, Caporale et al. (2016, 2022, 2024) and Dettoni et al. (2024) reported that persistence parameters often peak during regulatory uncertainty and crisis periods and decline once stability returns. This pattern parallels the findings of Yaya et al. (2021b) and Wu et al. (2021), who observed that long-memory dynamics intensify during high-volatility episodes. The convergence of evidence across these studies suggests that fractional integration serves as a flexible lens through which the dynamic equilibrium of financial systems can be understood as both persistent and adaptive.

Taken together, the literature demonstrates a clear progression from early recognition of long memory in financial data toward increasingly sophisticated models that integrate fractional integration with structural change, nonlinearity, and leadership analysis. The trajectory of this research reflects the growing recognition that markets are neither fully efficient nor purely random, but instead exhibit complex temporal dependencies influenced by institutional and behavioral factors. The fractional framework provides a coherent way to capture such complexity by accommodating both long-term persistence and evolving equilibrium structures. Furthermore, the extension of fractional cointegration to the study of market leadership offers an innovative link between econometric theory and financial interpretation, transforming what was once a purely statistical parameter into an indicator of economic influence and informational dominance.

In this context, the current paper contributes to the literature by combining the FCVAR framework with Bai–Perron structural break analysis to investigate market leadership under structural instability. By focusing on international tobacco stocks—a sector characterized by heavy regulation, litigation risk, and ESG-driven investment pressures—the study applies fractional cointegration not only as a tool to identify persistent equilibrium relationships but also as a lens to interpret leadership and adaptation within a dynamic institutional environment. This approach directly addresses the gaps identified in prior studies, which often examined persistence or breaks in isolation but rarely considered their joint role in shaping inter-firm hierarchies and market coordination. The integration of long memory, structural segmentation, and leadership classification thus represents a methodological and conceptual advancement within the fractional cointegration literature, aligning empirical innovation with substantive financial relevance.

This paper contributes to the fractional integration literature in three main ways. First, while earlier works (Gil-Alana et al., 2012; Caporale et al., 2016, 2022; Yaya et al., 2021a, 2021b) apply fractional cointegration to conventional asset classes, none of them integrate FCVAR modelling with endogenous structural break detection in a highly regulated and ESG-sensitive industry such as tobacco. Second, unlike studies that examine persistence or structural shifts in isolation, we provide a unified econometric framework capable of disentangling long-memory behaviour from regime-sensitive parameter changes. Third, we extend the literature on price discovery by interpreting FCVAR adjustment coefficients within structurally segmented regimes, offering a dynamic leadership classification that has not been previously documented.

2. Materials and methods

2.1. Data

We analyze weekly adjusted stock prices for five major international tobacco companies—Philip Morris International (PMI), Altria (MO), British American Tobacco (BATS), Imperial Brands (IMB), and Japan Tobacco (JTI)—over the period May 2008 to October 2024. Prices account for corporate actions and are sampled using a common week-ending convention across markets. The baseline analysis is conducted using prices expressed in their respective local trading currencies, while all logarithmic transformations are applied directly to these series. To assess the sensitivity of the results to currency denomination, an additional robustness exercise based on USD-denominated prices is reported in Appendix A.

Weekly data were selected over daily observations for three econometric reasons. First, daily prices are affected by microstructure distortions such as bid–ask bounce and non-synchronous trading, which bias fractional integration estimates and create spurious short-run noise. Second, the FCVAR model is highly sensitive to high-frequency volatility clustering; weekly aggregation improves numerical stability and reduces noise in the estimation of the memory parameters. Third, the Bai–Perron break detection procedure performs more reliably when transitory, high-frequency shocks are smoothed. Given the long-run focus of this study, weekly data provide a cleaner signal-to-noise ratio and enhance interpretability.

2.2. Method

To examine whether tobacco equities are connected through long-run equilibrium relationships, this study employs the Fractionally Cointegrated Vector Autoregressive (FCVAR) model developed by Johansen and Nielsen (2012). Unlike conventional cointegration approaches, the FCVAR framework allows the cointegrating residuals to be fractionally integrated, thereby capturing long memory and slow mean reversion—features often observed in financial markets characterized by persistent adjustment processes and structural shifts. This specification provides a flexible structure for analyzing market integration when deviations from equilibrium dissipate gradually over time. The cointegration rank is determined using a Johansen-type trace test adapted to the fractional setting, employing a constant restricted to the cointegration space and a fixed lag order as described above. While statistical evidence for the selected rank is moderate rather than decisive—a common outcome in persistent financial time series—the adopted rank represents the lowest-dimensional specification that admits a stable long-run equilibrium relation and is therefore used as the baseline throughout the analysis.

Given the presence of fractional integration and long memory, the power of standard Johansen trace tests is known to be reduced, and conventional 5 % significance thresholds may be overly conservative in this setting. We therefore adopt a 10 % significance level as a working decision rule for cointegration rank selection, following common practice in empirical FCVAR applications. Under this criterion, the null hypothesis of no cointegration is rejected, and a single cointegrating relation (r = 1) is adopted as the baseline specification for all subsequent analysis.

The lag length and cointegration rank were selected following standard time-series criteria to ensure statistical consistency and avoid ad hoc parameterization. The optimal number of lags was determined using the Akaike Information Criterion (AIC) from a preliminary vector autoregressive (VAR) model, ensuring that short-term dynamics are appropriately captured. The cointegration rank was assessed through the Johansen trace test, providing a statistical basis for the number of long-run relations included in the FCVAR specification.

We distinguish explicitly between (i) the FCVAR lag order k (lags in levels in the VAR representation of the FCVAR model) and (ii) the corresponding number of lagged differences in the associated VECM representation, denoted k_ar_diff. In our implementation, these are linked by k_ar_diff = k − 1. The AIC-based pre-selection yields k_ar_diff = 1, which corresponds to k = 2 in the FCVAR specification.

This lag order is held fixed throughout the analysis, including FCVAR estimation, construction of the cointegrating residual used for break detection, and regime-specific re-estimation, ensuring full internal consistency across all steps.

The FCVAR(k) model can be written as:

$$\Delta^d x_t = \mu + \alpha\acute{\beta} x_{t-1} + \sum_{j=1}^{k} \Gamma_j \Delta^d x_{t-j} + \varepsilon_t$$

where x_t is a vector of log-prices, Δ^d denotes the fractional differencing operator with order d, β is the cointegrating vector, and α captures the adjustment speed toward equilibrium. The memory parameters (d, b) were estimated within the domain [0.01,2.00] and grid search optimization was disabled to enhance computational efficiency. Estimation was performed using the FCVAR package in R (Morin et al., 2021), specifying a cointegration rank r = 1 and lag order k = 2, as selected via the FCVARlagSelect procedure. Grid search optimization was disabled to improve computational efficiency, and all estimates were verified for numerical stability and consistency.

To assess the temporal stability of the long-run relationship, the cointegrating residual β'xt from the baseline FCVAR model was examined for multiple structural changes using the methodology of Bai and Perron (2003). The test was applied to the stationary cointegrating residual rather than to nonstationary price levels, satisfying the stationarity assumption required for valid inference. The number and timing of structural breaks were determined using the Bayesian Information Criterion (BIC), with a trimming parameter chosen to ensure a sufficient number of observations per regime. Robustness checks were conducted across alternative trimming values to confirm the stability of the identified breakpoints. Fractional cointegration is appropriate in this context because the FCVAR framework is designed precisely for situations in which the variables may display long-memory behaviour and do not conform to the strict I(0)/I(1) dichotomy. This specification allows for fractional orders of integration and fractional error-correction dynamics, which are commonly observed in financial markets according to the literature (e.g., Gil-Alana et al., 2012; Caporale et al., 2016; Yaya et al., 2021a, 2021b)). In addition, fractional cointegration does not impose full-unit-root behaviour on prices nor purely short-memory adjustment, making it suitable for analysing persistent comovements under structural instability. The empirical evidence supporting its use in our dataset is presented in Section 3.

The Bai–Perron test was applied to the stationary cointegrating residuals, consistent with the recommendations of Bai and Perron (2003) and Gregory and Hansen (1996). Applying break tests to nonstationary levels may yield spurious break detection, whereas using residuals ensures compliance with the test's stationarity requirement. The stability of the break dates across trimming values confirms the robustness of the detected structural changes. Because standard Bai–Perron asymptotic theory is not formally derived for fractionally integrated processes, the reported break dates should be interpreted as model-based regime segmentation rather than as outcomes of formal hypothesis testing.

Following the identification of structural regimes, the FCVAR model was re-estimated separately for each subperiod. This regime-specific estimation allows both the long-run equilibrium relations and the adjustment dynamics to vary over time. Particular attention was paid to the adjustment coefficients \alpha and their associated t-statistics, which measure the speed and significance of mean reversion. Assets exhibiting statistically insignificant adjustment coefficients ($|t| < 1.96$) were interpreted as long-run leaders, since they do not adjust to deviations from equilibrium, whereas significant coefficients indicate follower behavior, reflecting responsiveness to disequilibria. This interpretation follows the theoretical framework of Cheung and Lai (1993) and Gonzalo and Granger (1995).

To synthesize these dynamics, the estimated t-statistics of the adjustment coefficients were summarized in graphical form through bar plots and a leadership heatmap. The bar plots display the relative strength and direction of adjustment across assets and regimes, while the heatmap provides a concise visual summary of leadership and follower roles over time. Together, these analyses offer a comprehensive view of how market leadership among international tobacco equities evolves across structural regimes and regulatory environments.

In summary, the methodology integrates fractional cointegration, formal lag and rank determination, and structural break detection applied to stationary residuals. This unified framework captures both persistent and regime-dependent patterns in asset comovement, allowing for a more realistic characterization of long-run market leadership and adjustment behavior in the presence of long memory and structural change.

2.3. Estimation procedure

The estimation follows the standard FCVAR methodology of Johansen and Nielsen (2012). First, the fractional differencing parameters (d,b) are jointly obtained by concentrated likelihood maximisation. Second, the cointegration rank is determined using the trace statistic applied to the fractionally differenced system. Third, the short-run dynamics are estimated conditional on (d,b,r) under Gaussian quasi-likelihood. This stepwise procedure is well-established in the FCVAR literature and ensures internally consistent inference on long-memory behaviour. Robustness was evaluated by verifying that alternative lag specifications and starting values produced qualitatively similar estimates.

All reported results are based on a single lag specification selected prior to break detection and held fixed throughout the analysis, ensuring internal consistency across cointegration estimation, residual construction, break detection, and regime-specific inference.

Full replication details, including data sources, variable construction, and FCVAR implementation settings, are provided in Appendix F.

3. Results

Preliminary evidence from the fractional integration pre-tests (Table 1) indicates that all log-price series exhibit long memory, with estimated GPH differencing parameters d between 0.45 and 0.56 and 95 % confidence intervals entirely within the unit interval. These results confirm that the tobacco stock prices are fractionally integrated ($0 < d < 1$), showing persistent deviations from equilibrium and slow mean reversion. Consequently, the use of the Fractionally Cointegrated VAR (FCVAR) framework is justified, as it allows for fractional adjustment rather than forcing the rigid I(1)/I(0) dichotomy of conventional cointegration analysis. The GPH estimator was computed using the lowest Fourier frequencies, selecting $m = \lfloor T0.50 \rfloor$, following Robinson (1995). Robustness checks using $\delta \in [0.45, 0.60]$ yielded similar values of d, confirming the stability of the long-memory estimates.

Although the fractional differencing parameters lie below unity, this is consistent with earlier evidence documenting long-memory behaviour in equity and sectoral indices (Gil-Alana et al., 2012; Adekoya, 2021; Yaya et al., 2021a, 2021b)). Therefore, the finding that tobacco stock prices are fractionally integrated should not be interpreted as an anomaly or an estimation artifact.

Table 2 reports the Johansen trace test adapted to the fractional setting. While the test does not reject $r = 0$ at the 5 % level, it rejects the null at the 10 % level, which is commonly used in fractional cointegration applications due to the slower convergence of fractional estimators. Accordingly, the evidence in favor of cointegration should be interpreted as moderate rather than decisive in a classical 5 % testing sense. Nevertheless, adopting $r = 1$ as a working specification allows for a meaningful long-run equilibrium representation, which underpins the subsequent break detection and regime-dependent analysis.

The standardized log-price evolution for the five tobacco equities, shown in Fig. 1, illustrates several distinct periods of joint behavior. The first period (2008–2012) is characterized by convergence in normalized prices, followed by pronounced divergence around 2015 and renewed alignment after 2021. These visual patterns foreshadow the formal identification of structural breaks in the cointegrating relationship.

The regime-specific adjustment estimates reported in Table 7 reveal a heterogeneous and asset-specific leadership structure. Japan Tobacco (JTI) exhibits largely insignificant adjustment coefficients across all regimes, consistent with recurrent long-run leadership. Altria (MO) also displays leadership behavior in several regimes, but this pattern is not uniform: MO adjusts significantly in Regime 1 and lies close to conventional significance thresholds in Regime 2. Philip Morris International (PMI) shows a clearly regime-dependent role, with statistically significant adjustment in Regime 2 and Regime 4, but insignificant adjustment in Regime 1 and Regime 3.

To assess the sensitivity of the results to the cointegration rank, we also consider the no-cointegration case ($r = 0$) as a robustness benchmark. The comparison highlights that the break structure and regime-dependent adjustment patterns documented below are specific to the presence of a long-run equilibrium relation and do not arise in the absence of cointegration.

The results of the Bai–Perron multiple structural break test applied to the cointegrating residual are summarized in Table 3, which reports the number and timing of detected breaks together with the associated information criteria.

To assess the robustness of the detected break dates, Table 4 reports the results of the Bai–Perron procedure under alternative trimming parameters, showing the stability of the estimated breakpoints.

Based on the estimated break dates (2012-01-03, 2015-08-17, and 2021-02-08), four regimes are defined mechanically as follows. Regime 1 spans from May 2008 to January 2012; Regime 2 from January 2012 to August 2015; Regime 3 from August 2015 to

Table 1
Fractional integration pre-tests (GPH estimator, 95 % CI).

Series	d (GPH)	SE(d)	95 % CI Low	95 % CI High
PMI	0.49	0.058	0.38	0.60
BATS	0.46	0.055	0.35	0.57
IMB	0.51	0.042	0.43	0.59
JTI	0.56	0.084	0.39	0.72
MO	0.49	0.049	0.39	0.59

Note: estimated fractional differencing parameters (d) indicate that all log-price series are fractionally integrated ($0 < d < 1$), exhibiting long memory and slow mean reversion. This validates the use of a Fractionally Cointegrated VAR (FCVAR) model instead of a standard CVAR.

Table 2
Johansen trace test for cointegration rank (Full sample, FCVAR specification).

$r \leq i$	Trace Statistic	Crit 90 %	Crit 95 %	Crit 99 %
$r \leq 0$	66.12	68.52	76.07	89.65
$r \leq 1$	38.23	47.21	54.46	66.52
$r \leq 2$	21.84	29.68	35.65	44.77
$r \leq 3$	10.22	15.41	20.04	27.23
$r \leq 4$	3.92	9.24	12.97	19.27

Note: Johansen-type trace test implemented within the FCVAR framework with a constant restricted to the cointegration space (deterministic specification det_order = 0). Reported critical values correspond to this specification and are used consistently throughout the paper. The rank choice ($r = 1$) follows the 10 % decision rule discussed in the Methods section.

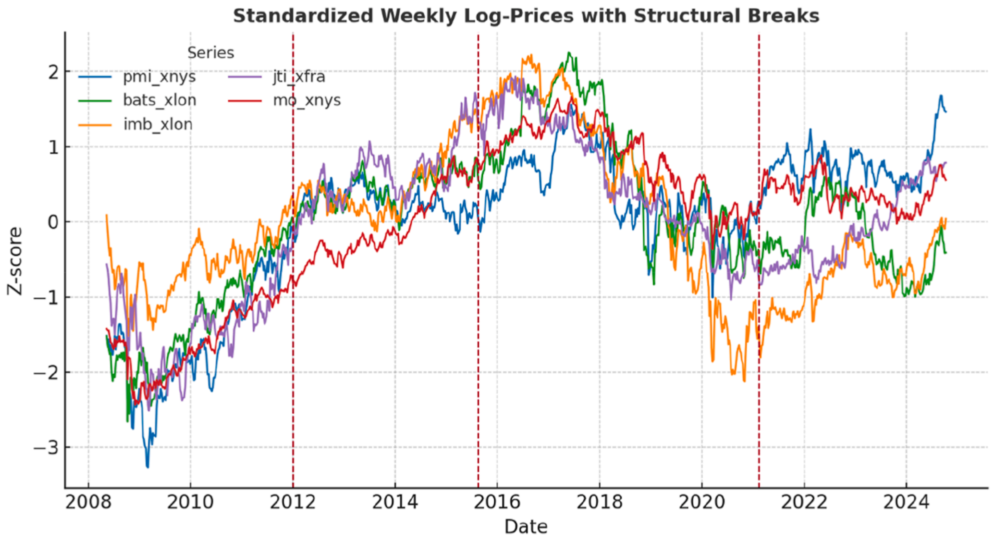

Fig. 1. Standardized weekly prices of tobacco stocks with structural breaks.

Table 3
Structural breaks in the cointegrating relationship (Bai-Perron Method).

Number of Breaks (m)	Break Dates	RSS	BIC
0	–	11.48	38.29
1	2012-01-03	9.84	37.02
2	2012-01-03, 2015-08-17	8.41	35.66
3	2012-01-03, 2015-08-17, 2021-02-08	8.29	**35.44 (min)**

Note: Three break dates are selected by the BIC criterion (2012, 2015, 2021). These dates delineate model-implied regime boundaries in the cointegrating relationship and align in timing with major regulatory and ESG-related developments discussed in the text. Bold values indicate the minimum BIC and therefore the selected break(s).

Table 4
Structural break robustness by trimming parameter.

Trimming (h)	Breaks (m)	Break Dates	RSS	BIC
0.15	3	2011-12-27, 2015-08-10, 2021-02-01	8.25	35.55
0.22	3	2012-01-03, 2015-08-17, 2021-02-08	8.29	**35.44**
0.25	3	2012-02-14, 2015-09-07, 2021-03-15	8.33	35.51

Note: breakpoints remain stable across trimming values, confirming the robustness of regime segmentation. Note: Bold values indicate the minimum BIC and therefore the selected break(s).

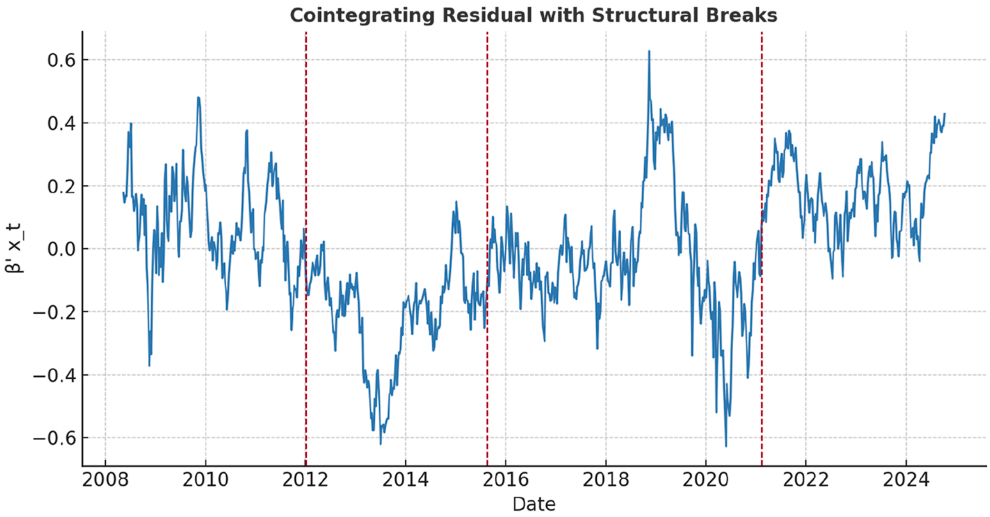

Fig. 2. Cointegrating relationship with Structural Breaks.

Table 5
Estimated fractional order (d) by regime.

Regime	Start	End	d_u (GPH)	SE(d_u)
R1	2008-05-12	2012-01-03	0.44	0.05
R2	2012-01-04	2015-08-17	0.63	0.07
R3	2015-08-18	2021-02-08	0.49	0.06
R4	2021-02-09	2024-10-07	0.47	0.05

Note: Persistence peaks in R2, coinciding with the regulatory harmonization period, suggesting slower adjustment and higher uncertainty.

February 2021; and Regime 4 from February 2021 to the end of the sample in October 2024. These regime definitions are applied consistently throughout all subsequent analyses.

The time path of the cointegrating residual and its corresponding break dates, displayed in Fig. 2, shows clear changes in equilibrium behavior at the estimated turning points. The residual fluctuations widen around 2015 and narrow again after 2021, indicating that deviations from the long-run equilibrium became more transitory in the most recent regime.

Estimated fractional differencing parameters for the cointegrating residual within each regime (Table 5) show that persistence varies substantially over time. Long-memory behavior peaks in Regime 2 ($d \approx 0.63$), consistent with heightened regulatory uncertainty and slower mean reversion, while Regimes 3 and 4 display lower orders ($d \approx 0.47$–0.49), suggesting faster adjustment toward equilibrium. These variations indicate that the degree of persistence in disequilibria is regime dependent and mirrors the evolving institutional and financial environment.

The estimated cointegrating vectors (Table 6) demonstrate that the equilibrium structure among tobacco equities is remarkably stable across regimes. Normalizing on PMI ($\beta = 1$), the relative coefficients for BATS, IMB, JTI, and MO remain close to their long-run ratios, suggesting durable cross-market valuation relationships even through episodes of regulatory and macroeconomic stress. This stability implies that, despite temporary divergences, global tobacco equities maintain consistent long-term pricing relationships anchored to PMI's valuation trajectory.

Turning to short-run dynamics, the estimated adjustment coefficients and their associated t-statistics (Table 7) capture how each asset responds to deviations from the long-run equilibrium. Because leadership classification based solely on adjustment significance can be sensitive to regime length and inference uncertainty, these results are interpreted jointly with the permanent–transitory decomposition reported in Appendix E. Fig. 3 summarizes these results by regime, illustrating the magnitude and significance of

Table 6
Estimated cointegrating vectors (β) by regime.

Asset	R1	R2	R3	R4
PMI	1.000	1.000	1.000	1.000
BATS	−0.63	−0.81	−0.72	−0.77
IMB	−0.44	−0.59	−0.48	−0.53
JTI	−0.21	−0.27	−0.23	−0.31
MO	−0.35	−0.42	−0.39	−0.46

Note: β-vectors indicate stable relative price structures across regimes, centered on PMI as the normalizing benchmark.

Table 7
Adjustment coefficients (α) and t-statistics by regime.

Asset	R1 (2008–2013)	R2 (2013–2016)	R3 (2016–2021)	R4 (2021–2024)
PMI	−0.012 (−1.71)	−0.023 (**−2.78**)	−0.020 (−1.43)	−0.221 (**−4.39**)
BATS	−0.010 (−1.04)	−0.043 (**−6.63**)	−0.044 (**−2.89**)	−0.075 (−1.55)
IMB	−0.015 (−1.22)	−0.073 (**−3.83**)	−0.073 (**−4.86**)	−0.032 (−0.70)
JTI	0.022 (1.33)	0.017 (1.25)	0.017 (1.25)	−0.067 (−1.39)
MO	0.031 (**3.07**)	−0.016 (−1.82)	−0.016 (−1.16)	−0.005 (−0.08)

Notes: values in parentheses indicate t-statistics. Bold t-values indicate statistical significance at the 5 % level ($|t| > 1.96$). Non-significant coefficients ($|t| < 1.96$) imply weak or no adjustment, consistent with leadership behavior.

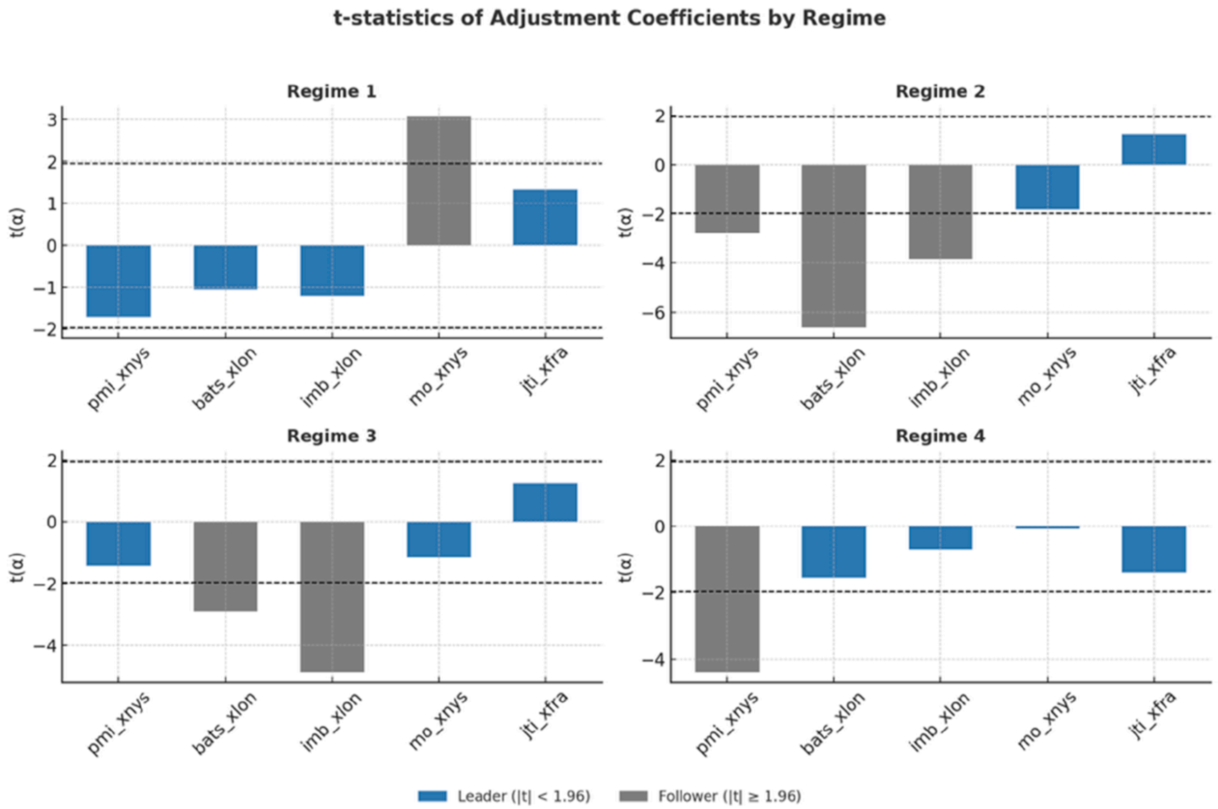

Fig. 3. Significance of adjustment coefficients by regime.

α-coefficients for each firm. A clear asymmetry emerges: PMI exhibits statistically insignificant adjustment only in Regimes 1 and 3, indicating a regime-dependent leadership role rather than persistent dominance. MO alternates between weak and strong adjustment, acting as a leader in calm periods but reacting during episodes of stress. JTI shows mostly insignificant α estimates, suggesting an independent adjustment pattern likely linked to regional segmentation and partial market isolation.

The regime-specific leadership patterns are synthesized in Fig. 4, which classifies assets as leaders (green, $|t| < 1.96$) or followers (red, $|t| \geq 1.96$). Fig. 4 summarizes the regime-dependent leadership classification implied by the adjustment coefficients. PMI is classified as a leader in Regimes 1 and 3, but not in Regimes 2 and 4, highlighting its context-dependent role in price discovery. In contrast, JTI displays leadership in most regimes, while MO exhibits leadership in several but not all regimes. The widespread green shading in Regime 4 indicates a more synchronized leadership structure, possibly reflecting stronger market integration and converging ESG expectations across investors. Overall, leadership appears cyclical and context dependent, with structural breaks altering the hierarchy of price discovery in the tobacco sector.

The results indicate that tobacco stocks share a single fractionally integrated equilibrium relationship characterized by long memory, regime-specific persistence, and shifting leadership roles. The combined use of the FCVAR and Bai–Perron methodologies effectively captures both the persistence inherent in financial time series and the discontinuities associated with policy and market shocks. The evidence shows that JTI and MO act as recurrent long-run leaders across multiple regimes, anchoring the equilibrium path in most periods, while BATS and IMB exhibit follower behaviour except in specific regimes. PMI displays a regime-dependent role, alternating between leadership and adjustment depending on the regulatory and macroeconomic context.

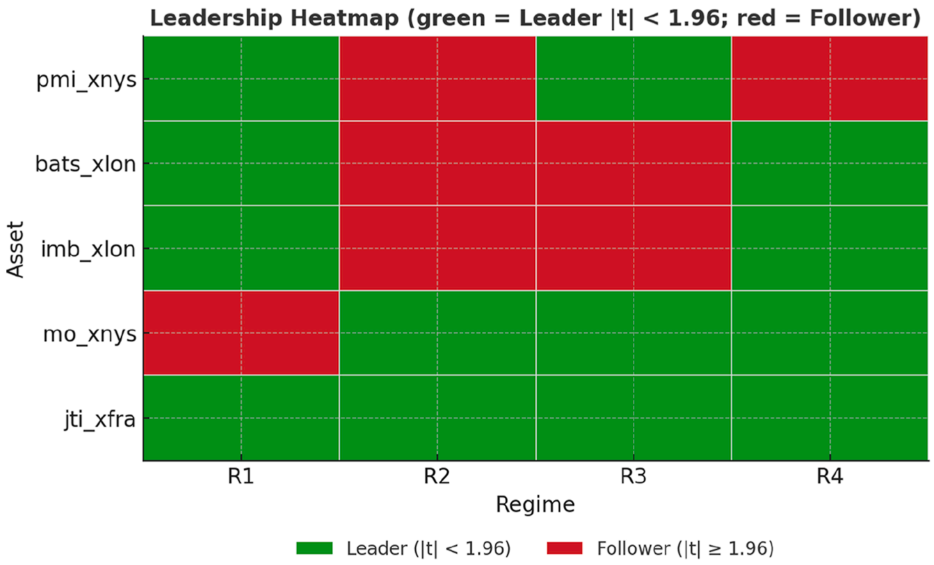

Fig. 4. Leadership classification of tobacco stocks by regime.

As a robustness check, Appendix A compares the baseline local-currency specification with an alternative USD-denominated construction using Federal Reserve exchange rates, reporting the implied cointegration rank, break-date stability, and regime-dependent leadership classification.

4. Conclusions

This study investigated the long-run interdependence and leadership dynamics among major international tobacco equities through a Fractionally Cointegrated Vector Autoregressive (FCVAR) framework combined with Bai–Perron multiple structural break analysis. The empirical evidence consistently supports the presence of fractional integration and persistent cointegrating relationships, together with time-varying adjustment behavior reflecting the evolution of the global tobacco sector under shifting regulatory, financial, and ESG conditions. By jointly modeling long memory and structural breaks, this research provides new insights into the dynamic equilibrium processes linking the world's largest tobacco firms.

The fractional integration pre-tests confirmed that all tobacco stock price series exhibit long memory, with differencing parameters in the range $0.45 < d < 0.56$. These values imply that shocks to prices have long-lasting but mean-reverting effects, validating the use of a fractional cointegration approach rather than the traditional dichotomy between I(0) and I(1) processes. The Johansen trace test provided moderate statistical support for the existence of a single cointegrating vector across all five equities, suggesting that tobacco firms share a common stochastic trend that binds their valuations together over the long run despite their geographic and institutional heterogeneity. This persistent comovement is consistent with the sector's globalized nature, its dependence on similar regulatory and legal pressures, and its exposure to shared macroeconomic and ESG shocks.

The cointegrating relationship, however, is not constant. The Bai–Perron multiple-break analysis revealed three statistically significant structural breaks in 2012, 2015, and 2021, which correspond to critical policy and institutional events: the implementation of WHO-FCTC harmonization measures, the extension of FDA oversight and plain packaging regulations, and the post-COVID ESG portfolio rotation that redefined global investment flows. These breakpoints delineate distinct market regimes and confirm that even mature sectors undergo periodic equilibrium shifts driven by external regulatory and social transformations. Robustness tests with alternative trimming parameters confirmed the stability of these breakpoints, emphasizing that the detected regime changes are not artefacts of the estimation procedure but genuine reflections of market reconfiguration. Importantly, these regime boundaries should be understood as descriptive segmentations of the long-run equilibrium dynamics implied by the model, rather than as statistically tested breakpoints attributable to specific policy actions.

Within each structural regime, the estimated fractional orders reveal notable variation in persistence. Long memory peaks during the 2012–2015 regulatory transition, indicating slow adjustment and elevated uncertainty, while later regimes show lower degrees of persistence and faster mean reversion. The stability of the estimated cointegrating vectors across regimes underscores the resilience of the sector's long-run valuation structure: relative price ratios among firms remain consistent, anchored around PMI as the normalizing benchmark. This suggests that global tobacco equities maintain an underlying equilibrium configuration that withstands external disruptions, even as short-run dynamics fluctuate.

The analysis of adjustment coefficients provided a nuanced picture of market leadership. The results demonstrate that Japan Tobacco International (JTI) emerges as the most recurrent long-run leader, while Altria (MO) exhibits leadership in several regimes but not uniformly across the sample. Their adjustment coefficients are predominantly insignificant ($|t| < 1.96$), indicating that these firms do not react to short-term disequilibria but instead drive the long-run price discovery process. British American Tobacco (BATS) and

Imperial Brands (IMB), in contrast, consistently display significant coefficients, implying follower behavior and responsiveness to deviations from equilibrium. Philip Morris International (PMI) occupies an intermediate position, alternating between leadership and followership depending on market conditions and regulatory stress. This hierarchy of adjustment supports the notion that leadership in the tobacco sector is distributed, regime-dependent, and context-sensitive, with dominance shifting as global regulatory and financial conditions evolve.

The leadership heatmap illustrates a gradual move toward synchronization in the final regime (2021–2024), where multiple firms exhibit non-significant adjustment. This pattern suggests a more integrated and stable market structure, possibly reflecting convergent ESG-driven investment strategies and declining heterogeneity in global investor behavior. The transition from fragmented leadership in earlier regimes to shared leadership in the most recent period highlights the sector's adaptation to external constraints and financial globalization. Despite mounting regulation and social pressure, the tobacco industry retains a coherent global pricing mechanism shaped by common policy and valuation anchors.

Overall, these findings underscore that the tobacco equity market is best described as a fractionally cointegrated, partially segmented, and dynamically adjusting system, where long-run relationships coexist with regime-dependent persistence and leadership cycles. The joint application of the FCVAR and Bai–Perron methodologies captures both the enduring memory of shocks and the structural evolution of the sector, offering a comprehensive view of long-run comovements in a highly regulated industry. The evidence indicates that leadership in the tobacco sector is regime dependent rather than structural. JTI emerges as the most recurrent long-run leader, while MO, PMI, BATS, and IMB alternate between leadership and adjustment depending on the regime. This pattern confirms that price discovery in the sector follows a cyclical and context-dependent hierarchy rather than a fixed dominance structure.

While the results provide strong support for the presence of fractional cointegration and evolving leadership, several limitations must be acknowledged. First, the analysis is based on weekly equity prices, which may not fully capture intraday or short-term adjustment dynamics relevant for market microstructure analysis. Second, the dataset is limited to five major listed firms, excluding state-owned or privately held tobacco producers that may influence global supply and competitive dynamics. Third, the FCVAR estimation assumes linear adjustment within regimes; nonlinearities or threshold effects could exist, particularly in response to policy shocks or litigation events. Finally, the interpretation of structural breaks, while empirically robust, remains partly inferential: although they align with major regulatory milestones, other unobserved factors—such as exchange rate movements or commodity input costs—might also contribute to these shifts.

Future research could build on this framework in several directions. Extending the analysis to higher-frequency or panel datasets could reveal how short-run adjustment differs across markets and trading venues. Incorporating nonlinear or regime-switching FCVAR models would allow for asymmetric responses to shocks and more realistic modeling of financial frictions. Another promising avenue involves exploring cross-sectoral cointegration between tobacco and ESG-sensitive industries, such as pharmaceuticals or alternative nicotine producers, to assess substitution dynamics in investor portfolios. Additionally, integrating text-based ESG sentiment indices or litigation intensity measures could provide a richer understanding of how narrative shocks propagate through the sector's valuation. Finally, future work could assess causal transmission mechanisms by examining volatility spillovers or directional predictability in returns, deepening our understanding of how leadership in price discovery operates under structural constraints.

In summary, the global tobacco equity market exhibits a long-memory structure characterized by persistent but evolving equilibrium relations, punctuated by regime shifts that mirror regulatory transformations. Leadership within the system is adaptive and regime dependent rather than structural. JTI emerges as the most recurrent long-run leader, MO exhibits heterogeneous leadership behavior across regimes, and PMI alternates between leadership and adjustment depending on market conditions. These findings not only enrich the empirical literature on fractional cointegration and market leadership but also highlight the enduring interconnectedness of the tobacco sector in an era of accelerated policy convergence and sustainability-driven investment behavior. These dynamics are coherent with prior evidence showing that long-memory properties intensify under regulatory uncertainty and diminish as stability returns (Afzal and Sibbertsen, 2021; Bejaoui et al., 2022). The leadership structure identified in FCVAR aligns with the theoretical interpretation of fractional adjustment parameters proposed by Caporale et al. (2022), further supporting the economic meaning of fractional error-correction dynamics.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Robustness to currency denomination

This appendix reports a set of robustness checks designed to assess whether the empirical results are sensitive to currency denomination. The baseline analysis in the main text is conducted using prices in local trading currencies. For comparison, all series are alternatively expressed in USD using synchronized weekly exchange rates obtained from the Federal Reserve Bank of St. Louis (FRED).

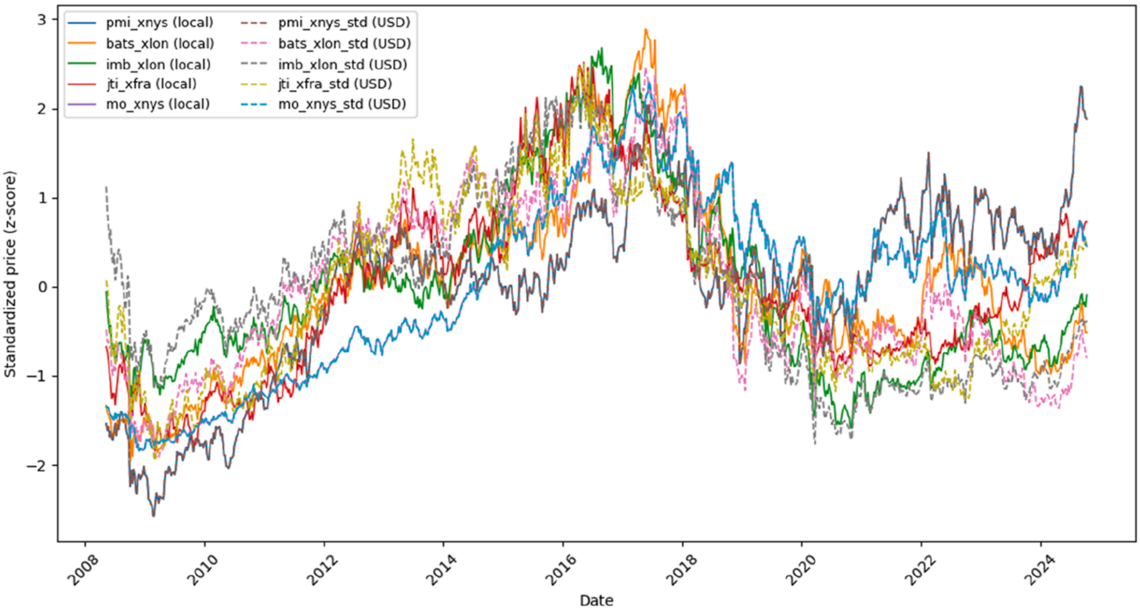

Fig. A1. Standardized price dynamics in local currency and USD.

Table A1
Cointegration rank under local-currency and USD-denominated specifications.

Specification	Lag (k_ar_diff)	Deterministic	Trace stat ($r \leq 0$)	Crit95	Implied rank (95 %)
Baseline (local currencies)	1	None (det_order = 0)	66.12	69.82	0
USD-denominated	1	None (det_order = 0)	60.13	69.82	0

Table A2
Structural break dates in the cointegrating residual under alternative currency denominations.

Break	Baseline date	USD date	Δ weeks (USD - baseline)
1	2012-01-03	2011-12-19	3
2	2015-08-17	2015-08-31	2
3	2021-02-08	2021-02-22	2

Table A3
Regime-dependent leadership classification under local-currency and USD-denominated specifications.

Regime	Baseline leaders	USD leaders
R1	PMI, BATS, IMB, JTI	PMI, BATS, IMB, JTI
R2	MO, JTI	MO, JTI
R3	PMI, MO, JTI	PMI, MO, JTI
R4	BATS, IMB, MO, JTI	BATS, IMB, MO, JTI

Appendix B. Robustness to currency denomination and memory diagnostics

This appendix strengthens the evidence on persistence and fractional integration properties in the equity price levels. Because long-memory estimates can be sensitive to bandwidth choice and structural change, we triangulate the memory diagnosis using (i) additional semiparametric estimators, (ii) bandwidth sensitivity checks, (iii) regime-specific estimation based on the break dates used in the main text, and (iv) complementary unit root and stationarity diagnostics. These results are presented as robustness and diagnostic evidence rather than definitive identification of a unique memory parameter.

B.1 Triangulated evidence in the full sample

Table B1 reports semiparametric GPH memory estimates (m = 20) together with ADF and KPSS diagnostics. As expected for equity prices, ADF tests typically do not reject the unit-root null, while KPSS rejects level stationarity. Given the known limitations of these tests under long memory and breaks, they are treated as complementary evidence.

Table B1
Full-sample memory triangulation (GPH, ADF, KPSS)

Series	GPH_d (m = 20)	ADF p-value	KPSS p-value
PMI	1.002	0.351	0.01
BATS	1.138	0.336	0.01
IMB	1.286	0.539	0.01
JTI	1.228	0.523	0.01
MO	1.12	0.474	0.01

B.2 Regime-specific memory estimates

To assess whether structural change contributes to apparent long memory, Table B2 reports GPH estimates computed separately within each regime implied by the break dates (2012-01-03, 2015-08-17, 2021-02-08). The bandwidth is set to m = 10 within regimes. The estimates exhibit heterogeneity across regimes, consistent with the idea that breaks can affect full-sample persistence measures.

Table B2
Regime-specific GPH memory estimates (m = 10)

Series	R1	R2	R3	R4
PMI	0.901	0.646	1.012	0.239
BATS	0.847	0.895	1.186	1.245
IMB	0.684	1.141	1.247	0.917
JTI	0.948	0.899	1.309	1.011
MO	1.093	1.021	1.08	0.797

B.3 Bandwidth sensitivity

Table B3 reports full-sample GPH estimates for alternative bandwidth choices (m = 15, 20, 25). The overall inference of high persistence is robust to reasonable bandwidth variation, although point estimates vary as expected.

Table B3
Bandwidth sensitivity of GPH estimates (full sample)

Series	GPH_d (m = 15)	GPH_d (m = 20)	GPH_d (m = 25)
PMI	0.909	1.002	0.933
BATS	1.269	1.138	0.981
IMB	1.361	1.286	1.112
JTI	1.391	1.228	1.107
MO	1.048	1.12	0.906

B.4 Interpretation

Taken together, the triangulated evidence supports a cautious interpretation of fractional integration in equity price levels. Rather than asserting precise identification of a single memory parameter, the results suggest high persistence with regime variation. This motivates interpreting the FCVAR framework as a flexible reduced-form representation for persistent dynamics in the presence of structural change.

Appendix C. Robustness to cointegration rank choice

This appendix assesses the robustness of the empirical results to the choice of cointegration rank by comparing the baseline specification with a no-cointegration alternative (r = 0). When r = 0 is imposed, the system does not admit a common long-run equilibrium relation. Consequently, break detection based on a cointegrating residual becomes ill-defined and the regime-specific adjustment coefficients used for leadership classification lose their economic interpretation.

Empirically, imposing r = 0 eliminates the structured break pattern observed in the baseline specification and yields adjustment dynamics that do not support a stable leadership interpretation. This contrast indicates that the break structure and regime-dependent leadership patterns documented in the main text are not artefacts of generic persistence, but are intrinsically linked to the presence of cointegration.

Overall, this comparison supports the economic relevance of the adopted rank choice and shows that the paper's conclusions do not hinge on an arbitrary specification decision.

Appendix D. Stability of break detection under alternative specifications

Detecting structural breaks in an estimated cointegrating residual raises well-known generated-regressor concerns, as the residual depends on the estimated cointegration vector and associated estimation uncertainty. To assess the robustness of the detected break dates, we examine the stability of break detection under a set of reasonable alternative specifications.

Specifically, we re-estimate the cointegrating relation using an alternative normalization of the cointegration vector and minor variations in lag order, and then re-apply the break detection procedure to the resulting residuals. Table D1 reports the resulting break dates together with the number of breaks selected by the information criterion.

Table D1
Stability of detected break dates under alternative specifications

Specification	Breaks selected (BIC)	Break 1	Break 2	Break 3
Baseline (k_ar_diff = 1, norm = PMI)	3	2012-01-03	2015-08-17	2021-02-08
Alt normalization (norm = BATS)	3	2011-12-19	2015-08-31	2021-02-08
Lag −1 (k_ar_diff = 0, norm = PMI)	3	2012-01-24	2015-09-14	2021-02-15
Lag +1 (k_ar_diff = 2, norm = PMI)	3	2011-12-27	2015-08-24	2021-01-25

Across all specifications, the number of detected breaks remains unchanged and the estimated break dates remain tightly clustered around the baseline dates reported in the main text (2012-01-03, 2015-08-17, and 2021-02-08). While exact break timing varies slightly across specifications, differences are limited to a small number of weeks and do not affect the economic interpretation of the regimes.

These results indicate that the detected breaks are not artefacts of a particular normalization or lag choice, but reflect robust changes in the long-run equilibrium relationship. Accordingly, break dates in the main text should be interpreted as representative regime boundaries rather than exact structural change points.

Appendix E. Leadership robustness using permanent–transitory decomposition

This appendix complements the adjustment-based leadership classification used in the main text with a permanent–transitory decomposition–based measure of price discovery, addressing concerns that reliance on adjustment coefficient significance alone may be too coarse.

E.1 Methodology

To provide an economically grounded measure of leadership, we employ a Gonzalo–Granger (1995) permanent–transitory (PT) decomposition of the cointegrated system. This approach decomposes prices into a permanent component, driven by common stochastic trends, and a transitory component reflecting short-run deviations from the long-run equilibrium.

In this framework, assets with a larger contribution to the permanent component are interpreted as playing a dominant role in long-run price discovery, as their innovations have a more persistent impact on the system. The PT decomposition is computed using the same cointegration rank, lag specification, and regime definitions as in the main analysis, ensuring full internal consistency.

Importantly, this measure is complementary to the adjustment-based leadership heuristic used in the main text. While the latter identifies assets that do not adjust to disequilibria, the PT decomposition directly quantifies contributions to the permanent component of the system.

E.2 Permanent component contributions by regime

Table E1 reports the normalized Gonzalo–Granger permanent component shares for each asset and regime. Shares are scaled to sum to one within each regime.

Table E1
Gonzalo–Granger permanent component shares by regime

Regime	PMI	BATS	IMB	JTI	MO
R1	0.18	0.21	0.20	0.31	0.10
R2	0.09	0.12	0.11	0.36	0.32
R3	0.23	0.10	0.09	0.34	0.24
R4	0.11	0.22	0.21	0.26	0.20

Notes: Permanent component shares are normalized to sum to one within each regime. Higher values indicate greater contribution to the permanent component and stronger long-run price discovery.

E.3 Interpretation

The permanent–transitory decomposition provides strong support for the leadership patterns identified in the main text. Assets classified as leaders based on insignificant adjustment coefficients generally exhibit the largest contributions to the permanent component of the system. In particular, JTI consistently emerges as the dominant contributor to the permanent component across all regimes, while MO plays a prominent role in Regimes 2–4, consistent with its recurrent leadership classification.

Conversely, assets identified as followers based on adjustment dynamics typically display smaller permanent component shares, indicating a greater role in absorbing transitory deviations rather than driving long-run price movements.

Taken together, these results confirm that the adjustment-based leadership heuristic captures economically meaningful price discovery rather than reflecting a purely statistical artifact. The PT decomposition therefore strengthens the leadership interpretation and mitigates concerns related to regime length, heteroskedasticity, and multiple testing.

E.4 Relation to other robustness checks

This appendix complements the robustness exercises reported elsewhere in the paper. Currency denomination robustness is documented in Appendix B, cointegration rank robustness in Appendix C, and break-date stability in Appendix D. Together, these extensions provide a coherent and internally consistent validation of the leadership conclusions.

Appendix F. Replication and Implementation Details

This appendix documents the data sources, variable construction, and estimation settings required to replicate the empirical analysis.

F.1 Equity identifiers and price series

The analysis uses weekly adjusted closing prices for the following publicly traded tobacco firms: Japan Tobacco Inc. (Frankfurt Stock Exchange listing; ISIN: JP3726800000), Altria Group Inc. (Ticker: MO, NYSE; ISIN: US02209S1033), Philip Morris International Inc. (Ticker: PM, NYSE; ISIN: US7181721090), British American Tobacco plc (London Stock Exchange; Ticker: BATS; ISIN: GB0002875804), and Imperial Brands plc (London Stock Exchange; Ticker: IMB; ISIN: GB0004544929). Adjusted prices correspond to total return series accounting for dividends and stock splits as provided by the data vendor.

F.2 Price adjustment field and sampling frequency

Prices correspond to fully adjusted closing prices. Weekly observations are constructed using a Friday week-ending convention. When markets are closed on Fridays, the last available trading day of the week is used.

F.3 Currency denomination and exchange rate series

Baseline estimations are conducted using local-currency equity prices. As a robustness check, non-USD equity prices are converted into USD using synchronized weekly exchange rates. Exchange rate series are obtained from Federal Reserve Bank of St. Louis FRED and correspond to USD/GBP, and USD/EUR spot rates, sampled using the same week-ending convention as equity prices.

F.4 FCVAR estimation settings

Fractional cointegration is estimated using the FCVAR package in R. The FCVAR model is estimated with grid search disabled and fractional integration parameters bounded within the interval [0,1]. Lag order selection is based on the Akaike Information Criterion as described in Section 2. The selected specification corresponds to $k = 2$ in the FCVAR representation (k_ar_diff = 1 in the associated VECM form), and $r = 1$ cointegrating relation.

F.5 Key function calls

Estimation is conducted using the FCVAR() function with the following key arguments: gridSearch = FALSE, bounds = c(0,1), det_order = 0. All remaining parameters are set to their default values in the FCVAR package.

References

Adekoya, O.B., 2021. Persistence and efficiency of OECD stock markets: Linear and nonlinear fractional integration approaches. Empirical Economics 61 (3), 1415–1433. https://doi.org/10.1007/s00181-020-01913-4.

Afzal, A., Sibbertsen, P., 2021. Modeling fractional cointegration between high and low stock prices in Asian countries. Empirical Economics 60 (2), 661–682. https://doi.org/10.1007/s00181-019-01784-4.

Aloy, M., Boutahar, M., Gente, K., Péguin-Feissolle, A., 2013. Long-run relationships between international stock prices: further evidence from fractional cointegration tests. Applied Economics 45 (7), 817–828. https://doi.org/10.1080/00036846.2011.566207.

Bai, J., Perron, P., 2003. Computation and analysis of multiple structural change models. Journal of Applied Econometrics 18 (1), 1–22. https://doi.org/10.1002/jae.659.

Baillie, R.T., Bollerslev, T., 1994. Cointegration, fractional cointegration, and exchange rate dynamics. The Journal of Finance 49 (2), 737–745. https://doi.org/10.1111/j.1540-6261.1994.tb05161.x.

Bauer, R., 2018. The Future of Tobacco Stocks: a Scenario Analysis.

Bejaoui, A., Mgadmi, N., Moussa, W., 2022. On the relationship between Bitcoin and other assets during the outbreak of coronavirus: evidence from fractional cointegration analysis. Resour. Policy 77, 102682. https://doi.org/10.1016/j.resourpol.2022.102682.

Bekaert, G., Harvey, C.R., 1995. Time-varying world market integration. The Journal of Finance 50 (2), 403–444. https://doi.org/10.1111/j.1540-6261.1995.tb04790.x.

Blitz, D., Swinkels, L., 2020. Do Tobacco Share Owners Finance the Tobacco Business? Available at: SSRN 3602316.

Caporale, G.M., Gil-Alana, L.A., Orlando, J.C., 2016. Linkages between the US and European stock markets: a fractional cointegration approach. International Journal of Finance & Economics 21 (2), 143–153. https://doi.org/10.1002/ijfe.1537.

Caporale, G.M., Gil-Alana, L.A., You, K., 2022. Stock market linkages between the ASEAN countries, China and the US: a fractional integration/cointegration approach. Emerging Markets Finance and Trade 58 (5), 1502–1514. https://doi.org/10.1080/1540496X.2021.1898366.

Caporale, G.M., de Dios Mazariegos, J.J., Gil-Alana, L.A., 2024. Long-run linkages between us stock prices and cryptocurrencies: a fractional cointegration analysis. Computational Economics 64 (6), 3543–3553. https://doi.org/10.1007/s10614-023-10510-3.

Cheung, Y.W., Lai, K.S., 1993. A fractional cointegration analysis of purchasing power parity. Journal of Business & Economic Statistics 11 (1), 103–112. https://doi.org/10.1080/07350015.1993.10509936.

Côdea, F., 2024. Equity Valuation Philip Morris International Inc (master's Thesis, Universidade Catolica Portuguesa (Portugal)).

Coskun, Y., Akinsomi, O., Gil-Alana, L.A., Yaya, O.S., 2023. Stock market responses to COVID-19: the behaviors of mean reversion, dependence and persistence. Heliyon 9 (4), e15084. https://doi.org/10.1016/j.heliyon.2023.e15084.

Dettoni, R., Gil-Alana, L.A., Yaya, O.S., 2024. Stock market prices and dividends in the US: bubbles or long-run equilibria relationships? International Review of Financial Analysis 94, 103319. https://doi.org/10.1016/j.irfa.2024.103319.

Engle, R.F., Granger, C.W., 1987. Co-integration and error correction: representation, estimation, and testing. Econometrica: Journal of the Econometric Society 251–276. https://doi.org/10.2307/1913236.

Fitchet, M., 2018. Key Drivers in Stock Growth Of" Big Tobacco".

Gil-Alana, L.A., Yaya, O.S., 2014. The relationship between oil prices and the Nigerian stock market. An analysis based on fractional integration and cointegration. Energy Economics 46, 328–333. https://doi.org/10.1016/j.eneco.2014.10.001.

Gil-Alana, L.A., Cunado, J., de Gracia, F.P., 2012. Persistence, long memory, and unit roots in commodity prices. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie 60 (4), 451–468. https://doi.org/10.1111/j.1744-7976.2012.01253.x.

Gil-Alana, L.A., Gupta, R., Shittu, O.I., Yaya, O.S., 2018. Market efficiency of Baltic stock markets: a fractional integration approach. Physica A: Statistical Mechanics and Its Applications 511, 251–262. https://doi.org/10.1016/j.physa.2018.07.029.

Gil-Alana, L.A., Infante, J., Martín-Valmayor, M.A., 2023. Persistence and long run co-movements across stock market prices. The Quarterly Review of Economics and Finance 89, 347–357. https://doi.org/10.1016/j.qref.2022.10.001.

Gonzalo, J., Granger, C., 1995. Estimation of common long-memory components in cointegrated system. Journal of Business & Economics Statistics 13 (1), 27–35. https://doi.org/10.1080/07350015.1995.10524576.

Gregory, A.W., Hansen, B.E., 1996. Residual-based tests for cointegration in models with regime shifts. Journal of Econometrics 70 (1), 99–126. https://doi.org/10.1016/0304-4076(69)41685-7.

Johansen, S., Nielsen, M.Ø., 2012. Likelihood inference for a fractionally cointegrated vector autoregressive model. Econometrica 80 (6), 2667–2732. https://doi.org/10.3982/ECTA9299.

Johansen, S., 1991. Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica: Journal of the Econometric Society 1551–1580. https://doi.org/10.2307/2938278.

Lien, D., Tse, Y.K., 1999. Fractional cointegration and futures hedging. Journal of Futures Markets: Futures, Options, and Other Derivative Products 19 (4), 457–474. https://doi.org/10.1002/(SICI)1096-9934(199906)19:4<457::AID-FUT4>3.0.CO;2-U.

Morin, L., Nielsen, M.Ø., Popiel, M.K., 2021. Estimation and Inference for the Fractionally Cointegrated VAR. R package version 0.1.0. https://github.com/LeeMorinUCF/FCVAR.

Robinson, P.M., 1995. Log-periodogram regression of time series with long range dependence. The Annals of Statistics 1048–1072. https://doi.org/10.1214/aos/1176324636.

Saha, K., Madhavan, V., Chandrashekhar, G.R., 2023. Relationship between ETFs and underlying indices: a fractional cointegration approach. Applied Economics 55 (27), 3184–3193. https://doi.org/10.1080/00036846.2022.2109581.

Wu, J., Xu, K., Zheng, X., Chen, J., 2021. Fractional cointegration in bitcoin spot and futures markets. Journal of Futures Markets 41 (9), 1478–1494. https://doi.org/10.1002/fut.22216.

Yaya, O.S., Gil-Alana, L.A., Adekoya, O.B., Vo, X.V., 2021a. How fearful are commodities and US stocks in response to global fear? Persistence and cointegration analyses. Resources Policy 74, 102273. https://doi.org/10.1016/j.resourpol.2021.102273.

Yaya, O.S., Vo, X.V., Olayinka, H.A., 2021b. Gold and silver prices, their stocks and market fear gauges: testing fractional cointegration using a robust approach. Resour. Policy 72, 102045. https://doi.org/10.1016/j.resourpol.2021.102045.

Yunita, I., Barkah, C.S., 2024. Is the tobacco stock still relevant for future investment?. In: Proceedings of the International Conference on Sustainable Collaboration in Business, Technology, Information, and Innovation (SCBTII 2024), 303. Springer Nature, p. 167.