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External Trade Competitiveness Index (ETCI): a sectoral and granular perspective on the Peruvian export basket

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Abstract

Building on the Competitor-Based Real Exchange Rate (CBRER) proposed by Gonzaga and Rojas (2026), this paper develops an External Trade Competitiveness Index (ETCI) that provides a more accurate measure of Peruvian export competitiveness. Unlike the Multilateral Real Exchange Rate (TCRM) –a traditional REER measure— published by the Central Reserve Bank of Peru, the ETCI is constructed from product- and destination-level export unit values and explicitly accounts for competition in third markets. The framework is further improved through a systematic treatment of unit value bias. A two-stage identification procedure first detects structural product heterogeneity using fixed-effects models and then assesses whether changes in tariff-subheading composition generate economically meaningful distortions in aggregate unit values. Affected products are subsequently corrected using two strategies recommended by the International Monetary Fund: increasing product granularity and trimming extreme observations.

The corrected ETCI indicates a cumulative gain in export competitiveness of 3.7% between 2000 and 2024, in sharp contrast with the 6.7% cumulative loss implied by the conventional REER. Compared with previous versions, the proposed refinements moderate the measured competitiveness gains while preserving their overall economic interpretation. Finally, validation and robustness exercises show that the ETCI captures both the structural and cyclical dimensions of export competitiveness and remains robust under alternative weighting schemes.

Keywords: export competitiveness; third-market competition; unit values; real exchange rate; competitor-based indices.

JEL: F14, F31, C43, C23.

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1 Introduction

The measurement of external competitiveness plays a central role in understanding export performance and assessing the resilience of open economies to external shocks. This issue has become particularly relevant for Peru, where recent improvements in the external position have been driven primarily by exceptionally favorable terms of trade. In the first quarter of 2026, the country had accumulated 25 consecutive quarters of trade surplus, reaching an annualized level equivalent to 11.5% of GDP, the highest since trade statistics are reported. However, despite the strength of this commodity price boom, export volume growth has remained relatively weak, limiting the extent to which favorable external prices have translated into larger external accounts surpluses. This contrast highlights that fully benefiting from positive external shocks requires more than favorable international prices; it also depends on the ability of domestic producers to expand market shares by improving productivity, reducing costs, and competing more effectively in international markets. Consequently, developing rigorous measures of export competitiveness is essential for understanding both the transmission of external shocks and the long-run sustainability of Peru's external position.

Although the Real Effective Exchange Rate (REER) remains the standard benchmark for measuring international competitiveness, its traditional formulation has well-known limitations that may distort the competitive pressures actually faced by exporters. In particular, conventional REER measures rely on trade-partner rather than competitor weights, ignore competition in third markets, and typically use aggregate price indices that may poorly represent export prices. These shortcomings have motivated an extensive literature aimed at refining REER-based measures through alternative weighting schemes, more appropriate price indicators, and greater product disaggregation (McGuirk 1986; Zanello and Desruelle 1997; Bayoumi, Lee, and Jayanthi 2006). Among these contributions, Stein et al. (2018) represents the most comprehensive methodological advance by explicitly incorporating third-market competition and export-basket similarity into a competition-adjusted REER using highly disaggregated product–destination trade data. For the Peruvian case, De la Cuba and Ferreyra (2011) construct a competitor-based real exchange rate for non-traditional exports, documenting substantial heterogeneity across sectors and products. More recently, Aguilar, Mendoza, and Quineche (2026) proposed an updated REER for Peru that incorporates third-market competition and time-varying trade weights within the conventional REER framework, providing complementary evidence on the importance of accounting for evolving competitive structures in measuring external competitiveness.

Building on these insights and on previous methodological contributions developed at the country level (De la Cuba and Ferreyra 2011; Bank of Spain 2017; Colombo and León Murillo 2018; Center for Production Studies (CEP), Ministry of Productive Development of Argentina 2021), Gonzaga and Rojas (2026) proposed a new export competitiveness index for Peru named the *Competitor-Based Real Exchange Rate* (CBRER). The CBRER was based on three methodological pillars: (i) the use of implicit export prices (or unit values) instead of consumer price indices, (ii) time-varying competitor baskets and completely variable aggregation weights, and (iii) competitor baskets defined at the product–destination level. Although the CBRER represented an important methodological advance over the conventional REER, several challenges remained. These include the reliance on international raw trade data subject to reporting errors, heterogeneous measurement units for quantities and values, and inconsistencies in bilateral trade flows; the potential unit value bias arising from within-product heterogeneity; and the absence of a comprehensive validation and robustness assessment.

Accordingly, this paper extends the original framework in three directions, giving rise to a revised measure, hereafter referred to as the *External Trade Competitiveness Index* (ETCI). The ETCI is designed to measure the international competitiveness of Peruvian exports relative to foreign competitors in third markets, that is, the ability of Peruvian exporters to place their products at more competitive prices in international markets, while excluding domestic producers by construction.

These improvements are introduced in three stages. First, we replace the original trade database with BACI, developed by Gaulier and Zignago (2010). This change is not merely a substitution of data sources. BACI reconciles mirror trade flows and applies statistical corrections that improve the consistency of unit values—with respect to the UN Comtrade records—which is especially important for an index based on implicit export prices. In practice, adopting BACI required rebuilding the full product–destination–competitor structure of the index, but it provides a cleaner and more internally consistent database in which remaining extreme unit values are more likely to reflect genuine product heterogeneity rather than reporting errors. Additional information on the BACI database is provided in Section 2.

Second, we address one of the main sources of measurement error identified in the original methodology: product heterogeneity within broad HS 6-digit classifications. Unit values are widely used as proxies for trade prices because they can be derived from customs records at relatively low cost. However, their interpretation as price measures is valid only when the underlying product category is sufficiently homogeneous. When an aggregate heading contains varieties with different price levels or quality characteristics, changes in the internal product mix may alter the observed unit value even if the prices of the underlying varieties remain unchanged. This is the source of unit value bias: the measured unit value combines genuine price movements with compositional changes across heterogeneous items (Silver 2007; International Monetary Fund 2009). To mitigate this source of bias, we introduce a two-stage heterogeneity identification procedure designed to identify products affected by heterogeneity.

Once these products are identified, we apply targeted intervention strategies consistent with the recommendations of International Monetary Fund (2009). The Manual emphasizes that unit value indices can be improved by increasing stratification whenever more detailed product information is available and by applying data-deletion routines to detect and treat abnormal observations. In this paper, these principles are translated into two correction strategies: increasing product granularity and applying trimming procedures when extreme unit values are likely to reflect distortions associated with the unit value bias. These procedures reduce the influence of compositional effects on implicit prices and, consequently, improve the measurement of export competitiveness.

Third, we complement the original framework with a comprehensive validation and robustness assessment. While Gonzaga and Rojas (2026) focused on the construction of the competitiveness indicator, this paper evaluates whether the refined index provides a reliable measure of export competitiveness by confronting it with economic evidence, historical episodes, and alternative methodological specifications.

The remainder of the paper is organized as follows. Section 2 presents the construction of the ETCI, including the adoption of the BACI database, the aggregation methodology, the heterogeneity identification procedure, and the correction strategies applied to the affected products. Section 3 reports the empirical results of these procedures and compares the heterogeneity-corrected ETCI with its uncorrected counterpart at both the product and aggregate levels, together with the validation of the index. Section 4 discusses the strengths and limitations of the proposed methodology. Finally, Section 5 concludes and outlines avenues for future research.

2 Methodology

The construction of the ETCI follows a rigorous framework designed to capture the granular dynamics of Peruvian exports. This section details the data sources, the mathematical architecture of the index, and the procedures for ensuring its empirical validity.

2.1 Data Sources and the BACI Database

The primary dataset employed in this study to compute unit values —the foundational input for the ETCI— is the BACI database, developed by the Centre d'Études Prospectives et d'Informations Internationales (CEPII). BACI provides a comprehensive reconciliation of international trade data reported by approximately 150 countries to the United Nations Statistics Division via the COMTRADE database. By utilizing the *mirror flow* principle, BACI resolves the common discrepancies observed in bilateral trade reporting, where the exports reported by a country often differ from the corresponding imports reported by its partner (Gaulier and Zignago 2010).

The superiority of the BACI database stems from its rigorous methodology for reconciling these bilateral flows. As detailed by Gaulier and Zignago (2010), BACI addresses inconsistencies by applying a weighting system that considers the reliability of each country's reporting, alongside the systematic estimation of cost, insurance, and freight (CIF/FOB) ratios. This reconciliation process is crucial for generating consistent time series, as it accounts for the potential accuracy variance in reporting across different jurisdictions and product categories. Furthermore, BACI facilitates the standardization of trade flows into a unified weight unit, minimizing errors arising from heterogenous reporting practices.

While BACI serves as the primary source for global trade dynamics, this study incorporates granular administrative data for the heterogeneity analysis. This internal database, sourced from the Peruvian customs authority (SUNAT) and facilitated by the BCRP's Balance of Payments Statistics Department, provides the disaggregated detail required to investigate structural tariff subheadings. Additionally, for product groups where heterogeneity indicates significant structural change, we incorporate the United States International Trade Commission (USITC) database [1]. These supplementary datasets represent essential refinements to the previous version of the ETCI, specifically designed to mitigate compositional bias and quality-induced distortions that do not reflect genuine price shifts. These methodological enhancements are discussed in detail in the subsequent sections of this chapter.

2.2 The Proposed External Trade Competitiveness Index (ETCI)

The calculation of the competitiveness indicator departs from the traditional approach based on aggregate price indices by incorporating an *implicit export price* for each product. This price is computed as the ratio between the FOB export value and the exported quantity:

$$p_j^{ik} = \frac{\text{FOB Value (USD)}}{\text{Net Weight (kg)}}, \qquad j \in \mathcal{J}_{ik},\ k \in \mathcal{K}_i.$$

Where $\mathcal{J}_{ik}$ denotes the set of competitor countries exporting product i to destination market k, and $\mathcal{K}_i$ denotes the set of destination markets considered for product i. Both sets are product-specific and therefore vary across products. Likewise, let $\mathcal{I}_s$ denote the set of products belonging to sector s, and $\mathcal{S}$ the set of sectors considered in the analysis.

[1] https://dataweb.usitc.gov/trade/search/GenImp/SITC

The bilateral competitiveness indicator between Peru and competitor j for product i in destination market k is then defined as

$$ETCI_j^{ik} = \frac{p_j^{ik}}{p_{\text{Peru}}^{ik}},$$

where both the numerator and denominator are expressed in U.S. dollars, thereby eliminating direct exchange-rate effects and isolating differences in relative export prices.

2.2.1 Aggregation Framework

The bilateral ETCIs are aggregated through four successive levels using weighted geometric averages.

Level 1: Product–market. For each product i and destination market k, the bilateral ETCIs are aggregated across all competitors supplying product i to that market:

$$ETCI^{ik} = \prod_{j \in \mathcal{J}_{ik}} \left(ETCI_j^{ik}\right)^{w_j^{ik}},$$

where w_j^{ik} denotes the share of competitor j in total exports of product i to destination market k.

Level 2: Product. The product-level ETCI is obtained by aggregating across the ten principal destination markets of each product:

$$ETCI^{i} = \prod_{k \in \mathcal{K}_{i}} \left(ETCI^{ik}\right)^{w_k^{i}},$$

where $\mathcal{K}_i$ contains the ten main destination markets for product i, and w_k^i denotes the share of destination market k in Peru's exports of product i.

Level 3: Sector. Sectoral ETCIs are constructed by aggregating the product-level indices within each sector:

$$ETCI^{s} = \prod_{i \in \mathcal{I}_{s}} \left(ETCI^{i}\right)^{w_i^{s}},$$

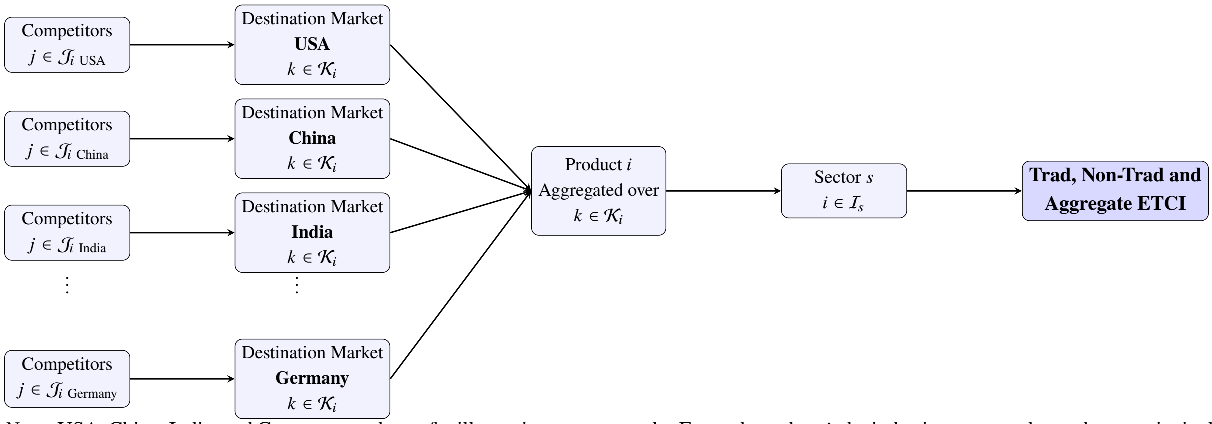
where w_i^s represents the export share of product i within sector s.

Level 4: Aggregate ETCI. Finally, the sectoral ETCIs are combined according to the share of each sector in its export segment (traditional or non-traditional) and then in total Peruavian exports:

$$ETCI = \prod_{s \in \mathcal{S}} \left(ETCI^{s}\right)^{w_s},$$

where w_s is the share of sector s in its respective segment. After aggregating Traditional and Non-traditional ETCIs, the result is a single ETCI for each year. The complete aggregation procedure is illustrated in Figure 1.

Figure 1: *ETCI aggregation scheme: competitors → destination markets → product → sector → aggregate ETCI.*



Note: USA, China, India, and Germany are shown for illustrative purposes only. For each product i, the index is aggregated over the ten principal destination markets, represented by the set $\mathcal{K}_i$. Likewise, $\mathcal{J}_{ik}$ denotes the set of competitor countries exporting product i to destination market k, which varies across products and destination markets.

2.2.2 Selection Strategy for ETCI Components

To calculate the ETCI for each product and destination market, it is necessary to define the sample of export products, the destination markets, and the corresponding basket of competitors for each market.

Determination of the product basket. Within each export group (traditional and non-traditional), the most relevant sectors –and its more representative products– in the average of the 2020-2024 period were selected, ensuring that the basket accurately reflects the current structure of Peruvian foreign trade. The choice is not merely descriptive but strategic: to capture the sectors that concentrate the bulk of international transactions and, therefore, effectively determine the dynamics of the country's external competitiveness.

The analysis considers a basket of 50 products spanning both traditional and non-traditional exports. Together, these products account for 93.9% of Peruvian exports in 2020-2024, which guarantees that the proposed index is built on the basis of export reality and not on a marginal set of products. In particular, the traditional product basket covers 95.1% of shipments from that group, while the non-traditional basket concentrates 79.1% of non-traditional exports over the last five years. This broad coverage not only ensures statistical representativeness but also provides robustness to the ETCI estimates.

TABLE 1: *Selected traditional and non-traditional product basket with HS Code Mapping*

Group (% of total)	Sector (% of total)	Products (HS code)
Traditional (72.3%)	Fishing (4.3%)	Fishmeal (2301.20), Fish oil (1504.20)
	Agricultural (2.3%)	Coffee (0901.11), Cotton (5201.00), Sugar (1701.99)
	Mining (85.3%)	Copper concentrates (2603.00), Refined copper (7403.11), Gold (7108.12), Lead (2607.00) Zinc concentrates (2608.00), Refined zinc (7901.11), Iron (2601.11)
	Hydrocarbons (8.1%)	Crude oil (2709.00), Oil derivatives (2710.00), Natural gas (2711.11), Propane gas (2711.12)
Non-Traditional (27.4%)	Agribusiness (50.4%)	Grapes (0806.10), Blueberries (0810.40), Avocados (0804.40), Mangoes (0804.50) Tangerines (0805.20), Bananas (0803.00), Fresh asparagus (0709.20), Onions (0703.10) Preserved asparagus (2005.60), Quinoa (1008.90), Cocoa beans (1801.00), Cocoa butter (1804.00) Dried peppers (0904.20), Ginger (0910.10)
9	Textiles (8.9%)	Cotton t-shirts (6109.10), Cotton shirts (6105.10), Cotton jerseys (6110.20) Other textile fiber T-shirts/vests (6109.90)
	Chemicals (11.6%)	Sulfuric acid (2807.00), Dyes (3203.00), Polypropylene films (3920.20) Lakes (3202.00), Zinc oxide and peroxide (2817.00)
	Steel and Metallurgy (9.0%)	Copper wire rod (7408.11), Unalloyed zinc (7901.12), Raw silver (7106.91) Refined copper plates and sheets (7409.19), Jewelry excl. silver (7113.19)
	Fishing (9.0%)	Preserved squid (1605.90), Frozen squid (0307.49), Frozen shrimps and prawns (0306.13) Fish livers and roes (0303.80), Frozen mackerel (0303.74), Other frozen fish (0303.79)

Note: The shares reported for the Traditional and Non-Traditional groups correspond to their average participation in Peru's total exports over the 2020–2024 period. Sectoral shares represent each sector's average contribution within its respective export group. Because these shares are computed as period averages and the basket does not include all export sectors, they do not necessarily sum to 100 percent.

DETERMINATION OF THE MAIN DESTINATION MARKETS. From the CEPII BACI database, information on Peruvian exports by product and by destination market is obtained. For each product i, the ten main destination markets for Peruvian exports are selected. These will constitute the reference upon which the external competitiveness of each product will be evaluated.

DETERMINATION OF THE COMPETITOR BASKET. For each destination market k, the competitor basket is defined by all countries j that record positive exports of product i to that specific market. This approach ensures that the definition of competition is fully endogenous to the product and destination. Furthermore, the relative weight of each competitor j is determined by its share in the total exports of product i to market k, denoted as w_j^{ik}, which serves as the fundamental weight for the initial stage of aggregation.

While the product basket remains fixed throughout the sample period—as detailed in Table 1—the baskets of destination markets and competitors are time-variant. Specifically, in each year, the analysis identifies the most relevant destination markets, and within each of these, it considers the effective competitors. Similarly, although the product basket is predefined, its constituent weights are dynamic, reflecting the evolving importance of each product within the country's annual export portfolio. By allowing market and competitor composition to fluctuate alongside yearly trade values, the index captures the structural shifts and geographic diversification of the country's trade, thereby providing a more faithful representation of its evolving competitive position in the global economy.

2.3 Formal Assessment of Product Heterogeneity Problem

The empirical strategy developed to address within-product heterogeneity is motivated by the unit value bias discussed in the Introduction. We begin by conducting a systematic review of the Peruvian National Tariff classification to identify export products whose HS 6-digit headings contain additional national subheadings and therefore require a more detailed assessment. The resulting Heterogeneity Assessment Guide, presented in Appendix A, defines the set of products eligible for the formal analysis. We then determine whether these products are effectively affected by heterogeneity through the proposed two-stage assessment framework. Finally, only those products diagnosed as heterogeneous are subject to the appropriate refinement strategy in the construction of the corrected ETCI.

2.3.1 Identification of the Heterogeneity Problem

The two-stage validation approach adopted in this study mirrors the formal decomposition of unit value bias. According to Silver (2007), the divergence between a unit value index and a true price index is mathematically driven by the interaction of a *relative price effect* and a *relative quantity effect*. The first stage of our methodology addresses the price effect by statistically verifying the existence of structural dispersion among subheadings. However, as established by Silver and Mahdavy (1989), such structural differences only distort the aggregate measure if the internal composition of the heading is unstable. Thus, the second stage serves as a diagnostic for the quantity effect, identifying the compositional shifts that trigger the bias (Silver 2007).

Stage 1: Identification of Structural Price Heterogeneity. The first stage consists of exploiting the panel data structure obtained from administrative reports to construct a statistical test for the existence of structural heterogeneity. The panel was constructed for each potentially heterogeneous product according to the Heterogeneity Assessment Guide (Appendix A). This preliminary screening reduced the scope of the formal evaluation from the full ETCI export basket to a subset of 22 products for which the existence of structural price heterogeneity was deemed plausible on technical grounds. For each product, the unit of observation was the subheading (k) into which the National Tariff divides it (totaling K subheadings), and the temporal unit was the year within the 2000–2024 period.

The model is specified as follows:

$$\ln(UV^i_{k,t}) = \alpha + \alpha^i_k + \epsilon^i_{k,t}$$

where:

- $UV^i_{k,t}$ denotes the unit value of the k-th national subheading, $k = \{1, 2, \ldots, K\}$, belonging to product i at time t ($t = \{2000, 2001, \ldots, 2024\}$).
- α is the intercept representing the average unit value (export price proxy) of the base category.
- α^i_k represents the product-specific structural effect. It captures persistent price differentials caused by quality, variety, or technical specifications inherent to subheading k.

- $\epsilon^i_{k,t}$ is the idiosyncratic error term.

This regression is replicated independently for each of the 22 products that entered into this formal analysis. We perform a formal F-test on the joint significance of the fixed effects α^i_k. Rejection of the null hypothesis ($H_0 : \alpha_1 = \alpha_2 = \cdots = \alpha_K$) confirms that the subheadings possess statistically distinct price levels, satisfying the primary condition for a heterogeneity problem.

To complement these results, we leverage the panel data structure to estimate error variance decomposition and mean differences between subcategories through an ANOVA analysis. The first approach decomposes the error variance into components attributable to structural price differentials (σ^2_u) and idiosyncratic shocks (σ^2_e) specific to each subheading. The ratio of the former to total variance is denoted by ρ; higher values of ρ provide stronger evidence of product heterogeneity. The second approach evaluates whether average unit values differ significantly across subheadings by comparing *between-group* and *within-group* variation. Specifically, the ANOVA statistic is constructed as the ratio of the mean square between groups (MS_B) to the mean square within groups (MS_W):

$$F = \frac{MS_B}{MS_W} = \frac{SS_B/(K-1)}{SS_W/(N-K)},$$

where K is the number of subheadings and N is the total number of observations.

Under the null hypothesis of equal mean unit values across subheadings, both quantities estimate the same underlying variance, implying an F-statistic close to unity. Consequently, failure to reject the null indicates that between-group variation is not sufficiently larger than within-group variation, supporting the treatment of the product as homogeneous. Conversely, a sufficiently large F-statistic provides evidence that systematic price differences across subheadings exceed idiosyncratic variation, supporting the presence of structural product heterogeneity.

Additionally, information is available for each subheading disaggregated by destination market. This subheading-destination market combination allows us to construct an extended panel with a larger number of observations than the reduced panel. This approach is particularly critical for products with limited temporal coverage, as the classification into detailed subheadings was not fully recorded prior to 2017.

In such cases, or when the aforementioned methods fail to yield conclusive evidence, we utilize the extended panel. The extended model is specified as follows:

$$\ln(UV^i_{k,m,t}) = \alpha + \alpha^i_{k,m} + \beta^i_t + \epsilon^i_{k,m,t}$$

where $UV^i_{k,m,t}$ denotes the unit value of the k-th subheading of product i exported to destination market m at time t, $\alpha^i_{k,m}$ captures the structural effect of the subheading-market combination and β^i_t captures product-specific time effects common to all subheadings and destination markets.

The hypothesis test is restricted to the joint significance of the fixed effects α^i_k within each market m, ensuring that subheading heterogeneity is not confounded by market-specific price differentials:

$$H^m_0 : \alpha^i_{k_1,m} = \alpha^i_{k_2,m} = \cdots = \alpha^i_{k_K,m}$$

By testing the significance of subheadings within the same market, we isolate the structural heterogeneity of the product from the potential distortion caused by destination-specific factors. Further empirical details regarding the implementation of this methodology are provided in the Results section.

Stage 2: Assessment of Compositional Instability. The existence of structural price differences (α_k^i) only compromises the aggregate index if the internal composition of subheadings shifts significantly over time. To detect this composition effect, we assess the structural stability of each product i by calculating a Structural Change Index (SCI) that measures the accumulated drift of subheading weights ($w_{k,t}^i$) relative to a fixed base year ($w_{k,base}^i$):

$$SCI_{i,t} = \frac{1}{2}\sum_{k\in K} |w_{k,t}^i - w_{k,base}^i|$$

where k represents each subheading into which the product i can be disaggregated.

This index ranges from 0 (perfect stability) to 1 (complete replacement of the product mix). To operationalize the threshold for high instability, we adopt a detailed diagnosis based on a double-threshold criterion:

1. **Relative Structural Change (Crit. 1 in Table 6):** This distribution-based criterion identifies products whose structural change is persistently large relative to the rest of the export basket. To this end, we construct the empirical distribution of all annual $SCI_{i,t}$ observations across products and years, where each observation corresponds to the SCI of product i in year t. Since the SCI is a normalized index, values are directly comparable across products. A product satisfies this criterion if its $SCI_{i,t}$ exceeds the 75th percentile of the full-sample distribution in at least three years, not necessarily consecutively. Persistent exceedance suggests that changes in product composition are sufficiently recurrent to invalidate the 6-digit unit value as a proxy for the underlying price trend.

2. **Absolute Severity (Crit. 2 in Table 6):** While the previous criterion captures structural change in relative terms, this criterion evaluates its absolute magnitude. For each product, we compute the three-year moving average of the SCI and classify the product as heterogeneous whenever this smoothed index exceeds the threshold of 0.15 at least once during the sample period. This threshold identifies sustained departures from the base-year product composition that are unlikely to be explained by transitory fluctuations.

Products meeting either condition are classified as exhibiting significant structural change, allowing us to conclude that the heterogeneity inherent in the product has evolved throughout the study period.

Decision of Intervention Framework. The final methodological step consists of determining whether a product requires intervention in the ETCI construction. Table 2 summarizes the decision rule. Products for which the panel-based diagnostics provide evidence of structural heterogeneity are subsequently evaluated using the SCI to assess whether such heterogeneity is sufficiently persistent and severe to justify intervention. Only under these conditions are granularity refinement, trimming, or deletion routines implemented. Otherwise, the aggregate 6-digit unit value is retained.

TABLE 2: *Decision Matrix for Product Intervention*

Panel-Based Heterogeneity Evidence	SCI Diagnostic	Product Treatment
Evidence of structural heterogeneity	Structural change (SCI meets crit. 1 or crit. 2)	Granularity refinement, trimming, or deletion routines
Evidence of structural heterogeneity	Stable	Maintain 6-digit unit value
No evidence of structural heterogeneity	Not applicable	Maintain 6-digit unit value

2.3.2 Treatment of Structural Heterogeneity in UV-based Indices

For products requiring intervention, we implement two alternative correction strategies following the recommendations of International Monetary Fund (2009). The choice between them depends on data availability and the underlying source of heterogeneity.

Strategy 1: Increased product granularity. The preferred correction consists of replacing the original HS 6-digit unit value with a more disaggregated measure whenever a sufficiently granular and internationally comparable source is available. This strategy directly addresses the source of the bias by separating varieties that are aggregated within the same product heading but exhibit different price levels or trajectories.

In practice, however, this approach is constrained by data availability. Although Peru reports highly disaggregated customs information, comparable data at the same level of detail are not systematically available for all competitors and destination markets. For this reason, we exploit the United States International Trade Commission (USITC) database, which reports United States (U.S.) import flows by trading partner at the 10-digit HS level, the highest level of detail. This allows us to construct more granular unit value indices for products where the U.S. represents the dominant destination market. Accordingly, this strategy is applied only when the U.S. market accounts for a sufficiently large share of Peruvian exports of the product, ensuring that the corrected series remains representative of the product's external competitiveness.

A related granularity-based opportunity arises when revisions to the Harmonized System introduce a finer product classification than the original aggregate heading. Such revisions typically reflect the increasing economic relevance and differentiation of products that were previously grouped within a single HS category. Accordingly, even in the absence of an alternative high-granularity database, a corrected version of the ETCI can exploit these revisions by adopting the more disaggregated classification from the corresponding revision onward. This approach allows the index to distinguish products with different price dynamics that would otherwise remain combined within a single aggregate heading while preserving long-run comparability.

Strategy 2: Trimming of extreme unit values. When no suitable granular alternative is available, we apply a statistical trimming procedure. This correction follows the recommendation of International Monetary Fund (2009), which emphasizes that unit values derived from customs records may display extreme movements due to compositional shifts, reporting errors, changes in quantity units, or abrupt variation in product quality within the same trade classification.

The use of trimming is particularly relevant in the present context because the BACI database already incorporates extensive cleaning procedures aimed at improving data quality, harmonizing quantity units, and reconciling reporting discrepancies across trading partners. As a result, extreme unit value movements that remain after this harmonization process are less likely to reflect simple measurement errors and more likely to be associated with changes in the underlying composition of heterogeneous products.

The trimming procedure excludes observations located below the 5th percentile or above the 95th percentile of the empirical unit-value distribution. These percentiles are computed separately for each product-destination market pair, pooling observations across years but not across destination countries. This design avoids treating systematic price differences across markets as outliers, while still mitigating the influence of extreme observations within each market-specific distribution.

2.4 Validation and Robustness of the ETCI

To assess whether the ETCI constitutes an economically meaningful measure of external competitiveness rather than a purely statistical construct, the index is subjected to a three-stage validation and robustness strategy. The objective is to determine whether the ETCI is capable of capturing real competitiveness dynamics, reproducing historically documented economic episodes, and remaining robust to alternative methodological assumptions.

2.4.1 Economic Validation: External-Sector Performance

The first validation stage evaluates whether movements in the ETCI are systematically associated with observable indicators of Peru's external performance. The underlying premise is that, if the ETCI captures meaningful competitiveness dynamics, improvements in the index should coincide with —or precede— stronger external outcomes.

Validation is conducted at both the macroeconomic and sectoral levels according to data availability. At the macroeconomic level, the aggregate ETCI is contrasted with the evolution of Peru's trade balance, current account balance, and an internal analytical measure of the volume component underlying variations in the current account balance. This latter indicator is constructed as part of an analytical decomposition routinely used to understand the factors driving expansions or contractions in Peru's current account position. Specifically, it isolates changes associated with net export performance by removing the contribution of terms-of-trade effects from the current account decomposition, thereby separating quantity-related dynamics from external price movements. As such, it provides a particularly suitable benchmark for validating a competitiveness indicator intended to capture real external competitiveness dynamics.

Given the strong long-run trends observed in Peru's external balances during the sample period, exports, trade balance, and current account are evaluated in first differences, whereas the volume effect of current account decomposition is analyzed in levels, consistent with its construction as a contribution to annual variations in the current account balance. Lagged relationships are additionally explored to assess whether competitiveness improvements precede external-sector performance.

At a more disaggregated level, the ETCI is contrasted with export-volume dynamics whenever sufficiently detailed information is available. For traditional activities, validation is implemented at the product level using annual exported quantities for key commodities with product-specific ETCI availability. The traditional-products panel includes fish meal, fish oil, coffee, cotton, sugar, copper, iron, gold, lead, zinc, crude oil, and natural gas. For non-traditional activities, validation is conducted at the sectoral level and includes the Agribusiness, Textile, Fishing, Chemical, and Steel and Metallurgy sectors.

Given the absence of sufficiently detailed and homogeneous physical-volume information for individual non-traditional products, the analysis relies on sectoral export volume indices rather than direct quantity measures.

In both panels, the dependent variable is defined as the first difference of the logarithm of the corresponding export-volume measure. For traditional products, export quantities are measured in thousands of tons, except for natural gas, which is expressed in thousands of cubic meters. For non-traditional sectors, the transformation is applied to the corresponding export quantity indices. This specification focuses the analysis on export-growth dynamics, improves comparability across products and sectors with markedly different scales, and mitigates the influence of long-run trends in export volumes. In practice, the transformed variable displays a relatively stable distribution centered around zero, making it well suited for panel estimation exploiting within-unit variation over time. Under this specification, sustained improvements in competitiveness (greater product or sectoral ETCI) are expected to be associated with stronger export-volume growth.

2.4.2 Historical Coherence Analysis

The second validation stage evaluates the historical coherence of the ETCI by cross-referencing its trajectory with documented economic events affecting Peru's external competitiveness.

To identify these episodes, an exhaustive review of macroeconomic and sectoral documents is conducted, including *Notes of Studies* produced by the Central Bank of Peru —particularly those associated with the *Quarterly Macroeconomic Report* and the *Balance of Payments Report*—, *Inflation Reports*, *Annual Reports*, and sectoral production reports published by the National Institute of Statistics and Informatics (INEI), especially the *Technical Production Reports*. Greater emphasis is placed on annual and medium-term assessments, since high-frequency monthly reports may temporarily magnify shocks or disruptions that ultimately dissipate when evaluated over broader time horizons.

Based on this documentary review, economically relevant episodes affecting Peru's export competitiveness are identified, including large-scale productive investments, sectoral supply expansions, climatic and biological shocks, and disruptions affecting export-oriented activities. Products are assigned to each event according to the economic channels through which competitiveness is expected to be affected. The expected response may be positive, negative, differentiated across products, or controversial.

The historical coherence assessment relies on two complementary metrics. The first evaluates the cumulative change in competitiveness within the evaluation window associated with each episode:

$$GW_{ie} = \frac{ETCI_{i,T}}{ETCI_{i,0}} - 1,$$

where GW_{ie} denotes the growth window for product i during episode e, and $ETCI_{i,0}$ and $ETCI_{i,T}$ represent the product i ETCI values at the beginning and end of the corresponding evaluation period, respectively.

The second metric compares the average annual competitiveness performance observed during the evaluation window with the product's historical performance outside that window. First, the annualized growth rate within the evaluation window is computed as:

$$g^{W}_{ie} = \left(\frac{ETCI_{i,T}}{ETCI_{i,0}}\right)^{\frac{1}{T}} - 1,$$

where T denotes the number of years in the evaluation window.

The relative performance metric is then defined as

$$RP_{ie} = g_{ie}^{W} - \bar{g}_{i}^{O},$$

where $\bar{g}_i^O$ represents the average annual growth rate of the ETCI for product i outside the evaluation window [2].

For episodes associated with an expected positive competitiveness effect, a product–event pair is classified as historically coherent whenever at least one of the two metrics indicates an improvement in competitiveness consistent with the historical narrative:

$$HC_{ie} = 1 \quad \text{if} \quad GW_{ie} > 0 \ \text{ or } \ RP_{ie} > 0.$$

Similarly, for episodes associated with an expected negative competitiveness effect, coherence is established whenever at least one of the two metrics indicates a deterioration in competitiveness:

$$HC_{ie} = 1 \quad \text{if} \quad GW_{ie} < 0 \ \text{ or } \ RP_{ie} < 0.$$

For differentiated episodes, the expected sign is defined separately for each product according to the economic channels through which the event is expected to affect competitiveness. Finally, controversial episodes are evaluated according to a different criterion. Rather than requiring a systematic competitiveness gain or loss, coherence is established when the observed responses are not uniformly positive according to both metrics, reflecting the absence of a clear *ex ante* prediction regarding the direction of the competitiveness effect.

2.4.3 Robustness Checks: Alternative Weighting Schemes

The robustness of the ETCI is evaluated by comparing the baseline index with three alternative aggregation schemes that differ in the way export weights and competitive structures are defined. The objective is to assess whether the main competitiveness patterns remain stable under alternative assumptions regarding the evolution of Peru's export composition and international competitors.

The first robustness exercise replaces contemporaneous weights with lagged weights for calculation and aggregation process. The alternative weighting scheme is implemented from the product–market ETCI, where competitor weights by market are computed using the export structure observed in period $t-1$, and is then propagated sequentially through the remaining levels of aggregation. Under this specification, competitor baskets continue to evolve over time. This approach mitigates potential simultaneity between export performance and contemporaneous trade shares by ensuring that the weighting system is predetermined with respect to the competitiveness measure being computed.

The second exercise smooths the export structure through backward-looking three-year moving averages. The alternative weighting scheme is introduced from the lowest level of the ETCI construction, where competitor weights are computed using the average export shares observed over the previous three years in specific markets as well. The resulting product–market ETCIs are then aggregated sequentially

[2] When the period outside the evaluation window is split into two segments, $\bar{g}_i^O$ is computed as the geometric mean of all annual ETCI growth rates observed in those segments. Otherwise, it is computed using the same formula than g_{ie}^W.

using the same moving-average principle at each subsequent stage of the index, including the aggregation across destination markets, products, sectors and, finally, the aggregate ETCI. As an illustration, the moving-average weights used to aggregate product-level ETCIs into sectoral indices are defined as:

$$\bar{w}_{i,t}^{MA-3,s} = \frac{1}{3}\left(w_{i,t}^{s} + w_{i,t-1}^{s} + w_{i,t-2}^{s}\right),$$

where $w_{i,t}^{s}$ denotes the share of product i in total exports of its corresponding sector s. An analogous procedure is applied to the remaining levels of aggregation. As in the first robustness check, competitor identities remain fully time-varying so that the ETCI continues to reflect changes in the effective competitive environment.

Finally, a fixed 2013–2017 weighting specification is implemented to evaluate the sensitivity of the ETCI to the definition of the competitive structure. For each product, a single fixed basket of competitors is constructed by first identifying competitors across its ten destination markets and then consolidating repeated competitors into a unique basket using their average export shares over 2013–2017. This procedure internalizes the destination-market dimension into the construction of the fixed competitor weights, allowing the market dimension to be omitted during the subsequent aggregation. The reference period is centered on 2013–2017 because it provides a representative baseline for Peru's export structure while avoiding the extremely small or negligible export shares observed for several products during the early years of the sample. Product, sectoral and aggregate weights are likewise fixed at their average values over 2013–2017, providing a benchmark in which neither competitor composition nor aggregation weights vary over time.

Importantly, all three robustness exercises are implemented using the methodology designed to correct the baseline ETCI. Accordingly, the heterogeneity adjustments introduced for the seven affected products are preserved throughout all alternative specifications. The robustness analysis therefore isolates the effect of alternative weighting and competition structures without altering the underlying product-level corrections.

3 Results

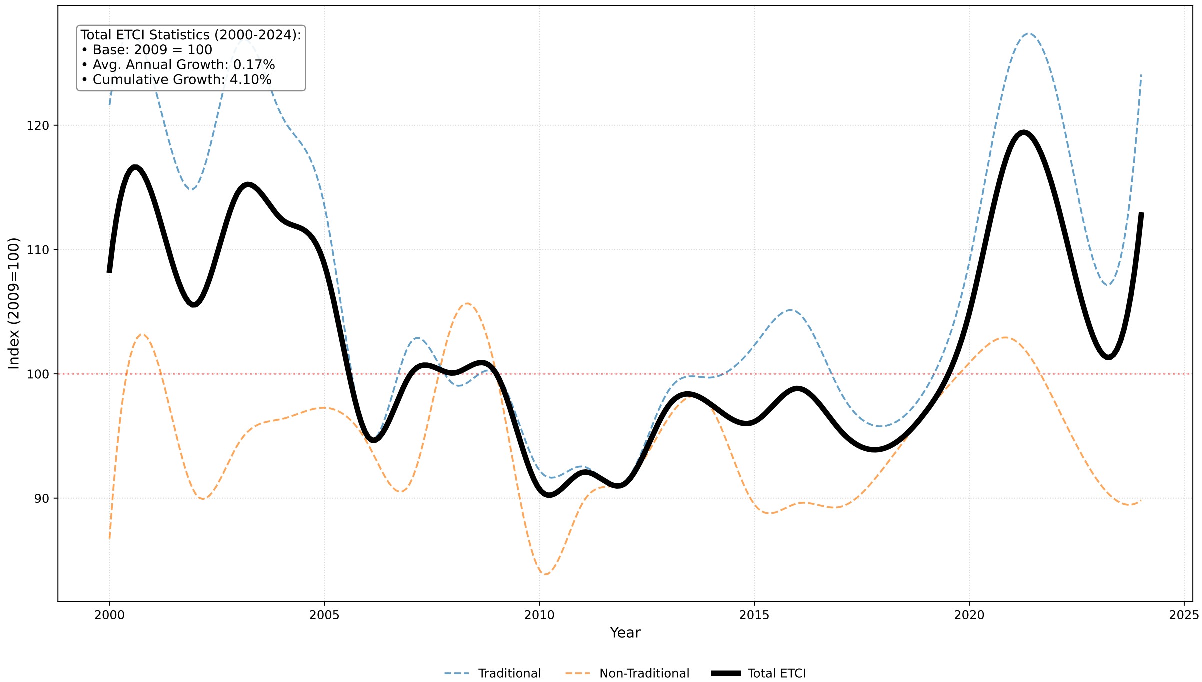
The results are presented in five stages. First, we describe the evolution of the baseline ETCI[3] at the aggregate, sectoral, and product levels. Second, we assess whether price heterogeneity across tariff subheadings constitutes a relevant measurement problem by identifying products exhibiting economically meaningful and statistically significant differences in unit values. Third, we implement alternative correction strategies for the products identified as heterogeneous and evaluate how these adjustments affect competitiveness dynamics across products, sectors, and aggregate export baskets. Fourth, we validate the corrected ETCI and assess the robustness of its main results by examining its relationship with external-sector performance, its consistency with major historical episodes, and its sensitivity to alternative weighting schemes. Finally, we benchmark the corrected ETCI against alternative competitiveness measures, including the previous CBRER, the official TCRM, and nominal exchange-rate movements.

[3] Throughout the paper, the term *baseline ETCI* refers to the initial BACI-based version of the index, prior to the product-level heterogeneity corrections introduced in this study.

3.1 Aggregate and Sectoral General Dynamics of the baseline ETCI

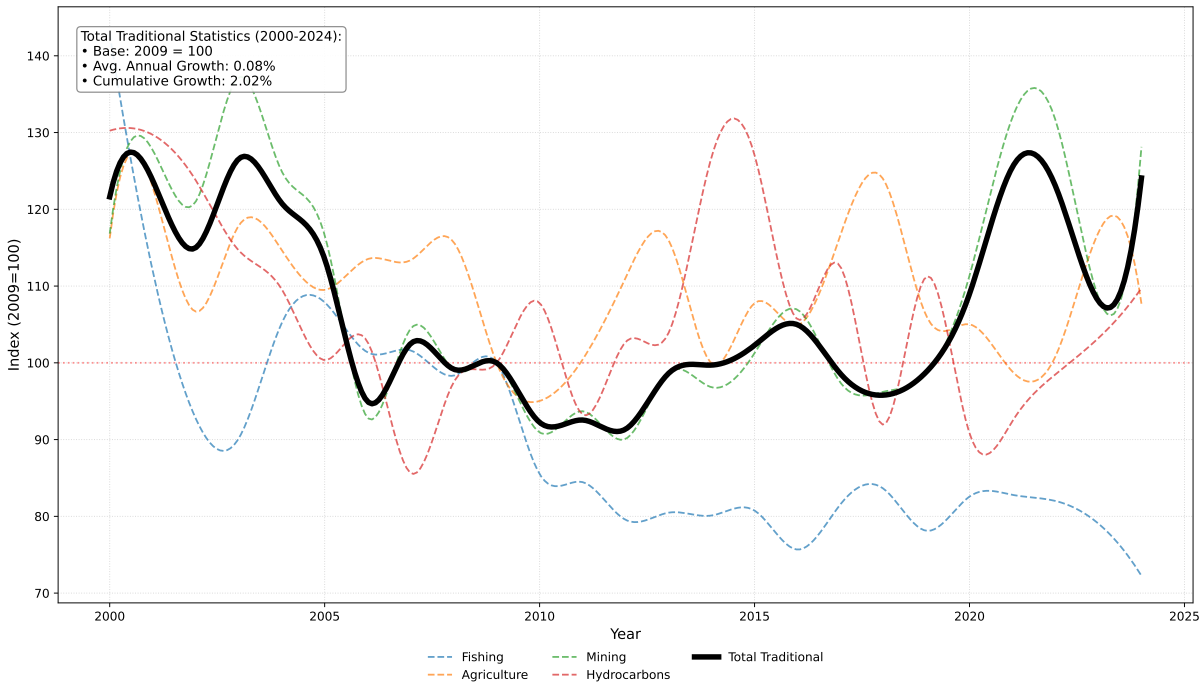
The baseline aggregate ETCI shows a cumulative expansion of 4.1% over the 2000–2024 period, equivalent to an average annual growth rate of 0.17%, driven by the favorable performance of both traditional and non-traditional exports. Despite this positive long-run trend, the index exhibits substantial fluctuations over time, including a prolonged deterioration between 2008 and 2013 and a temporary setback around 2021. A sectoral decomposition reveals that these aggregate dynamics are strongly influenced by the Mining sector, reflecting its dominant weight within Peru's export basket. At the same time, Hydrocarbons follow a partially distinct trajectory, contributing to periods of divergence within the traditional export sector. These findings highlight that aggregate competitiveness outcomes reflect both sector-specific developments and the interaction of sectors with different relative importance within the export basket.

Figure 2: *ETCI evolution: Traditional, Non-traditional and Aggregate index*



Throughout the study period, the ETCI for traditional exports exhibited a structural improvement, recording a cumulative increase of 2.0% and an average annual growth rate of 0.08%. This aggregate performance was primarily driven by the Mining sector, which accounted for 78.6% of traditional exports on average over 2000–2024, and achieved a notable competitiveness gain of 18.3%. As will be discussed later in this chapter, this improvement coincides with the period in which several large-scale copper and gold projects started operations, suggesting that the ETCI captures competitiveness dynamics consistent with major developments in Peru's mining sector.

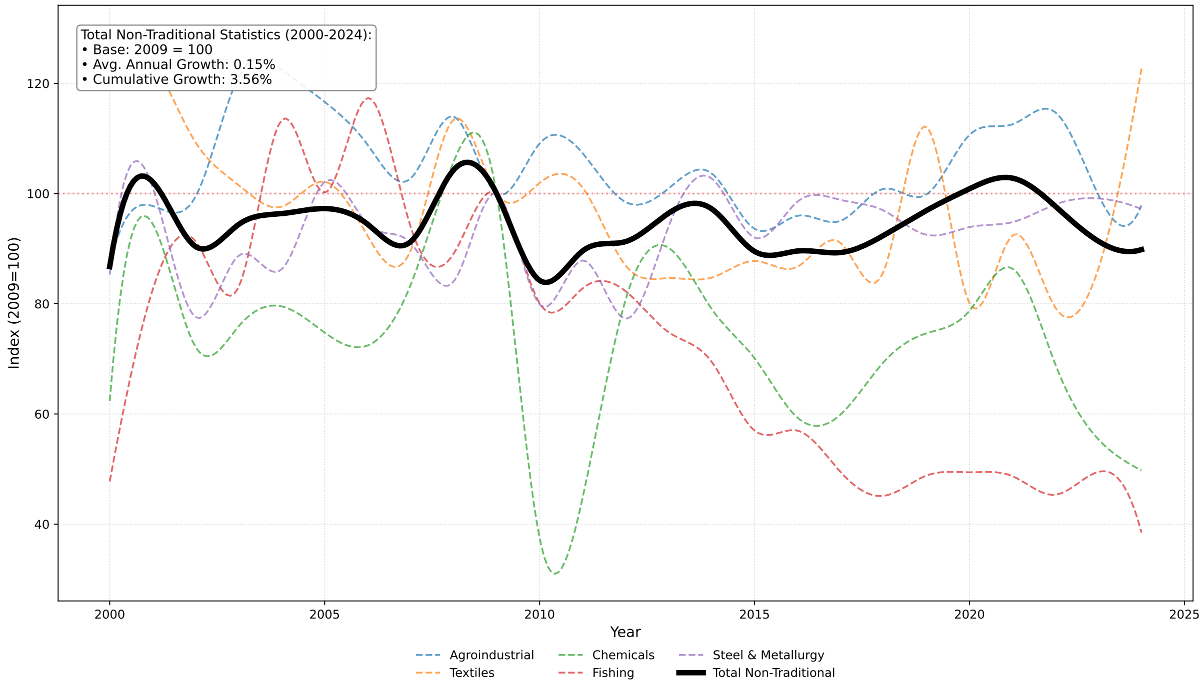
FIGURE 3: *Traditional ETCI: Aggregate index and sectoral index evolution*



In that same period, the non-traditional exports ETCI recorded an improvement in competitiveness, exhibiting a cumulative increase of 3.6% and an average annual growth rate of 0.15%. This positive aggregate performance was primarily driven by the strong perfomance of Agribusiness sector and the the resilience of Steel and Metallurgy segment, which registered competitiveness gains of 12.2% and 14.0%, respectively.

Within the Agribusiness sector, the observed increase in the ETCI coincides with the favorable evolution of high-value export products, such as onions, preserved asparagus, tangerines, avocados, and blueberries. As will be discussed later in this chapter, this pattern is broadly consistent with the timing of major irrigation projects and the progressive diversification of Peru's agricultural export basket. Furthermore, the Steel and Metallurgy sector maintained a trajectory of sustained competitiveness gains, particularly during periods of favorable commodity-market conditions. Although improvements were observed across most products within the sector, the strongest gains were concentrated in precious metal jewelry and copper derivatives. One possible explanation is that Peru's abundant mineral endowment allowed these downstream activities to benefit from relatively lower input costs during commodity booms, helping them preserve more competitive prices than their international counterparts.

FIGURE 4: *Non-traditional ETCI: Aggregate index and sectoral index evolution*



3.2 Assessment of Heterogeneity Bias in the ETCI Export Basket

To assess the presence of price heterogeneity across tariff subheadings, we constructed separate panel datasets for each product exhibiting additional tariff disaggregation and estimated product-specific fixed-effects models with subheading effects, from which we derived three indicators. The first is the *Share of Between-Subheading Variation* (ρ), which captures the relative importance of systematic differences across subheadings within the total variation of unit values. The second is a *Subheading Price Effects Test*, based on the joint significance of subheading-specific effects in a Dummy Variable Least Squares (DVLS) specification. The third is an *ANOVA Mean Equality Test*, which evaluates whether between-subheading variation is sufficiently large relative to within-subheading variation to reject the hypothesis of equal means.

The three indicators provide complementary evidence regarding the relevance of heterogeneity. Higher values of the ρ parameter indicate that a larger share of total variation is explained by differences across subheadings, suggesting greater economic relevance of heterogeneity. In the case of the DVLS specification, large p-values associated with the joint F-test imply that the null hypothesis of no subheading-specific price effects cannot be rejected, indicating the absence of systematic premiums or discounts relative to the reference category. Similarly, large p-values in the ANOVA framework imply that the null hypothesis of equal means across subheadings cannot be rejected, suggesting that between-subheading variation is not disproportionately large relative to within-subheading variation. Detailed results for each product, together with the corresponding heterogeneity diagnosis, are reported in Appendix B. Table 3 summarizes the main findings.

Table 3: *Panel Heterogeneity Diagnostics: Summary of main indicators*

Product	No. of Subheadings	Share of Between-Subheading Variation (ρ)	Subheading Price Effects Test (Prob > F)	ANOVA Mean Differences Test (Prob > F)	Diagnosis
Traditional Sectors					
Fishing					
Fishmeal	3	0.0523	0.275	0.316	Homogeneous
Fish Oil	2	0.1257	0.064	0.064	Homogeneous
Hydrocarbons					
Oil Derivatives	5	0.3306	0.000	0.000	Heterogeneous
Non-Traditional Sectors					
Agribusiness					
Mangoes†	2	0.3068	0.066	0.010	Extended Assessment
Bananas	3	0.0412	0.391	0.368	Homogeneous
Quinoa	2	0.0800	0.193	0.192	Homogeneous
Cocoa Beans	2	0.4452	0.020	0.020	Heterogeneous
Cocoa Butter	4	0.2161	0.000	0.000	Heterogeneous
Dried Peppers	3	0.1104	0.351	0.305	Homogeneous
Steel & Metallurgy					
Raw Silver	2	0.0333	0.3578	0.3578	Homogeneous
Textiles					
Cotton T-shirts	3	0.1489	0.028	0.016	Heterogeneous
Cotton Shirts	10	0.0770	0.000	0.032	Heterogeneous
Textile Fibers/Vests	2	0.0004	0.917	0.917	Homogeneous
Chemicals					
Dyes	10	0.3820	0.000	0.000	Heterogeneous
Polypropylene Films	2	0.0243	0.431	0.431	Homogeneous
Fishing					
Frozen Shrimps	7	0.2413	0.000	0.000	Heterogeneous

† A unique heterogeneity diagnosis could not be obtained from the reduced-panel analysis; therefore, this product is evaluated separately using the extended-panel approach.

The evidence presented in Table 3 reveals that structural price heterogeneity is far from being a generalized phenomenon across export products. In traditional sectors, products belonging to the same sector tend to exhibit similar pricing patterns. In the Fishing sector, both fishmeal and fish oil are classified as homogeneous, displaying low levels of between-subheading variation and failing to reject the null hypothesis of equal prices across tariff classifications. Although fish oil shows a stronger signal of heterogeneity than fishmeal, neither product satisfies the criteria required to diagnose structural price differences. In contrast, oil derivatives emerge as a clearly heterogeneous product, as the original HS-6 digit category aggregates products with substantially different physical and commercial characteristics, including light oils, medium oils, heavy oils, biodiesel mixtures, and waste oils, all of which may exhibit distinct pricing dynamics and competitiveness patterns.

The results for non-traditional exports are considerably more diverse. Within Agribusiness, only cocoa beans and cocoa butter exhibit robust evidence of heterogeneity, whereas bananas, quinoa, and dried Peppers behave as homogeneous commodities. The Textile sector also illustrates that heterogeneity is not a sector-wide characteristic but rather a product-specific feature. Cotton T-shirts and cotton shirts display systematic price differences across subheadings, while textile fibers/vests remain highly homogeneous. These price gaps appear to be associated with manufacturing characteristics such as dyeing techniques and fabric patterns, with striped garments consistently commanding price premia relative to simpler alternatives.

Finally, the remaining sectors reinforce the idea that heterogeneity arises when tariff classifications capture economically meaningful product distinctions. Raw silver does not exhibit systematic price differences associated with its tariff disaggregation, suggesting that aggregation at the HS 6-digit level is appropriate. By contrast, frozen shrimps and prawns are diagnosed as heterogeneous, with the evidence indicating that cooked products command systematically different prices than their raw counterparts. A similar pattern is observed in the Chemical sector, where dyes exhibit significant heterogeneity likely associated with differences in color formulations and product characteristics, whereas polypropylene films remain homogeneous.

While the baseline panel model successfully addresses most categories, certain products required an extension to a destination-level specification to ensure statistical reliability. This group includes cotton, coffee, zinc concentrates, tangerines, and ginger, which exhibit fewer than 10 annual observations per subheading, alongside sugar, which presents an extremely unbalanced structure between its subheadings (8 versus 23 observations). In these cases, the limited degrees of freedom from the baseline cross-subheading comparison expose the F-test to sample constraints and idiosyncratic market noise, increasing the risk of false positives or low statistical power.

A distinct justification applies to the case of Mangoes, which exhibits ambiguous and contradictory signals that preclude a definitive classification in the initial stage. While the ANOVA model rejects the null hypothesis of homogeneity at the 5% level ($p = 0.013$), the DVLS model fails to reach the same significance threshold ($p = 0.065$), yielding a result that is highly sensitive to the model specification. This statistical instability, coupled with a moderately unbalanced panel (11 versus 25 observations pf its subheadings), suggests that the aggregate signal is not robust enough to support a final verdict. Consequently, mangoes are moved to the destination-level diagnostic.

For those products, we formally identify structural heterogeneity by estimating a DVLS model with fixed effects for each subheading-market pair, while controlling for country-specific factors. This nested structure allows the model to isolate price dispersion within each specific destination. Specifically, for each market, a joint significance test (Wald test) is performed on the coefficients of the subheadings present. If the null hypothesis of price equality is rejected ($p < 0.05$), the market is classified as structurally heterogeneous, implying that the aggregate unit value for that destination is biased by the quality-mix.The table 4 shows the estimation results.

The extended panel analysis reveals that for cotton, coffee, and ginger, structural heterogeneity is the dominant feature of their international trade. In these cases, destination markets with significant price dispersion represent the largest share of the stable export volume, as shown in Table 4. Conversely, for sugar, zinc concentrates, mangoes, and tangerines, the aggregate unit value remains a reliable proxy, as the homogeneous segments of their markets command a higher relative weight. Consequently, only the first group will proceed to Stage 2 of the process to identify compositional biases.

Table 4: *Extended-Panel Heterogeneity Diagnostics: a destination-level analysis*

Product	**Market Group**	**N° Markets**	**Sum of Weights**	**Final Decision**
Cotton (5201.00)	Homogeneous	2	0.3026	Heterogeneous
	Heterogeneous	2	**0.4831**	
Coffee (0901.11)	Homogeneous	36	0.2790	Heterogeneous
	Heterogeneous	12	**0.5316**	
Ginger (0910.10)	Homogeneous	12	0.2738	Heterogeneous
	Heterogeneous	15	**0.3062**	
Sugar (1701.99)	Homogeneous	9	**0.8583**	Homogeneous
	Heterogeneous	3	0.3188	
Zinc concentrates	Homogeneous	8	**0.6896**	Homogeneous
	Heterogeneous	4	0.1523	
Mangoes (0804.50)	Homogeneous	34	**0.5879**	Homogeneous
	Heterogeneous	7	0.4116	
Tangerines (0805.20)	Homogeneous	11	**0.2523**	Homogeneous
	Heterogeneous	24	0.1199	

Note: The final decision is based on the dominance of the Sum of Weights. The Sum of Weights does not necessarily equal 1.00 due to the 5-year commercial stability filter and the arithmetic averaging of unbalanced panels.

Overall, the heterogeneity assessment reveals that structural price heterogeneity is a relatively concentrated phenomenon. Of the 22 products identified as potentially heterogeneous based on the existence of national tariff subheadings, only 10 exhibit sufficiently strong evidence to justify additional disaggregation beyond the HS 6-digit level. These products are summarized in Table 5.

Another important finding is that heterogeneity is predominantly a feature of non-traditional exports. While only three Traditional products are classified as heterogeneous, seven belong to Non-traditional sectors, particularly Agribusiness, Textiles, Chemicals, and Fishing. This pattern is consistent with the greater degree of product differentiation, processing intensity, and quality segmentation that characterizes non-traditional exports. Moreover, the products identified as heterogeneous tend to be those with a relatively large number of national tariff subheadings, suggesting that the Peruvian tariff schedule itself recognizes the economic relevance of these distinctions. Taken together, these results indicate that heterogeneity is not widespread across export products, but rather concentrated in a limited set of goods where aggregation may conceal economically meaningful differences in prices and product characteristics.

Table 5: *Summary of Products Identified as Structurally Heterogeneous*

Category	Sector	Product	HS Code	Subheadings
Traditional	Agricultural	Cotton	5201.00	4
	Agricultural	Coffee	0901.11	2
	Hydrocarbons	Oil derivatives	2710.00	5
Non-Traditional	Agribusiness	Cocoa beans	1801.00	2
	Agribusiness	Cocoa butter	1804.00	4
	Agribusiness	Ginger	0910.10	2
	Textiles	Cotton T-shirts	6109.10	3
	Textiles	Cotton shirts	6105.10	10
	Chemicals	Dyes	3203.00	9
	Fishing	Frozen shrimps and prawns	0306.13	7

Structural heterogeneity, however, is not sufficient by itself to generate a bias in unit value indices. As discussed in the methodology section, the bias emerges when the relative importance of heterogeneous subheadings changes over time, generating compositional shifts within a product category. Therefore, after identifying the products for which tariff subheadings capture economically meaningful price differences, the next step is to evaluate the extent to which their internal composition evolves over time. To do so, we compute the Structural Change Index (SCI) for the ten products identified as structurally heterogeneous in Table 5.

Figure 5 presents the kernel density estimate of the resulting SCI distribution. The density exhibits a clear bimodal pattern: a primary mass concentrated at low SCI values, corresponding to products with relatively stable internal compositions, and a secondary mode centered around $SCI \approx 0.35$, which identifies a group of products experiencing substantial compositional drift over time. This evidence suggests that, even among heterogeneous products, the magnitude of structural change varies considerably across goods.

To determine whether this variability compromises the representativeness of an individual product within the aggregate index, we implement an instability diagnostic based on a dual-threshold technical criterion, as described in the Methodology section. A product is classified as unstable if it meets at least one of the following conditions: (i) Relative Structural Change (Crit. 1), defined as the number of years in which a product's SCI exceeds the global 75th percentile, with a threshold of at least three years; or (ii) Absolute Severity (Crit. 2), identified when the 3-year moving average of a product's SCI exceeds a critical threshold of 0.15 at any point during the study period.

FIGURE 5: *Estimated kernel distribution of the SCI*

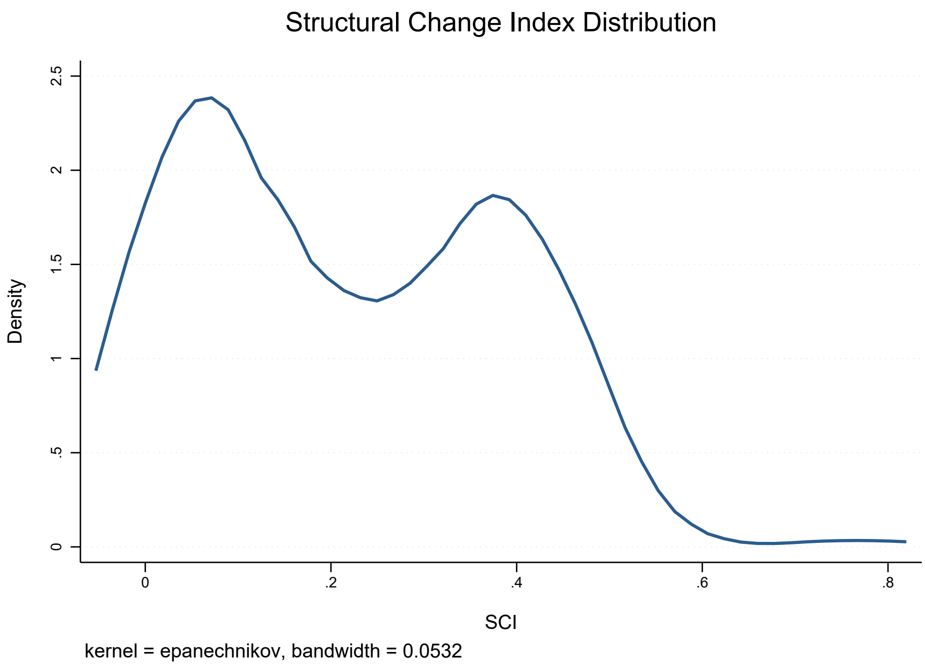


TABLE 6: *Compositional Shift Diagnostics: Relative and absolute Criteria*

Category	Sector	Product	Crit. 1 (P75)	Crit. 2 ($MA3 > 0.15$)	Diagnosis
Traditional	Agricultural	Cotton	3	5	Structural change
	Agricultural	Coffee	0	0	Stable
	Hydrocarbons	Oil derivatives	2	5	Structural change
Non-Traditional	Agribusiness	Cocoa beans	0	0	Stable
	Agribusiness	Cocoa butter	2	5	Structural change
	Agribusiness	Ginger	0	0	Stable
	Textiles	Cotton T-shirts	5	5	Structural change
	Textiles	Cotton shirts	1	5	Structural change
	Chemicals	Dyes	4	5	Structural change
	Fishing	Frozen shrimps and prawns	0	5	Structural change

Among the products exhibiting significant structural change, cotton T-shirts, dyes, and frozen shrimps and prawns stand out, as they trigger recurrent alerts under both the relative persistence and absolute severity criteria. Likewise, products such as cocoa butter, oil derivatives, cotton, and cotton shirts display a sustained compositional drift that weakens the assumption of structural stability. In contrast, products such as coffee, ginger, and cocoa beans maintain relatively stable structures throughout the sample period.

To sum up, the assessment of price heterogeneity reveals that only a limited segment of Peru's export basket exhibits economically meaningful and persistent heterogeneity capable of affecting the interpretation of aggregate unit values. The evidence identifies **cotton, oil derivatives, cocoa butter, cotton T-shirts, cotton shirts, dyes, and frozen shrimps and prawns** as the products for which structural differences across tariff subheadings (see Table 6), combined with compositional changes over time, justify technical intervention in the construction of the ETCI.

3.3 The ETCI with Heterogeneity Correction

For the seven products identified as problematic two alternative interventions were considered following the recommendations of International Monetary Fund (2009): (i) replacing the original international trade classification with a more granular database, or (ii) implementing a deletion routine aimed at excluding extreme unit values, which may reflect abrupt changes in quality composition rather than genuine price movements. The increased-granularity strategy described in the Methodology could only be implemented selectively. In practice, the required conditions were satisfied for only three of the seven products identified as problematic, corresponding to two sectors.

The first case includes cotton shirts and cotton T-shirts from the Textile sector. For cotton T-shirts, the U.S. remained the main destination market throughout the entire sample period, accounting on average for 74.31% of Peruvian exports. Other destination markets exhibited substantially lower shares, including Brazil (9.11%), Venezuela (7.45%), and Canada (3.68%). A similar pattern is observed for cotton shirts, for which the U.S. also constituted the main export market during the analysis period, with an average participation of 67.74%. Brazil represented the only secondary market with a relatively significant share (11.38%), while France and Germany accounted for only 6.64% and 4.31% of exports, respectively. The third product corresponds to the Non-traditional Fishing sector: frozen shrimps and prawns. In this case, the U.S. also represented the largest destination market during the sample period, although with a lower average share of 57.53%. Other relevant markets included China (18.53%), Spain (15.02%), and Korea (11.00%). Overall, the dominant role of the U.S. provides the main justification for replacing the BACI-based indices with indices constructed from highly disaggregated U.S. import records.

The results obtained from the replacement procedure reveal substantial product-level differences between the baseline ETCI and the corrected ETCI. For cotton T-shirts, the corrected ETCI exhibits a considerably stronger deterioration in competitiveness over the full sample period. While the original BACI-based index recorded a cumulative decline of 23.1%, the corrected index shows a much larger contraction of 50.8%. Similarly, the average annual rate of decline increased from 1.1% to 2.9%. The corrected series also displays substantially greater volatility, with the standard deviation rising from 18 to 41 and the coefficient of variation increasing from 24.0% to 36.5%. The differences are particularly pronounced during the 2000–2010 subperiod, where the corrected index indicates a cumulative fall of 52.9%, compared to only 10.5% in the original series.

A similar pattern emerges for cotton shirts. Although both indices suggest a long-term deterioration in competitiveness, the corrected ETCI reveals different cyclical dynamics and a higher degree of volatility. While the cumulative decline remains broadly similar (25.3% versus 24.1% in the original BACI-based measure), the differences between the two series become more pronounced at the beginning and toward the end of the sample period. In particular, the corrected ETCI records a much larger decline during 2000–2010 (43.6% versus 29.8%), followed by a stronger post-2020 recovery (69.0% versus 51.0%). Moreover, the standard deviation increases from 21 to 47 and the coefficient of variation from 21.2% to 36.0%, suggesting that the more granular classification captures sharper fluctuations in relative prices and competitiveness conditions within the U.S. market.

The case of frozen shrimps and prawns also reveals a different pattern of adjustment. The BACI-based ETCI suggests a slight cumulative improvement in competitiveness over the full sample period (2.7%), whereas the corrected index instead points to a cumulative deterioration of 18.6%. In contrast to the textile products, however, the corrected series exhibits lower volatility, with the coefficient of variation declining from 7.9% to 5.9%. This result suggests that part of the variability observed in the original series may have reflected compositional distortions arising from heterogeneous product mixes across export destinations

A different correction strategy was implemented for oil derivatives. Unlike the textile and fishing products discussed previously, no highly disaggregated alternative database equivalent to the USITC records was available for this product. Nevertheless, an important source of hidden heterogeneity emerged from changes in the Harmonized System classification itself. Beginning in 2012, the original HS code 271000 was subdivided into five more detailed categories: 271012, 271019, 271020, 271091, and 271099. While the BACI database preserves the aggregate structure of the original code in order to maintain consistency and long-run comparability, the UN Comtrade database reports the new subdivision explicitly.

To account for this additional information, the corrected ETCI incorporates these additional HS subdivisions from 2012 onward, treating them as distinct subheadings within the broader product category. This approach increases the degree of product granularity and allows the index to differentiate between oil derivatives with potentially different quality characteristics and price trajectories. In addition, a limited data-cleaning procedure is applied to mitigate the influence of extreme observations within the newly identified subheadings, although the corrected series still relies on a database with less extensive cleaning procedures than BACI.

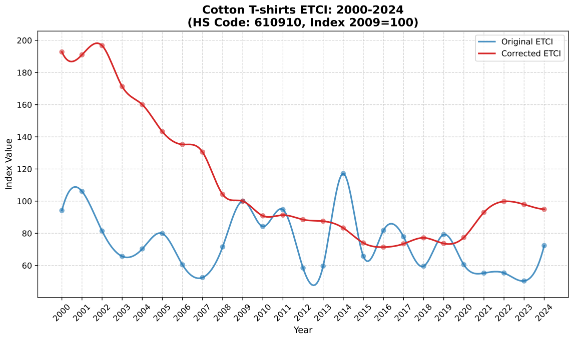
The correction substantially alters the estimated competitiveness trajectory of oil derivatives. While the original BACI-based index suggested a cumulative deterioration of 16.4% over the full sample period, the corrected series indicates a more moderate decline of 7.7%. Since the introduction of the new HS subdivisions in 2012, both indices follow broadly similar trajectories, although the corrected ETCI tends to remain slightly below the original series. The divergence becomes particularly pronounced after 2020: whereas the original ETCI points to a cumulative contraction of 12.0%, the corrected index exhibits a strong recovery of 25.4%. The corrected ETCI also displays moderately higher volatility, with the standard deviation increasing from 12 to 14 and the coefficient of variation from 11.9% to 12.9%.

For the remaining three problematic products, the previous correction strategy could not be implemented; instead, an alternative recommendation was adopted: the application of deletion routines for unusual unit value changes. The trimming correction was ultimately applied to three products: cotton, cocoa butter, and dyes.

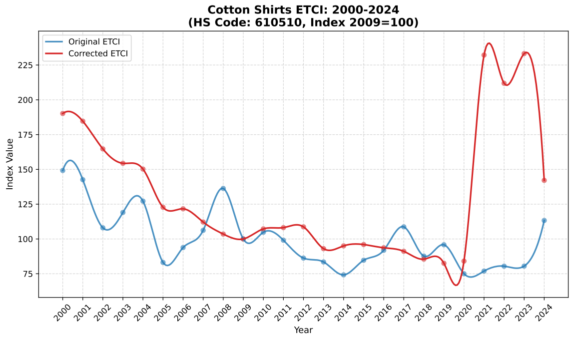
The results of the procedure are illustrated in the last three panels of Figure 6. The filtering statistics reveal substantial asymmetry and heavy-tailed distributions in the implicit price data, consistent with the presence of extreme observations and compositional distortions. On average, the deletion routine excluded 12.61% of the observations for cocoa butter, 11.11% for cotton, and 10.80% for dyes. In addition, the distributions of implicit prices exhibited pronounced positive skewness, with coefficients of 6.557, 4.640, and 6.557, respectively, alongside elevated kurtosis values, indicating the presence of significant outliers and fat tails in the data.

The comparison between the original and corrected ETCIs suggests that the trimming procedure was effective in reducing the influence of extreme observations while preserving the overall competitiveness signal of each product. In the case of cocoa butter, both indices indicate a similar long-term deterioration in competitiveness, with the corrected ETCI recording a cumulative decline of 33.9%, compared with 28.8% in the original series. The correction nevertheless reduced volatility, with the standard deviation falling from 12 to 10 and the coefficient of variation from 13.9% to 11.6%. The cyclical evolution also remains broadly unchanged, including the post-2020 period, where both indices point to a pronounced deterioration in competitiveness (−26.9% versus −25.1%).

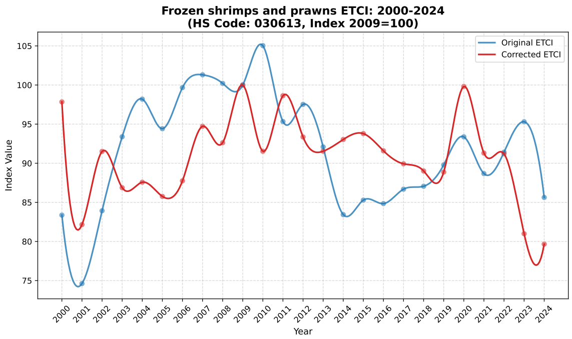
Figure 6: *Product-Level Comparison between the original BACI-based ETCI and the corrected ETCI*



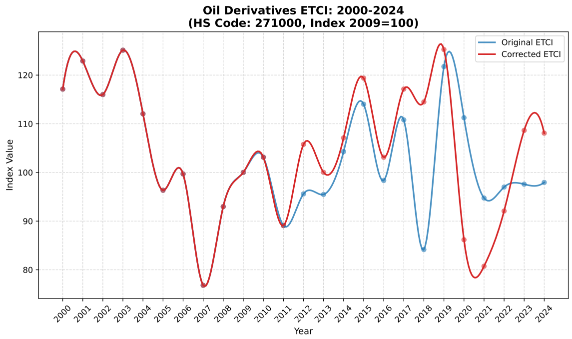
(a) *Textiles – Cotton T-shirts*



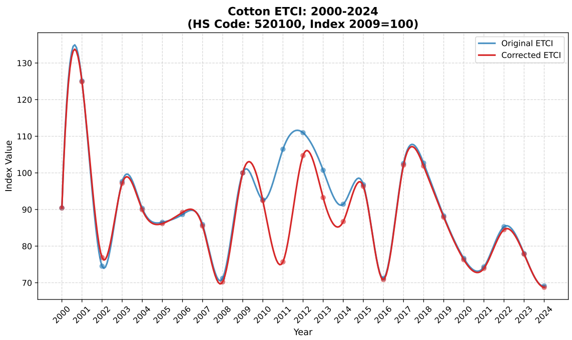
(b) *Textiles – Cotton shirts*



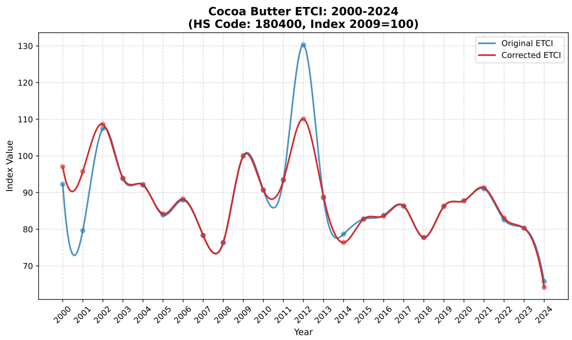
(c) *Non-traditional Fishing – Frozen shrimps and prawns*



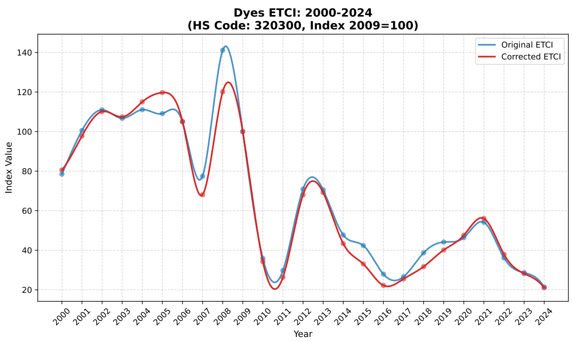
(d) *Hydrocarbons – Oil derivatives*



(e) *Agricultural sector – Cotton*



(f) *Agribusiness sector – Cocoa butter*



(g) *Chemical sector – Dyes*

For dyes, the corrected ETCI preserves the broad long-run downward trend observed in the original series, with only minor changes in the overall competitiveness signal. The cumulative decline changes only marginally, from 72.8% to 73.9%, indicating that the trimming procedure does not materially alter the long-run evolution of the index. Likewise, the dispersion of the series remains broadly unchanged, with the standard deviation remaining at 35 and the coefficient of variation increasing only slightly from 52.8% to 55.0%. Although some cyclical movements differ modestly across subperiods, the corrected series continues to display the same broad pattern of competitiveness dynamics as the original ETCI.

A similar result is obtained for cotton. Both the original and corrected ETCI indicate an almost identical long-run deterioration in competitiveness, with cumulative declines of 23.5% and 24.0%, respectively. The cyclical dynamics also remain remarkably stable across sub-periods, with only negligible differences in the estimated changes before and after trimming. Unlike the previous cases where the intervention mainly affected the level or variability of the series, the trimming procedure for cotton produces only a modest reduction in dispersion, as reflected in the decline of the standard deviation from 14 to 13 and the coefficient of variation from 15.3% to 14.8%. These results suggest that the original series was already relatively robust to the presence of extreme unit values, so the trimming procedure leaves the competitiveness signal virtually unchanged.

TABLE 7: *Sectoral Implications of Product-Level Corrections*

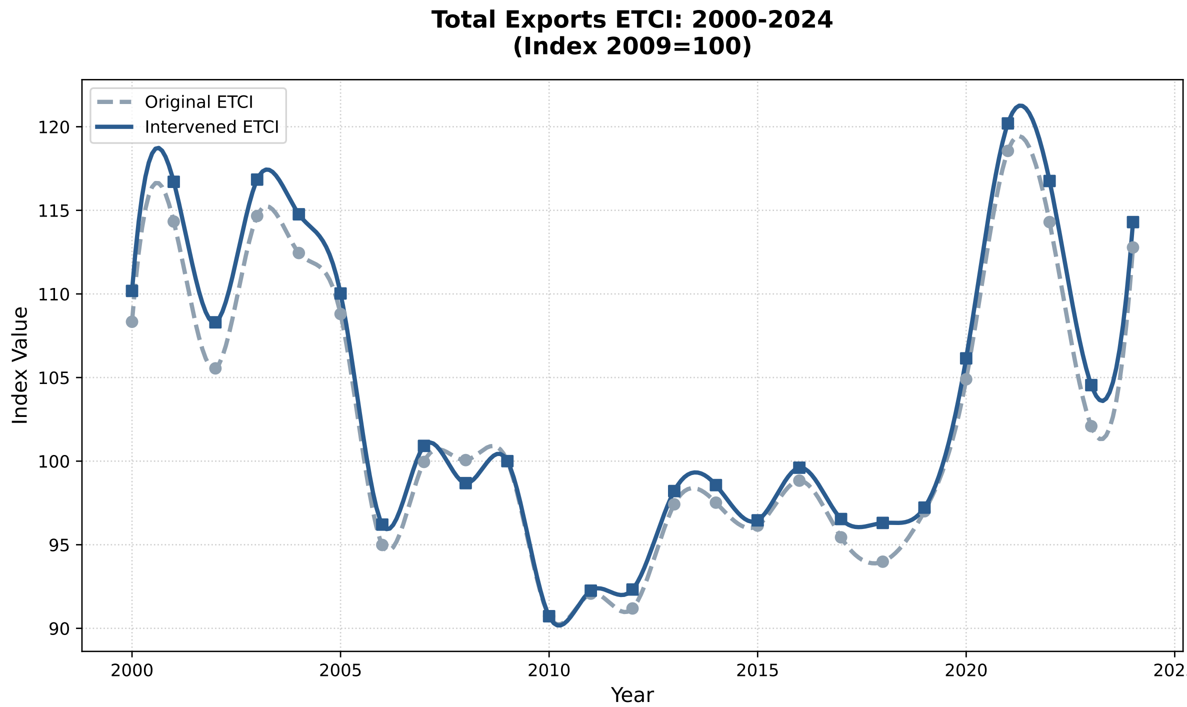
	Traditional Sectors			**Non-Traditional Sectors**				
Statistic	**Agricultural**	**Hydrocarbons**	**Total**	**Agibusiness**	**Textiles**	**Chemicals**	**Fishing**	**Total**
Panel A: Corrected ETCI								
Avg. annual growth	-0.3	-0.5	0.1	0.5	-1.8	-1.0	-1.2	0.0
Cum. growth 2000–2010	-18.2	-17.2	-24.2	24.9	-43.3	-41.4	53.8	-10.9
Cum. growth 2010–2020	10.5	-22.3	17.7	1.4	-12.4	114.4	-34.5	29.7
Cum. growth 2020–2024	2.5	38.0	14.7	-11.6	30.7	-37.3	-25.3	-12.6
Std. deviation	7.9	13.9	11.7	8.9	27.0	16.5	23.2	6.8
CV (%)	7.2	12.8	10.9	8.5	24.6	22.8	32.4	6.8
Panel B: Original ETCI								
Avg. annual growth	-0.3	-0.7	0.1	0.5	-0.1	-0.9	-0.9	0.1
Cum. growth 2000–2010	-18.2	-17.2	-24.2	25.1	-19.7	-39.9	67.7	-2.9
Cum. growth 2010–2020	10.5	-15.7	18.2	1.4	-21.4	110.1	-38.3	19.8
Cum. growth 2020–2024	2.5	20.8	13.8	-11.6	53.1	-36.8	-22.1	-11.0
Std. deviation	7.9	12.8	12.0	8.9	13.9	16.4	23.5	5.3
CV (%)	7.2	12.0	11.1	8.6	14.2	22.5	32.7	5.6

Notes: Shaded cells indicate statistics exhibiting economically meaningful differences between the original and corrected ETCIs.

Although corrections were implemented at the product level, their aggregation across sectors yields heterogeneous implications, as detailed in Table 7. Broadly, the adjustments do not fundamentally alter the long-run competitiveness narrative for the majority of Peru's export sectors; Traditional Agriculture, Agribusiness, and Non-traditional Fishing exhibit nearly identical growth and volatility trajectories before and after the correction. However, aggregation decisions prove non-innocuous in sectors where the corrected products represent either a large export share or are subject to severe composition biases. This is particularly visible in Textiles, where the corrected ETCI uncovers substantially different decade-long dynamics and nearly doubles the measured volatility (the coefficient of variation rises from 14.2% to 24.6%). Similarly, Hydrocarbons experience meaningful shifts in their cyclical patterns, as seen in cumulative growth for the 2020–2024 period. Consequently, the adjustment refines sectoral precision without distorting the aggregate export narrative. Figures showing the complete evolution of the original and corrected sectoral ETCIs are provided in Appendix C.

The final part of the heterogeneity-adjustment exercise evaluates the extent to which the product-level corrections modify the aggregate ETCIs for Traditional exports, Non-traditional exports, and the overall export basket. Since the interventions were implemented only for seven products, the aggregate effects are naturally more limited than those observed at the product level. As shown in the Table 7, the traditional export sector experiences only marginal changes after the corrections are introduced. The original Traditional ETCI recorded a cumulative increase of 2.0% over the full sample period, compared to 2.4% in the corrected series, while the average annual growth rate remained practically unchanged at approximately 0.1%. Similarly, volatility indicators exhibit almost no variation, and the coefficient of variation moves only from 11.1% to 10.9%. This limited effect is expected, since mining products — which were not identified as structurally heterogeneous — continue to dominate the aggregate dynamics of traditional exports.

FIGURE 7: *Comparison between the baseline and corrected aggregate ETCI for Peru after heterogeneity adjustments.*



	Original ETCI	Intervened ETCI
Cumulative growth	4.1	3.7
Average annual growth	0.2	0.15
Cumulative growth 2000–2010	-16.3	-17.7
Cumulative growth 2010–2020	15.6	17.0
Cumulative growth 2020–2024	7.5	7.7
Standard deviation	8.0	9.0
C.V.	8.2	8.7

By contrast, somewhat larger adjustments are observed in the non-traditional sector, where the corrected products represent a more important share of total exports and where unit value heterogeneity tends to be more pronounced. Although the long-run competitiveness pattern remains broadly similar, the corrected ETCI displays noticeable differences across subperiods. For instance, the cumulative growth during 2000–2010 changes from −2.9% in the original series to −10.9% in the corrected measure, while during 2010–2020 the corrected ETCI exhibits a stronger recovery (29.7% compared to 19.8%). The corrected series also presents slightly higher volatility, with the standard deviation increasing from 5.3 to 6.8 and the coefficient of variation from 5.6% to 6.8%.The complete evolution of the original and corrected ETCIs for traditional exports and non-traditional aggregates is also presented in Appendix C.

At the aggregate level, the overall ETCI for Peru remains remarkably stable after the heterogeneity adjustments. The baseline index recorded a cumulative increase of 4.1% over the sample period, while the intervened ETCI shows a very similar increase of 3.7%. The main cyclical patterns are likewise preserved across both series, both over the full sample and within each subperiod, with only modest differences in the magnitude of the fluctuations.

3.4 Validation and Robustness of the ETCI

3.4.1 Economic Validation: External-Sector Performance

As shown in Table 8, the proposed competitiveness measure exhibits economically meaningful positive associations with Peru's external-sector performance. In particular, the ETCI displays a considerable contemporaneous correlation with the volume component of the current account decomposition, suggesting that improvements in competitiveness are closely associated with stronger quantity-driven contributions to changes in the current account balance.

By contrast, the relationship between competitiveness and broader external aggregates —namely exports, trade balance, and current account balance— appears to materialize more gradually. The strongest associations emerge after approximately two to three years, indicating that competitiveness gains may require time to propagate through export performance and external adjustment mechanisms. Importantly, these relationships remain positive and economically relevant over longer horizons.

For trade balance and current account, both correlation measures and the coefficients obtained from simple OLS specifications are statistically significant at the 5% level. For the volume effect and the exports, the relationship remains statistically distinguishable from zero at the 10% significance level, consistent with a more direct but comparatively noisier adjustment process.

Table 8: *Economic validation of the ETCI using selected lag structures*

	Exports	Trade Balance	Current Account	Volume Effect
Selected ETCI lag	$t-3$	$t-2$	$t-2$	contemporaneous
Pearson correlation	0.410	0.406	0.459	0.354
	(0.052)	(0.049)	(0.024)	(0.083)
Spearman correlation	0.527	0.483	0.391	0.397
	(0.010)	(0.017)	(0.059)	(0.049)
OLS coefficient	301.707	194.247	212.100	0.074
	(0.052)	(0.049)	(0.024)	(0.083)

At a more disaggregated level, economic validation is further assessed through panel estimations relating the ETCI to export-volume performance for traditional products and non-traditional sectors, following the structure described in the methodology.

Table 9 reports the results for traditional export products. After controlling for unobserved product-specific heterogeneity through fixed effects, the ETCI exhibits a positive and statistically significant association with export-volume growth across all specifications. In the baseline model, the estimated coefficient implies that a one-unit increase in the ETCI is associated with approximately 0.14 percentage points higher growth in exported volume. Evaluated at the within-product variation of the ETCI, a one-standard-deviation increase in competitiveness corresponds to an increase of approximately 5.7 percentage points in annual export-volume growth[4], indicating economically meaningful effects.

Importantly, the ETCI coefficient remains positive, statistically significant, and remarkably stable after introducing controls for commodity-boom episodes and major disruptions to international trade, including the global financial crisis and the COVID-19 pandemic. This robustness suggests that the estimated relationship is not driven exclusively by exceptional external events. Moreover, the positive association between the ETCI and export-volume growth is consistent with the contemporaneous relationship previously documented between the aggregate ETCI and the volume component of the current account decomposition, reinforcing the interpretation of the ETCI as a proxy for real external competitiveness.

Table 9: *Economic Validation of the ETCI: Traditional Products*

	(1) Baseline	(2) Commodity Boom	(3) + Crisis Control
ETCI	0.0014**	0.0014**	0.0014**
	(0.0005)	(0.0006)	(0.0006)
Commodity cycle dummy		-0.0151	-0.0203
		(0.0220)	(0.0204)
Crisis period dummy			-0.0324
			(0.0329)
Product FE	Yes	Yes	Yes
Commodity boom control	No	Yes	Yes
Crisis control	No	No	Yes
Observations	288	288	288
Products	12	12	12
Within R^2	0.010	0.010	0.011
ρ	0.013	0.013	0.012

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For non-traditional activities, the analysis is conducted at the sectoral level using export-volume indices for the Agribusiness, Textile, Fishing, Chemical, and Steel and Metallurgy sectors. Table 10 reports the corresponding fixed-effects estimations. Across specifications, the ETCI coefficient remains positive, suggesting that improvements in competitiveness are systematically associated with stronger export-volume performance at the sectoral level, although the estimated relationship is statistically less precise than in the traditional-products case.

The results also indicate that controlling for periods of major global disruptions is particularly important for understanding the dynamics of non-traditional exports. Once crisis episodes are explicitly accounted for, the explanatory power of the model increases substantially, with the within (R^2) rising from

[4] The standardized effect is computed using the within-product standard deviation of the ETCI (($\sigma_{ETCI}^{within} = 40.9$)), consistent with the identifying variation underlying the fixed-effects estimator.

0.037 to 0.160. At the same time, the crisis-period variable enters with a large and statistically significant negative coefficient, highlighting the importance of adverse global conditions in shaping short-run export dynamics in non-traditional sectors.

Table 10: *Economic Validation of the ETCI: Non-Traditional Sectors*

	(1) Baseline	(2) + Crisis Control
ETCI	0.0014	0.0016*
	(0.0009)	(0.0007)
Crisis period dummy		-0.1320***
		(0.0268)
Sector FE	Yes	Yes
Crisis control	No	Yes
Observations	125	125
Sectors	5	5
Within R^2	0.037	0.160
Between R^2	0.000	0.000
Overall R^2	0.020	0.120
ρ	0.115	0.138

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Overall, while the evidence for non-traditional sectors is comparatively weaker than that obtained for traditional products, the results remain qualitatively consistent with the proposed interpretation of the ETCI. A natural explanation lies in the more aggregated nature of the data: unlike the traditional-products panel, which exploits product-level information, the non-traditional analysis relies on broad sectoral export-volume indices, making it more difficult to fully account for underlying heterogeneity despite the use of fixed effects. Additional evidence suggests that sectors differ in their exposure to adverse external conditions, reinforcing the notion that persistent heterogeneity plays a more important role in the non-traditional export basket.

3.4.2 Historical Coherence Analysis

Following an extensive review of the main reports and technical documents describing Peru's economic performance, we identified 16 episodes that are expected to have had meaningful implications for the country's external competitiveness. These episodes, summarized in Table 11, are classified according to their underlying nature, including institutional and trade-policy reforms, productive-capacity expansions, adverse supply-side shocks, and global external disturbances. Several episodes affected more than one sector, while others represent well-known milestones in Peru's recent economic history.

Table 11: *Competitiveness-Relevant Episodes Identified for the Historical Coherence Analysis*

Code	Episode	Event Year(s)	Affected Sector(s)
Panel A. Institutional and Trade Policy Reforms			
EA1	Consolidation of the Agricultural Promotion Regime	2000	Agribusiness
EA2	Entry into Force of the Peru–United States Trade Promotion Agreement	2009	Multiple export sectors
EA3	Entry into Force of the Peru–China Free Trade Agreement	2010	Mining, Fishing, Agribusiness
EA4	Entry into Force of the Peru–European Union Trade Agreement	2013	Multiple export sectors
EA5	New Agricultural Promotion Framework	2021	Agribusiness
Panel B. Productive Capacity Expansion and Export Diversification			
EB1	Camisea Start-Up and Natural Gas Expansion	2004	Hydrocarbons
EB2	LNG Export Consolidation	2010	Hydrocarbons
EB3	Commissioning of Large-Scale Mining Projects	2013 (Toromocho) 2015 (Constancia) 2015 (Cerro Verde expansion) 2016 (Las Bambas)	Mining
EB4	Irrigation Projects and Agro-Export Diversification	2000 (Consolidation of Chavimochic II effects) 2014 (Olmos) 2015–2017 (Major Advances in Majes-Siguas II)	Agribusiness
EB5	Emergence of the Blueberry Export Industry	2013	Agribusiness
Panel C. Adverse Supply-Side Shocks			
EC1	Coffee Rust Disease (Roya Amarilla)	2012–2014	Agriculture
EC2	El Niño Costero	2017	Agribusiness, Fishing
EC3	El Niño and Warming Shock	2023–2024	Agribusiness, Fishing
EC4	Mining Social Conflicts and Operational Disruptions	2021–2023	Mining
EC5	Paralization of Chavimochic III	2016	Agribusiness
Panel D. External and Global Shocks			
ED1	Intensified Competition from Asian Producers	2012–2014	Textiles

To operationalize the historical episodes presented in Table 11, we defined evaluation windows and identified the products most likely to be affected based on the underlying economic transmission channels. This procedure allowed us to formulate an *ex ante* assessment of the expected competitiveness response associated with each episode, which could be positive, negative, differentiated across products, or controversial. While differentiated episodes imply that the same event may benefit some products while adversely affecting others, controversial episodes correspond to cases where the expected effects are inherently ambiguous. In these situations, the historical coherence assessment focuses on whether the observed responses conform to the anticipated pattern of heterogeneity rather than on a uniformly positive or negative outcome.

Table 12 summarizes the products evaluated, the corresponding evaluation windows, and the expected competitiveness response for each episode.

Table 12: *Evaluation Design for the Historical Coherence Analysis*

Code	Products Evaluated	Evaluation Window	Expected Competitiveness Response
EA1	Fresh Asparagus, Preserved Asparagus, Grapes, Avocados, Mangoes, Tangerines	2000–2005	Positive
EA2	Fresh Asparagus, Preserved Asparagus, Grapes, Avocados, Mangoes, Tangerines, Cotton T-shirts, Cotton Shirts	2008–2013	Positive
EA3	Copper Concentrates, Fishmeal, Fish Oil, Grapes, Avocados, Tangerines, Cotton T-shirts, Cotton Shirts, Cotton Jerseys	2009–2014	Differentiated
EA4	Coffee, Fresh Asparagus, Grapes, Avocados, Blueberries	2012–2017	Positive
EA5	Blueberries, Grapes, Avocados, Mangoes	2020–2024	Controversial
EB1	Natural Gas	2003–2008	Positive
EB2	Natural Gas	2009–2014	Positive
EB3	Copper Concentrates, Refined Copper, Gold, Iron	2012–2020	Positive
EB4	Fresh Asparagus, Preserved Asparagus, Grapes	2000–2005 (Consolidation of Chavimochic II effects)	Positive
EB4	Grapes, Avocados, Blueberries, Tangerines, Mangoes	2013–2018 (Olmos and Majes Siguas II)	Positive
EB5	Blueberries	2012–2017	Positive
EC1	Coffee	2011–2016	Negative
EC2	Fishmeal, Fish Oil, Grapes, Mangoes, Avocados	2016–2019	Negative
EC3	Fishmeal, Fish Oil, Mangoes, Avocados, Blueberries	2022–2024	Negative
EC4	Copper Concentrates, Refined Copper	2020–2024	Negative
EC5	Fresh Asparagus, Preserved Asparagus, Grapes, Avocados, Blueberries	2015–2020	Negative
ED1	Cotton T-shirts, Cotton Shirts, Cotton Jerseys	2011–2016	Negative

Applying the criteria described in the previous paragraphs and the coherence metrics formally defined in the methodology section, we evaluate the historical coherence of the competitiveness index at both the product and event levels. As discussed in the methodology, the first metric assesses the cumulative growth in competitiveness over the evaluation window associated with each episode, while the second evaluates the relative performance of competitiveness by comparing its average growth during the event period with its average growth outside that period. The resulting product-level assessments are then aggregated at the event level. An event is classified as coherent when a majority of the associated products exhibit responses consistent with the expected competitiveness effects.

Table 13 reports the results. Overall, 11 out of the 15 evaluated episodes satisfy the historical coherence criterion, indicating that the index is generally able to capture the direction of the competitiveness effects implied by major historical developments in Peru's export sectors. The strongest evidence of coherence is observed for episodes related to productive capacity expansion, irrigation infrastructure, and adverse supply-side shocks, several of which achieve coherence rates above 60 percent and, in some cases, full product-level coherence.

The results also reveal meaningful differences across policy episodes. The early agricultural promotion regime is classified as coherent, with most of the associated products exhibiting competitiveness gains consistent with the expected effects of the reform. In contrast, the new agricultural promotion framework (EA5) is classified as coherent under the controversial-event criterion, as competitiveness responses are heterogeneous across products rather than uniformly positive. This finding is consistent with the view that the marginal competitiveness gains associated with the regime had largely been exhausted after two decades of implementation.

Table 13: *Historical Coherence Validation Results*

Event	Products	Coherent Products	Coherence Rate (%)	Event Coherent
EA1	6	4	66.7	Yes
EA2	8	1	12.5	No
EA3	9	4	44.4	No
EA4	5	3	60.0	Yes
EA5	4	–	–	Yes
EB2	1	1	100.0	Yes
EB3	4	3	75.0	Yes
EB4	8	5	62.5	Yes
EB5	1	1	100.0	Yes
EC1	1	0	0.0	No
EC2	5	3	60.0	Yes
EC3	5	5	100.0	Yes
EC4	2	0	0.0	No
EC5	5	3	60.0	Yes
ED1	3	3	100.0	Yes
Total	**66**	**34**	**73.3**	**11/15 Yes**

Taken together, these findings provide substantial support for the historical validity of the competitiveness index. The product-level analysis indicates that a large majority of the evaluated episodes are consistent with the expected competitiveness responses derived from the historical narrative. Additional evidence reported in Appendix D and Appendix E further illustrates that some of these product-level responses translated into broader sectoral competitiveness dynamics and that the ETCI is capable of capturing heterogeneous patterns during complex shocks such as the COVID-19 pandemic, respectively.

3.4.3 Robustness tests

Table 14 shows that the main conclusions of the corrected ETCI remain remarkably robust to alternative weighting schemes. The current-weight, lagged-weight and three-year moving-average specifications all point to an overall improvement in Peru's export competitiveness, with cumulative gains of 3.7%, 10.1% and 4.4%, respectively, equivalent to average annual growth rates between 0.2% and 0.4%. The only qualitative difference among these three specifications is a marginal decline in the non-traditional ETCI under the three-year moving-average weights, reflecting a weaker performance of agribusiness together with a slightly larger contraction in textiles during the second decade of the sample.

By contrast, the fixed-weight specification exhibits substantially larger deviations, with cumulative competitiveness gains increasing to 12.7 % (annual average: 0.5%) and reversals in the direction of cumulative growth for the Non-traditional aggregate and for the Agribusiness, Steel and Metallurgy, Non-traditional Fishing, and Hydrocarbons sectors. These differences arise because the fixed specification suppresses the time variation in both the composition of competitors and the relative importance of products and sectors. Importantly, volatility remains remarkably stable across all specifications. The standard deviation of the aggregate ETCI fluctuates only between 9.7% and 10.2%, while the coefficient of variation ranges from 8.2% to 8.7 suggesting that the ETCI captures persistent changes in export competitiveness rather than fluctuations driven by the particular choice of weighting scheme.

Within the Traditional sector, the largest differences are concentrated in a small number of products rather than being widespread across that export basket. The fixed-weight specification reports substantially stronger cumulative competitiveness gains, primarily driven by gold, lead concentrates, and oil derivatives. In particular, gold exhibits by far the largest divergence, reflecting its highly fragmented competitor structure, while lead concentrates also shift from a cumulative decline under the current specification to a sizeable gain under fixed weights. In hydrocarbons, the main source of divergence is oil derivatives, whose competitor composition changes considerably throughout the sample as exporters such as Russia, the United Arab Emirates, Singapore, Malaysia, and Korea gain relevance relative to competitors that dominated earlier years. By contrast, products with more persistent competitive structures, such as crude oil, display much smaller differences between specifications.

Relative to the current-weight ETCI, the divergence in the non-traditional segment under fixed weights is largely driven by Agribusiness, which accounts for most of the difference in the aggregate index. This sector experienced the largest transformation in its competitive landscape over the sample period, particularly in products such as grapes, avocados, and blueberries, where both the identity and the relative importance of competing exporters changed substantially as countries such as Mexico, China, Morocco, and South Africa gained relevance alongside traditional suppliers. As a result, the fixed-weight specification is unable to fully capture the structural transformation of Peru's agro-export basket and consequently understates the associated competitiveness gains. Chemicals partially offset this effect, as the decline in competitiveness is less pronounced under fixed weights than in the baseline specification, whereas Steel and Metallurgy contributes comparatively little to the aggregate differences because of their smaller share in non-traditional exports.

Overall, these results indicate that the fixed-weight approach tends to overstate long-run competitiveness gains in products characterized by substantial turnover in competitors, whereas the baseline ETCI is better suited to capture the evolving competitive landscape faced by Peruvian exports.

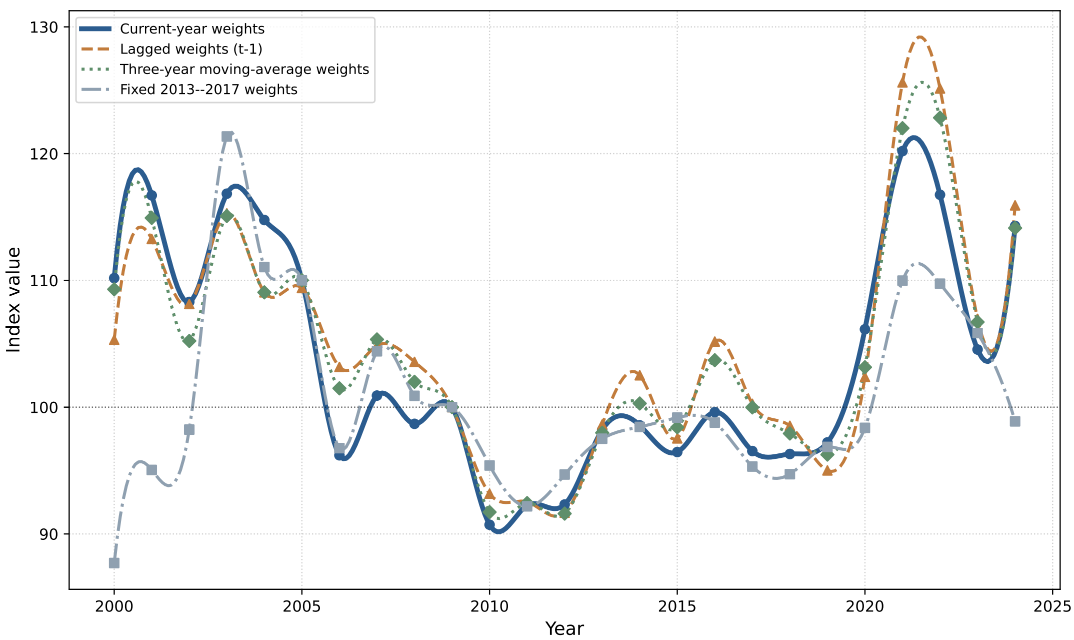
Table 14: *Robustness of the ETCI to alternative weighting schemes*

	Traditional				Non-Traditional				Total ETCI			
	Current	Lagged weights	3-year MA	Fixed weights	Current	Lagged weights	3-year MA	Fixed weights	Current	Lagged weights	3-year MA	Fixed weights
Cumulative growth	2.4	11.0	3.0	41.0	1.0	1.1	-0.8	-9.8	3.7	10.1	4.4	12.7
Average annual growth	0.1	0.4	0.1	1.4	0.0	0.0	0.0	-0.4	0.2	0.4	0.2	0.5
Growth by decades												
2000–2010	-24.2	-17.3	-22.8	15.4	-10.9	-6.7	-9.4	2.6	-17.7	-11.5	-16.1	8.8
2010–2020	17.7	10.1	12.8	11.0	29.7	17.9	20.0	-4.2	17.0	9.9	12.5	3.1
2020–2024	14.7	21.9	18.3	10.1	-12.6	-8.1	-8.8	-8.2	7.7	13.2	10.6	0.5
Volatility measures												
Standard deviation	14.3	14.1	13.8	14.9	6.0	6.3	5.6	6.6	10.2	10.0	9.7	7.8
CV (%)	10.9	10.8	10.5	11.9	6.8	7.2	6.4	7.3	8.7	8.6	8.2	7.3

Note: The baseline ETCI uses contemporaneous export weights. Alternative specifications use lagged weights, three-year moving-average weights, and fixed weights over the sample period. Growth rates and volatility measures are reported in percent.

Figure 8 confirms the robustness of the corrected version of the ETCI. The current-weight, lagged-weight, and three-year moving-average specifications follow almost identical trajectories throughout the sample, whereas the fixed-weight specification is the only one that departs systematically from the others, reflecting its inability to capture changes in competitor composition and export weights over time. The corresponding results for the traditional and non-traditional ETCIs are reported in Appendix F.

Figure 8: *Robustness of the Total ETCI under Alternative Weighting Schemes*



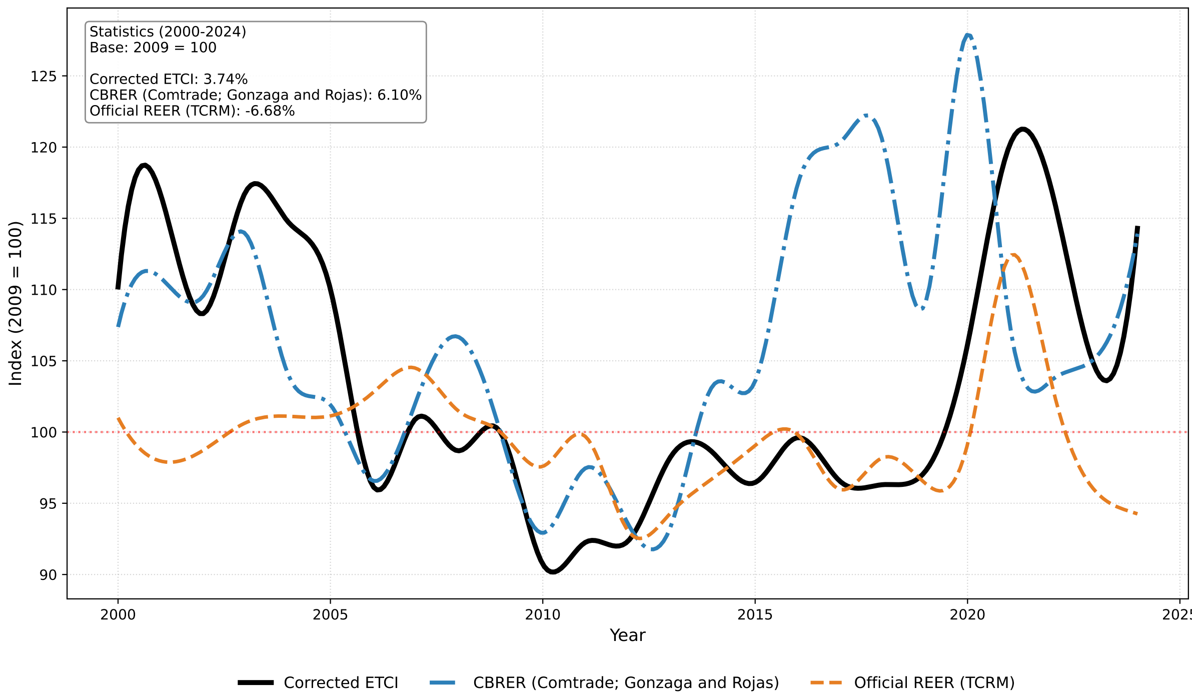
3.5 Benchmarking the ETCI Against Alternative Measures

The corrected ETCI indicates a cumulative improvement in Peru's export competitiveness of 3.7% between 2000 and 2024, equivalent to an average annual growth rate of approximately 0.15%. This positive trajectory continues to be driven primarily by traditional exports and is broadly consistent with the historical episodes discussed in the validation exercise. Compared with the previous version of the index developed by Gonzaga and Rojas (2026), which recorded a cumulative increase of 6.1%, the corrected ETCI provides a more moderate assessment of competitiveness gains.

The differences between both measures are not uniform across sectors. The methodological refinements introduced in this study have only limited implications for several export sectors, preserving the broad narrative of Peru's competitiveness dynamics. However, more substantial revisions emerge in hydrocarbons, textiles, non-traditional fishing, and selected agro-export activities, where differences in trade classification and product composition prove to be more relevant. In particular, sectors such as Textiles exhibit markedly different long-run trajectories, while Hydrocarbons display important revisions in their post-2020 dynamics. These findings suggest that the proposed adjustments improve the precision of the competitiveness index without fundamentally altering the main conclusions regarding Peru's export competitiveness.

A different perspective emerges when the corrected ETCI is contrasted with the official real effective exchange rate (TCRM). While the ETCI records a cumulative gain in competitiveness, the TCRM suggests a deterioration of 6.7% over the same period. Moreover, the TCRM exhibits substantially lower volatility (standard deviation of 3.9, compared with 9.0 for the ETCI), reflecting its construction based on consumer-price differentials and fixed trade weights. The divergences between the ETCI and the TCRM are particularly evident at the beginning of the sample and during the most recent years. From 2022 onward, the appreciation of the nominal exchange rate and favorable inflation differentials led the TCRM to signal a loss of competitiveness. Over the same period, however, the ETCI continued to indicate improvements in export competitiveness. These gains were largely associated with the strong performance of specific export products, particularly in the mining sector, in a period characterized by favorable international commodity-market conditions.

Figure 9: *Comparison between the ETCI, CBRER of Gonzaga and Rojas (2026) and BCRP's official REER*



Up to this point, the evidence suggests that the evolution of the ETCI reflects a combination of long-run and short-run determinants. The former include structural changes in Peru's productive capacity, export composition, and global market conditions, whose consistency with the ETCI has already been documented through the Historical Coherence Analysis. At the same time, short-run macroeconomic factors also contribute to yearly fluctuations in competitiveness. Among them, the nominal exchange rate provides a natural transmission channel. A nominal depreciation reduces production costs expressed in U.S. dollars, allowing Peruvian exporters to lower export prices while maintaining domestic-currency margins. Although this mechanism represents only one of several determinants of the ETCI, Table 15 shows that it is empirically relevant.

Table 15: *Correlation Between Competitiveness Indicators and Nominal Exchange Rate Movements*

Indicator	Corr. Bilateral	Corr. Multilateral
ETCI	0.43	0.49
Traditional ETCI	0.46	0.45
Non-traditional ETCI	0.13	0.16
Maximum sectoral ETCI correlation	0.46	0.45
	(Mining)	(Mining)
CBRER (Comtrade)	0.00	-0.12
Official REER (TCRM)	0.60	0.95

Notes: Correlations are computed using annual log changes. The bilateral exchange rate corresponds to the PEN/USD nominal exchange rate, while the multilateral exchange rate corresponds to the PEN exchange rate against a basket of currencies. The refined and corrected version of the ETCI is used.

The corrected ETCI exhibits a moderate positive correlation with both bilateral (0.43) and multilateral (0.49) nominal exchange-rate changes, suggesting that exchange-rate movements constitute an important, although not exclusive, determinant of export competitiveness. As expected, the association is slightly stronger for the multilateral measure, which better reflects the multiple competitors and destination markets incorporated into the ETCI. This relationship is driven primarily by the traditional export sector, particularly mining, whereas non-traditional exports display considerably weaker correlations. At the product level, the strongest positive associations are observed for cotton shirts, cotton T-shirts, copper concentrates, and some steel and metallurgy products.

In contrast, the official TCRM is much more closely associated with nominal exchange-rate movements, particularly with the multilateral measure, with a correlation of 0.95. This result is expected given that the nominal exchange rate constitutes one of the main components of the TCRM. By comparison, the corrected ETCI exhibits only a moderate correlation, indicating that nominal exchange-rate movements explain part—but not all—of its short-run dynamics. An additional finding is that the CBRER proposed by Gonzaga and Rojas (2026) exhibits virtually no systematic association with either bilateral or multilateral exchange-rate movements. This result suggests that the methodological refinements introduced in the present study produce an indicator whose short-run dynamics are more closely aligned with economically meaningful competitiveness mechanisms.

4 Discussion and Limitations

The corrected ETCI represents a substantial improvement over the original version proposed by Gonzaga and Rojas (2026), particularly by addressing hidden product heterogeneity and exploiting richer sources of product-level information. Nevertheless, several limitations remain and provide natural directions for future research.

- The heterogeneity diagnostics developed in this paper are applied exclusively to Peruvian export data. Consequently, whenever a product is identified as heterogeneous, the corresponding correction is assumed to be valid for all competing exporters. This assumption is primarily driven by data availability, as no internationally comparable database currently provides product-level information with the degree of detail required to replicate the analysis for all competitor countries. Extending the heterogeneity assessment to a broader set of exporters would constitute a valuable extension of the methodology.

- Even after increasing product granularity, some sources of heterogeneity remain unobservable because they are not recognized by existing trade classifications, which just have statistical purposes. Characteristics such as size, quality, color, production method (e.g., organic versus conventional), or other commercial attributes may generate systematic price differentials despite belonging to the same National Tariff heading. Since these dimensions are not reported in international trade statistics, they cannot currently be incorporated into the ETCI and therefore remain an unavoidable source of measurement error.

- The ETCI focuses on competition from third-country exporters within destination markets but does not explicitly account for competition from domestic producers. For many export products this omission is likely to be of limited quantitative importance because imports represent the main source of competitive pressure. However, in markets where domestic production satisfies an important share of local absorption, incorporating domestic producers could improve the measurement of competitiveness. One possible extension is the adjustment proposed by Stein et al. (2018), which allocates part of the destination-market weight to domestic production using value-added measures of tradable output and distributes the remaining weight among foreign competitors according to their relative importance in the destination market.

- Although the empirical evidence presented in this paper suggests that the ETCI primarily captures persistent changes in export competitiveness, the index also reflects temporary fluctuations arising from short-run shocks, including nominal exchange rate movements, commodity-specific disturbances, and other transitory factors. Consequently, the ETCI should be interpreted as an indicator of medium- and long-run competitiveness rather than as a tool for short-term forecasting or for extrapolating recent dynamics.

- Constructing the corrected ETCI requires product-specific diagnostics and tailored interventions, as each product may present a different source of heterogeneity and therefore require a different treatment. While this feature substantially improves measurement accuracy, it also limits the routine replication and periodic updating of the index. Future research could focus on developing more standardized and automated procedures that preserve the methodological rigor of the current approach while facilitating its regular implementation.

5 Conclusions

This paper develops a refined Export Trade Competitiveness Index (ETCI) designed to provide a more accurate measure of Peru's external competitiveness than conventional real effective exchange rate indicators. The motivation for developing such an indicator is particularly relevant in the Peruvian case, where recent terms-of-trade gains have not always translated into comparable export volume growth, highlighting the importance of distinguishing between price-driven improvements and underlying competitiveness dynamics.

Relative to the first version proposed by Gonzaga and Rojas (2026), the corrected ETCI introduces several methodological improvements. The construction now relies on the BACI database, whose reconciliation procedures considerably improve the consistency of international trade statistics. More importantly, the paper proposes a formal two-stage framework to identify when product heterogeneity within broad HS-6 classifications is sufficiently important to distort unit-value-based competitiveness measures. Products diagnosed with economically relevant compositional changes are then corrected using product-specific strategies aimed at increasing product granularity or removing extreme observations. Finally, the resulting index is subjected to an extensive validation exercise combining economic, historical, and methodological evidence.

The empirical analysis shows that product heterogeneity is considerably less pervasive than might initially be expected. Among the 50 products included in Peru's export basket, only 22 required a detailed assessment using more disaggregated information, 10 displayed statistically significant heterogeneity, and only 7 experienced sufficiently important compositional changes to justify correcting the ETCI. These corrections were concentrated in non-traditional exports, particularly textiles, fisheries, chemicals, and hydrocarbons. As a result, the corrected ETCI preserves the overall long-run pattern of Peru's competitiveness while eliminating several distortions at the product level.

At the aggregate level, the main conclusions remain remarkably robust. Peru experienced a sustained improvement in export competitiveness between 2000 and 2024, largely explained by the mining and agricultural sectors. After incorporating the corrections proposed in this paper, the estimated cumulative competitiveness gain declines only moderately, from 4.1% to 3.7%, suggesting that the original index captured the broad evolution of competitiveness reasonably well while overstating gains for a limited number of products. In contrast, the official multilateral real exchange rate indicates a cumulative competitiveness loss of 6.7% over the same period, illustrating the importance of incorporating product-specific export prices and explicit competitor structures into competitiveness measurement.

The validation exercises further support the economic relevance of the proposed indicator. The corrected ETCI exhibits the expected relationship with export volumes, trade balance, and current account, remains broadly consistent with major historical episodes affecting Peru's export sector, and proves robust to alternative weighting schemes, with the exception of fixed weights that fail to capture the substantial transformation of Peru's export basket over the last two decades. Together, these results suggest that the corrected ETCI provides a more informative representation of Peru's external competitiveness than existing aggregate indicators.

More broadly, this paper demonstrates that product heterogeneity is not merely a data issue but a measurable source of bias in unit-value-based competitiveness indicators. By combining systematic heterogeneity diagnostics with product-specific correction strategies, the methodology developed here offers a practical framework for improving competitiveness measures while preserving long-run comparability. Although implemented for Peru, the approach can be readily extended to other countries and may contribute to the construction of more informative export competitiveness indicators in settings where detailed trade information is available.

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Appendix A Identification of Potential Heterogeneous Headings

This appendix documents the Heterogeneity Assessment Guide used to identify export products for which the HS 6-digit classification may conceal relevant within-product price heterogeneity. The guide was constructed through a systematic comparison between the Peruvian National Tariff nomenclature and the classifications available in international trade databases. Products for which the Peruvian National Tariff provides additional disaggregation into 8- or 10-digit subheadings beyond the level available in international trade databases were flagged as candidates for further evaluation. This screening exercise reduced the scope of the formal heterogeneity assessment from the full ETCI export basket to a subset of 22 products. Table Appendix A.1 reports the corresponding subheadings and the level of detail required for each case.

A methodological exception applies to oil derivatives, tangerines, and ginger. In the BACI HS96 nomenclature, each product is recorded under a single 6-digit heading, whereas subsequent revisions of the Harmonized System subdivide these original headings into two or more new HS 6-digit categories. Throughout this study, these later categories are treated as subheadings of the original HS96 heading, allowing the additional product detail available in Comtrade to be readily incorporated while preserving the consistency of the historical series.

TABLE APPENDIX A.1: *Granular Heterogeneity Assessment: National Tariff Subheading Guide*

Category	Sector	Product	Subheading	Technical Description	Level of Detail
Traditional	Fishing	Fishmeal	2301.20.11	Fat content > 2% by weight.	8-dig
			2301.20.19	Fat content ≤ 2% by weight.	8-dig
			2301.20.90	Other non-fish flours.	8-dig
		Fish Oil	1504.20.10	Crude fish oils.	8-dig
			1504.20.90	Others.	8-dig
	Agricultural	Cotton	5201.00.10	Fiber length > 34.92 mm.	8-dig
			5201.00.20	Fiber length 28.57 mm - 34.92 mm.	8-dig
			5201.00.30	Fiber length 22.22 mm - 28.57 mm.	8-dig
			5201.00.90	Fiber length ≤ 22.22 mm.	8-dig
		Sugar	1701.99.10	Chemically pure sucrose.	8-dig
			1701.99.90	Others.	8-dig
		Coffee	0901.11.10	Coffee for sowing.	8-dig
			0901.11.90.00	Others.	8-dig
	Mining	Zinc Conc.	2608.00.00.10	Low-grade zinc concentrates.	10-dig
			2608.00.00.90	Others.	10-dig
	Hydrocarbons	Oil Derivatives*	2710.12	Light oils and preparations (Gasoline)	HS 6-dig
			2710.19	Medium and heavy oils (Diesel/Fuel)	HS 6-dig
			2710.20	Oils containing biodiesel	HS 6-dig
			2710.91	Waste oils containing PCBs	HS 6-dig
			2710.99	Other waste oils.	HS 6-dig
Non-Traditional	Agroexports	Mangoes	0804.50.10	Guavas.	10-dig
			0804.50.20.00	Mangoes and mangosteens.	10-dig
		Tangerines*	0805.21	Satsumas	HS 6-dig
			0805.22	Clementines	HS 6-dig
			0805.29	Other citrus hybrids	HS 6-dig
		Bananas	0803.00.11	Cavendish Valery type.	8-dig
			0803.00.12	Baby banana (Musa acuminata).	8-dig
			0803.00.19	Other fresh bananas.	8-dig
		Quinoa	1008.90.11	For sowing.	8-dig
			1008.90.19	Others.	8-dig
		Cocoa beans	1801.00.11	For sowing.	8-dig
			1801.00.19	Others.	8-dig
		Cocoa Butter	1804.00.11	Acidity level ≤ 1%.	8-dig
			1804.00.12	Acidity level > 1% but ≤ 1.65%.	8-dig
			1804.00.13	Acidity level > 1.65%.	10-dig
			1804.00.20	Cocoa fats and oils.	8-dig
		Dried peppers	0904.20.10.20	Paprika in pieces or slices.	10-dig
			0904.20.10.10	Other paprika.	10-dig
			0904.20.90	Other dried peppers.	8-dig
		Ginger*	0910.11	Neither crushed nor ground.	HS 6-dig
			0910.12	Crushed or ground.	HS 6-dig

Category	Sector	Product	Subheading	Technical Description	Level of Detail
Non-Traditional	Textiles	Cotton T-shirts	6109.10.00.31	Single uniform color (dyed/bleached).	10-dig
			6109.10.00.32	Different color yarns (striped).	10-dig
			6109.10.00.39	Other cotton T-shirts.	10-dig
		Cotton shirts	6105.10.00.41	Men's: Piece-dyed, with collar, partial opening and ribbed cuffs.	10-dig
			6105.10.00.42	Men's: Yarn-dyed (striped), with collar, partial opening and ribbed cuffs.	10-dig
			6105.10.00.49	Men's: Others, with collar, partial opening and ribbed cuffs.	10-dig
			6105.10.00.51	Men's: Piece-dyed, with collar and partial opening (no ribbed cuffs).	10-dig
			6105.10.00.52	Men's: Yarn-dyed (striped), with collar and partial opening (no ribbed cuffs).	10-dig
			6105.10.00.59	Men's: Others, with collar and partial opening (no ribbed cuffs).	10-dig
			6105.10.00.80	Other men's cotton shirts (without collar or partial opening).	10-dig
			6105.10.00.91	Boys': With collar, partial opening and ribbed cuffs.	10-dig
			6105.10.00.92	Boys': With collar and partial opening (no ribbed cuffs).	10-dig
			6105.10.00.99	Other boys' cotton shirts.	10-dig
		T-shirts/vests of textile fibers	6109.90.10	Of acrylic or modacrylic fibers	8-dig
			6109.90.90	Of other textile fibers.	8-dig
	Steel and Metallurgy	Raw Silver	7106.91.10	Unalloyed unwrought silver.	8-dig
			7106.91.20	Alloyed unwrought silver.	8-dig
	Chemicals	Dyes	3203.00.11	Logwood extract (Campeche).	8-dig
			3203.00.12	Chlorophylls.	8-dig
			3203.00.14	Annatto (achiote).	8-dig
			3203.00.15	Marigold (xanthophyll).	8-dig
			3203.00.16	Purple corn (anthocyanin).	8-dig
			3203.00.17	Turmeric (curcumin).	8-dig
			3203.00.19	Other vegetable dyes.	8-dig
			3203.00.21	Cochineal (carmine).	8-dig
			3203.00.29	Other animal dyes.	8-dig
		Polypropylene Films	3920.20.10	Metallized, thickness $\leq$ 25 microns.	10-dig
			3920.20.90	Others.	10-dig
	Fishing	Frozen Shrimps and Prawns	0306.13.11	Whole.	8-dig
			0306.13.12	Shell-off tails.	8-dig
			0306.13.13	Shell-on tails, raw.	8-dig
			0306.13.14	Shell-on tails, cooked in water or steam.	8-dig
			0306.13.19	Other frozen prawns (Penaeidae family).	8-dig
			0306.13.91	Freshwater shrimps (Macrobrachium genus).	8-dig
			0306.13.99	Others.	8-dig

Note: Highlighted rows represent subheadings accounting for the majority of export value within each product; products without highlights exhibit significant export flows across all subheadings.

*For these products, disaggregation is conducted at the HS 6-digit level to reconcile aggregate HS96 categories in the BACI database with the more granular headings found in recent versions.

Appendix B Supporting Evidence for the Structural Price Heterogeneity Assessment

I. Traditional products

Fishing sector. The variance decomposition analysis for the Fishing sector (Table Appendix B.1) provides statistical evidence to support the aggregation of subheadings at the 6-digit level. In both product categories, the idiosyncratic factor (σ_e) significantly outweighs the subheading-specific effect (σ_u), suggesting that fluctuations in unit values are primarily driven by exogenous market shocks rather than structural differences in quality or base pricing between tariff codes. Specifically, fish oil exhibits a substantially higher idiosyncratic volatility ($\sigma_e = 0.9345$) compared to fishmeal, where σ_e is only 0.4711. Furthermore, the Share of Between-Subheading Variation (ρ) for fish oil stands at 12.57%, nearly tripling the figure observed for fishmeal (5.23%). While both levels remain within thresholds that justify a homogeneity classification, these results indicate that fish oil is less homogeneous than fishmeal.

Table Appendix B.1: *Fishing Sector: Estimates of Variance Components*

	Fishmeal (2301.20)	**Fish Oil** (1504.20)
σ_u	0.1107	0.3543
σ_e	0.4711	0.9345
ρ	0.0523	0.1257
Observations (N)	65	50
Subheadings	3	2

Building upon the variance decomposition results, the DVLS model provides further evidence of the price homogeneity within the Fishing sector. Consistent with the dominance of idiosyncratic noise previously discussed, the estimated coefficients for individual subheadings fail to show a statistically significant premium or discount relative to their respective baselines. Specifically, the joint significance tests (F-tests) confirm that subheading-specific attributes do not systematically explain unit value fluctuations for either fishmeal ($p - value = 0.2750$) or fish oi ($p - value = 0.0640$). These findings reinforce the conclusion that stochastic market shocks, rather than structural differences between 8-digit codes, are the primary drivers of price dynamics in this sector.

Table Appendix B.2: *Fishing Sector: Heterogeneity Analysis through a DVLS Model*

	Fishmeal (2301.20)	**Fish Oil** (1504.20)
Reference Category (Base)	*Fat content > 2%* *(2301.20.11)*	*Crude fish oils* *(1504.20.10)*
Subheadings (vs. Base)		
Fat content ≤ 2% (2301.20.19)	-0.0537	
	(0.7659)	
Other non-fish flours (2301.20.90)	0.1592	
	(0.1981)	
Others (1504.20.90)		0.5011*
		(0.0640)
Constant (Mean of Base)	0.0667	0.1923
	(0.5002)	(0.2868)
F-test (Equality)	1.32	3.59
$Prob > F$ (Heterogeneity)	0.2750	0.0640
Observations	65	50

Notes: Standard errors are robust. Gray shading identifies product-specific subheadings.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, the results from the one-way ANOVA analysis (Table Appendix B.3) confirm that the differences in mean unit values across subheadings are not statistically significant at the 5% level for either product. The decomposition shows that the between-group variance ($SS_{Between}$) is negligible compared to the within-group variance (SS_{Within}), suggesting that the specific tariff classification contributes marginally to the observed price fluctuations. Although the F-statistic is greater than unity for both products –reflecting a slight signal from the subheadings– the resulting p-values fail to reject the null hypothesis of equal means. Consequently, the empirical evidence consistently points toward a high degree of structural homogeneity within the Fishing sector.

TABLE APPENDIX B.3: *Fishing Sector: One-way ANOVA and Pairwise Comparisons*

	Fishmeal (2301.20)	**Fish Oil** (1504.20)
Pairwise Comparisons (Diff.)		
2301.20.19 vs 2301.20.11	-0.0537	
(p-value)	(1.0000)	
2301.20.90 vs 2301.20.11	0.1592	
(p-value)	(0.7100)	
2301.20.90 vs 2301.20.19	0.2129	
(p-value)	(0.5150)	
1504.20.90 vs 1504.20.10		0.5011^{*}
(p-value)		(0.0640)
Variance Components		
$SS_{Between}$	0.5217	3.1385
SS_{Within}	13.7613	41.9183
F-statistic	1.18	3.59
$Prob > F$	0.3155	0.0640
Observations	65	50

Notes: Gray shading identifies Fishmeal-specific comparisons. Bonferroni adjustment applied.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

AGRICULTURAL SECTOR. The variance decomposition analysis for the Agricultural sector (Table Appendix B.4) provides statistical evidence on the degree of subheading heterogeneity. For cotton and sugar, the substantial between-subheading variance ($\sigma_u = 0.2551$ and 1.2739, respectively) and high ρ coefficients suggest that unit value fluctuations are significantly influenced by tariff-specific attributes. In contrast, coffee exhibits a relatively low intraclass correlation ($\rho = 16.68\%$) and a dominant idiosyncratic factor ($\sigma_e = 0.2583$), indicating that price dynamics for this product could be primarily driven by exogenous market shocks rather than structural differences in base pricing across subheadings.

Consistent with the variance estimates, the estimated DVLS coefficients (Table Appendix B.5) for individual subheadings in cotton and sugar show statistically significant premiums or discounts relative to their respective baselines ($p < 0.01$). Specifically, for sugar, the *Others* subheading (1701.99.90) shows a marked price difference of -1.8015 relative to the base. Conversely, for coffee, the subheading-specific attribute fails to show a statistically significant difference relative to its baseline ($p = 0.1982$), reinforcing the conclusion that tariff codes are not the primary drivers of price dynamics for this product.

Table Appendix B.4: *Traditional Agricultural Sector: Estimates of Variance Components*

	Cotton (5201.00)	**Sugar** (1701.99)	**Coffee** (0901.11)
σ_u	0.2551	1.2739	0.1156
σ_e	0.3006	0.6506	0.2583
ρ	0.4187	0.7931	0.1668
Observations (N)	25	31	18
Subheadings	3	2	2

Table Appendix B.5: *Traditional Agricultural Sector: Heterogeneity Analysis through a DVLS Model*

	Cotton (5201.00)	**Sugar** (1701.99)	**Coffee** (0901.11)
Reference Category (Base)	*Fiber length > 34.92 mm.* *(5201.00.10)*	*Chemically pure sucrose* *(1701.99.10)*	*Coffe for sowing* *(0901.11.10)*
Subheadings (vs. Base)			
Fiber length in]28.57, 34.92] mm.	-0.4717***		
(5201.00.20)	(0.0059)		
Fiber length in]22.22, 28.57] mm.	-0.0672		
(5201.00.30)	(0.7020)		
Others		-1.8015***	
(1701.99.90)		(0.0001)	
Others			-0.1634
(0901.11.90)			(0.1982)
Constant (Mean of Base)	1.4164***	1.2650***	1.4054***
	(0.0000)	(0.0035)	(0.0000)
F-test (Equality)	8.45	19.82	1.80
$Prob > F$ (Heterogeneity)	0.0019	0.0001	0.1982
Observations	25	31	18

Notes: Standard errors are robust. Shading identifies product-specific subheadings.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, the results from the one-way ANOVA models (Table Appendix B.6) confirm these findings.

For cotton and sugar, the F-statistics are statistically significant ($p < 0.01$), rejecting the null hypothesis of equal means. The decomposition highlights that for sugar, the between-group variance ($SS_{Between} = 19.2630$) is substantial, suggesting that tariff classification contributes systematically to price fluctuations. In contrast, for coffee, the ANOVA results ($p = 0.1982$) fail to reject the null hypothesis of equal means. Consequently, the reduced-panel evidence suggests structural homogeneity for coffee and potential heterogeneity for cotton and sugar. Nevertheless, as discussed in Sections 2 and 3, the results reported for this sector are those obtained from the extended panel analysis.

Table Appendix B.6: *Traditional Agricultural Sector: One-way ANOVA and Pairwise Comparisons*

	Cotton (5201.00)	Sugar (1701.99)	Coffee (0901.11)
Pairwise Comparisons (Diff.)			
5201.00.20 vs 5201.00.10	-0.4717**		
(p-value)	(0.0120)		
5201.00.30 vs 5201.00.20	0.4045**		
(p-value)	(0.0340)		
1701.99.90 vs 1701.99.10		-1.8015***	
(p-value)		(0.0000)	
0901.11.90 vs 0901.11.10			-0.1634
(p-value)			(0.1980)
Variance Components			
$SS_{Between}$	1.1234	19.2630	0.1202
SS_{Within}	1.9880	12.2734	1.0671
F-statistic	6.22	45.52	1.80
$Prob > F$	0.0072	0.0000	0.1982
Observations	25	31	18

Notes: Shading levels identify product-specific blocks. Bonferroni adjustment applied.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Mining sector. The variance decomposition analysis for the Mining sector (Table Appendix B.7) reveals a high degree of structural heterogeneity for zinc (2608.00). Unlike homogeneous sectors, the subheading-specific effect ($\sigma_u = 0.9513$) significantly outweighs the idiosyncratic factor ($\sigma_e = 0.3863$), resulting in a high intraclass correlation ($\rho = 85.84\%$). In turn, the DVLS model (Table Appendix B.8) provides further evidence of price differentiation. The estimated coefficient for the subheading 2608.00.00.90 is statistically significant at the 1% level ($\beta = 1.3453$, $p < 0.01$), confirming a systematic price premium relative to the *low grade* base subheading. This significant difference reinforces the conclusion that tariff-specific attributes are structural drivers of price dynamics in this sector.

TABLE APPENDIX B.7: *Mining Sector: Estimates of Variance Components*

	Zinc Concentrates (2608.00)
σ_u	0.9513
σ_e	0.3863
ρ	0.8584
Observations (N)	16
Subheadings	2

TABLE APPENDIX B.8: *Mining Sector: Heterogeneity Analysis through a DVLS Model*

	Zinc Concentrates (2608.00)
Reference Category (Base)	*Low grade* *(2608.00.00.10)*
Subheadings (vs. Base)	
Others	1.3453^{***}
(2608.00.00.90)	(0.0000)
Constant (Mean of Base)	-1.3782^{***}
	(0.0000)
F-test (Equality)	48.50
$Prob > F$ (Heterogeneity)	0.0000
Observations	16

Notes: Standard errors are robust. Subheadings refer to HS 10-digit codes.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The one-way ANOVA results are omitted since they are identical to those obtained from the DVLS model when the analysis is restricted to a single product across just 2 HS subheadings. This product is also taken to the extended-panel analysis, which ultimately classifies it as a homogeneous product.

HYDROCARBONS SECTOR. The variance decomposition analysis for the Hydrocarbon sector (Table Appendix B.9) provides clear statistical evidence of structural heterogeneity within oil derivatives (2710.00). The between-subheading variance ($\sigma_u = 2.3102$) significantly outweighs the idiosyncratic factor ($\sigma_e = 1.1828$), resulting in a high intraclass correlation coefficient ($\rho = 79.23\%$). This suggests that approximately 79% of the unit value variation is systematically explained by the subheading classification, confirming that price dynamics in this sector are driven by structural differences in product composition rather than solely by exogenous market shocks.

Table Appendix B.9: *Hydrocarbons Sector: Estimates of Variance Components*

	Oil Derivatives (2710.00)
σ_u	2.3102
σ_e	1.1828
ρ	0.7923
Observations (N)	78
Subheadings	5

By its part, the DVLS model (Table Appendix B.10) provides further evidence of these structural price differences. The estimated coefficients for the subheadings show statistically significant premiums or discounts relative to the *Light oils and gasoline* baseline (2710.12). Specifically, while *Medium and heavy oils* (2710.19) and *Waste oils (2710.91)* exhibit significant price discounts, other subheadings show distinct price premia. These significant coefficients ($p - value < 0.05$) reinforce the conclusion that tariff subheadings capture meaningful differences in product quality and market valuation.

Table Appendix B.10: *Hydrocarbons Sector: Heterogeneity Analysis through a DVLS Model*

	Oil Derivatives (2710.00)
Reference Category (Base)	*Light oils and gasoline (2710.12)*
Subheadings (vs. Base)	
Medium and heavy oils (2710.19)	-0.4010***
	(0.0087)
Oils containing biodiesel (2710.20)	0.8663*
	(0.0559)
Waste oils (PBCs) (2710.91)	-4.4253***
	(0.0000)
Other waste oils (2710.99)	1.4528**
	(0.0218)
Constant (Mean of Base)	-0.4176***
	(0.0001)
F-test (Equality)	13.62
$Prob > F$ (Heterogeneity)	0.0000
Observations	78

Notes: Standard errors are robust. Subheadings refer to HS 6-digit codes.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, the results from the one-way ANOVA (Table Appendix B.11) definitively reject the null hypothesis of equal means for oil derivatives ($p < 0.01$). The decomposition shows a substantial between-group sum of squares ($SS_{Between} = 1,471.18$) compared to the within-group variance, yielding a high F-statistic of 52.54. Consequently, the empirical evidence consistently points toward a high degree of structural heterogeneity within the Hydrocarbons sector, indicating that unit values at the 2710.00 heading are not homogeneous and that price fluctuations reflect distinct compositional segments of the oil derivative market.

Table Appendix B.11: *Hydrocarbons Sector: One-way ANOVA and Pairwise Comparisons*

	Oil Derivatives (2710.00)
Pairwise Comparisons (Diff.)	
2710.19 vs 2710.12	-0.4010***
(p-value)	(0.0080)
2710.20 vs 2710.12	0.8663*
(p-value)	(0.0550)
2710.91 vs 2710.12	-4.4253***
(p-value)	(0.0000)
2710.99 vs 2710.12	1.4528**
(p-value)	(0.0210)
2710.20 vs 2710.19	1.2673***
(p-value)	(0.0000)
2710.99 vs 2710.11	5.8781***
(p-value)	(0.0000)
Variance Components	
$SS_{Between}$	1,471.18
SS_{Within}	2,522.65
F-statistic	52.54
$Prob > F$	0.0000
Observations	901

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

II. Non-Traditional products

Agribusiness sector. The variance decomposition analysis for the Agribusiness sector (Table Appendix B.12) reveals a high degree of heterogeneity that distinguishes it from more traditional sectors. Several agribusiness products exhibit substantial subheading-specific effects (σ_u). A notable case is tangerines (0805.21), which presents an intraclass correlation (ρ) of 63.75%, indicating that the majority of the unit value variance is driven by structural differences between subheadings rather than temporary market fluctuations. Similarly, cocoa beans (1801.00) and mangoes (0804.50) show significant structural heterogeneity, with ρ values of 44.52% and 30.68%, respectively, suggesting that quality-related premiums or variety-specific pricing are fundamental drivers of their export performance.

In contrast, products such as bananas (0803.90) and quinoa (1008.50) align more closely with a commodity-like behavior, where the idiosyncratic factor (σ_e) significantly outweighs the subheading effect. Specifically, bananas exhibit the highest idiosyncratic volatility in the group ($\sigma_e = 0.7269$), resulting in a low ρ parameter of 4.12%, while quinoa follows a similar pattern with a ρ parameter of 8.00%. These results imply that for these specific goods, unit value fluctuations are primarily driven by exogenous shocks. Finally, products like cocoa butter, ginger, and dried peppers occupy an intermediate position, with ρ values ranging between 11.04% and 21.61%.

Table Appendix B.12: *Agribusiness Sector: Estimates of Variance Components*

	Mangoes (0804.50)	Tang. (0805.21)	Bananas (0803.90)	Ginger (0910.11)	Cocoa beans (1801.00)	Cocoa butter (1804.00)	Quinoa (1008.50)	Dried peppers (0904.21)
σ_u	0.2924	0.0984	0.1506	0.0961	0.4997	0.2499	0.1265	0.0607
σ_e	0.4395	0.0742	0.7269	0.1995	0.5578	0.4760	0.4290	0.1724
ρ	0.3068	0.6375	0.0412	0.1883	0.4452	0.2161	0.0800	0.1104
Obs. (N)	36	24	69	18	17	85	42	30
Subheadings	2	3	3	2	2	4	2	3

For Dried peppers and Bananas, HS codes reflect harmonized series. Tang: Tangerines.

To complement the previous analysis, the DVLS model was employed and the results are shown in Table Appendix B.13. The joint significance tests (F-tests) indicate that, at a 5% significance level, there is no statistical evidence of price heterogeneity for mangoes, bananas, ginger, quinoa, and dried peppers. These findings are highly consistent with the variance decomposition results, as these products –with the exception of mangoes– exhibit low Share of Between-Subheading Variation levels ($\rho < 20\%$).

In the specific case of mangoes, while the ρ coefficient suggests a moderate degree of structural variance (30.68%), the F-test fails to reject the null hypothesis of price equality at the 5% threshold ($p = 0.0655$). This marginal result places mangoes in a borderline category but reinforces the decision to prioritize the correction of more volatile products. Conversely, the high statistical significance found in the remaining agribusiness portfolio confirms that subheading-specific premiums are non-negligible.

The results from the One-way ANOVA (Table Appendix B.14) are broadly consistent with the variance decomposition and the DVLS model, providing a robust statistical basis for the identification of structural price breaks. A critical clarification is required regarding the case of mangoes (0804.50). While the previous DVLS regression yielded a marginal result at the 5% level ($p = 0.0655$), the F-test for the ANOVA model rejects the null hypothesis of equal means with a p-value of 0.0137. This rejection is driven by a between-group sum of squares ($SS_{Between}$) that is sufficiently large relative to the within-group idiosyncratic noise (SS_{Within}), unlike the cases of bananas or quinoa where stochastic volatility dominates the structural signal.

Following the tripartite reduced-panel validation of the variance components, the Wald tests from the DVLS model, and the ANOVA pairwise comparisons, the products classified as heterogeneous are tangerines, cocoa beans, cocoa butter, and mangoes. However, the final results reported for mangoes, tangerines, and ginger correspond to the extended-panel analysis.

Table Appendix B.13: *Agribusiness Sector: Heterogeneity Analysis through a DVLS Model*

	Mangoes	**Tang.**	**Bananas**	**Ginger**	**Cocoa beans**	**Cocoa butter**	**Quinoa**	**Dried peppers**
	(0804.50)	(0805.20)	(0803.90)	(0910.10)	(1801.00)	(1804.00)	(1008.90)	(0904.20)
Reference Category	*0804.50.10*	*0805.21*	*08003.90.11*	*0910.10*	*1801.00.11*	*1804.00.11*	*1008.90.10*	*0904.20.10.20*
Subheadings (vs. Base)								
0804.50.20	-0.4135*							
(p-value)	(0.0655)							
0805.22.00		0.1944***						
(p-value)		(0.0001)						
0805.29.00		0.1234***						
(p-value)		(0.0028)						
0803.00.12			-0.0175					
(p-value)			(0.9277)					
0803.00.19			0.2517					
(p-value)			(0.1988)					
0910.12.00				0.1359				
(p-value)				(0.1678)				
1801.00.19					-0.7066**			
(p-value)					(0.0236)			
1804.00.12						-0.1920		
(p-value)						(0.1572)		
1804.00.13						0.0497		
(p-value)						(0.7431)		
1804.00.20						0.4069***		
(p-value)						(0.0076)		
1008.90.19							-0.1789	
(p-value)							(0.1926)	
0904.20.10.10								0.0756
(p-value)								(0.2999)
0904.20.90								0.1201
(p-value)								(0.1627)
Constant (Mean Base)	0.4510**	0.0418	-0.1193	0.5533***	1.8096***	1.6932***	0.9330***	1.1060***
F-test (Equality)	3.62	12.73	0.95	2.09	6.34	6.27	1.76	1.09
$Prob > F$ (Heterog.)	0.0655	0.0002	0.3905	0.1678	0.0236	0.0007	0.1926	0.3513
Observations	36	24	69	18	17	85	42	30

Notes: Standard errors are robust. Shading identifies subheading-specific coefficients relative to their respective base.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Tang: Tangerines.

TABLE APPENDIX B.14: *Agribusiness Sector: One-way ANOVA and Pairwise Comparisons*

	Mangoes	**Tang.**	**Bananas**	**Ginger**	**Cocoa beans**	**Cocoa butter**	**Quinoa**	**Dried peppers**
	(0804.50)	(0805.21)	(0803.90)	(0910.11)	(1801.00)	(1804.00)	(1008.50)	(0904.20)
Pairwise Diff.								
.5020 vs. .5010	-0.4135**							
(p-value)	(0.0140)							
.2200 vs. .2100		0.1944***						
(p-value)		(0.0000)						
.2900 vs. .2100		0.1234**						
(p-value)		(0.0100)						
.1900 vs. .1100					-0.7066**			
(p-value)					(0.0200)			
.2000 vs. .1100						0.4069*		
(p-value)						(0.0870)		
.2000 vs. .1200						0.5989***		
(p-value)						(0.0030)		
Variance Comp.								
$SS_{Between}$	1.3059	0.1548	1.0732	0.0831	2.1148	3.0989	0.3237	0.0738
SS_{Within}	6.5678	0.1156	34.8730	0.6368	4.6668	18.3555	7.3601	0.8024
F-statistic	6.76	14.07	1.02	2.09	6.80	4.56	1.76	1.24
$Prob > F$	0.0137	0.0001	0.3678	0.1678	0.0198	0.0053	0.1922	0.3049
Observations	36	24	69	18	17	85	42	30

Notes: Shading identifies product-specific differences.

Non-significant pairs ($p > 0.10$) are omitted for brevity. Tang: Tangerines.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TEXTILE SECTOR. The results for the textile sector (Table Appendix B.15) reveals a more diverse structure than in primary sectors. For cotton T-shirts (6109.10), the intraclass correlation ($\rho = 0.1489$) suggests that approximately 15% of the unit value variation is explained by the subheading classification. In contrast, cotton shirts (6105.10) and textile T-shirts or vests (6109.90) show a lower structural dependence, with idiosyncratic factors (σ_e) accounting for the vast majority of volatility. These results indicate that while shirts and textile fibers T-shirts/vests could be homogeneous, T-shirts exhibit a moderate degree of subheading-specific pricing identity.

Table Appendix B.15: *Textile Sector: Estimates of Variance Components*

	Cotton T-shirts (6109.10)	**Cotton shirts** (6105.10)	**Fiber textile T-shirts/vests** (6109.90)
σ_u	0.1462	0.0861	0.0071
σ_e	0.3495	0.2980	0.3371
ρ	0.1489	0.0770	0.0004
Observations (N)	75	250	50
Subheadings	3	10	2

Building upon these findings, the DVLS model (Table Appendix B.16) identifies specific sources of heterogeneity. In cotton T-shirts, the *Striped* category (.32) shows a significant premium ($p = 0.0147$) over the uniform color base. Similarly, for cotton shirts, the F-test ($p = 0.0005$) strongly rejects homogeneity, driven by significant differences in *Yarn-dyed (striped)* men's shirts ($p = 0.0007$). Conversely, textile vests remain perfectly homogeneous ($p = 0.9170$). This suggests that for high-value-added textiles, physical characteristics like dyeing methods and patterns create significant price decoupling.

Table Appendix B.16: *Textile Sector: Heterogeneity Analysis through a DVLS Model*

	Cotton T-shirts (6109.10)	**Cotton shirts** (6105.10)	**Textile T-shirts/vests** (6109.90)
Reference Category (Base Subheading)	*Uniform Color (6109.10.00.31)*	*Men's Piece-dyed (6105.10.00.41)*	*Acrylic (6109.90.10)*
Subheadings (vs. Base)			
Striped (.32)	0.2526**		
(p-value)	(0.0147)		
Others (.39)	-0.0013		
(p-value)	(0.9888)		
Men's Yarn-dyed (.42)		0.2220***	
(p-value)		(0.0007)	
Men's Others cuffs (.49)		0.0272	
(p-value)		(0.6941)	
Men's Piece-dyed no cuffs (.51)		-0.0428	
(p-value)		(0.5463)	
Men's Yarn-dyed no cuffs (.52)		0.1048	
(p-value)		(0.1462)	
Men's Others no cuffs (.59)		-0.0237	
(p-value)		(0.7752)	
Men's Others no collar (.80)		-0.0304	
(p-value)		(0.7162)	
Boys' With collar (.91)		-0.0690	
(p-value)		(0.2805)	
Boys' With collar no cuffs (.92)		0.0258	
(p-value)		(0.7663)	
Boys' Others (.99)		-0.0236	
(p-value)		(0.8082)	
Other textile fibers (.90)			0.0100
(p-value)			(0.9170)
Constant (Mean of Base)	3.4805***	3.6545***	3.4269***
F-test (Equality)	3.75	3.45	0.01
$Prob > F$ (Heterogeneity)	0.0281	0.0005	0.9170
Observations	75	250	50

Notes: Standard errors are robust. Shading identifies product-specific subheadings.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The one-way ANOVA results (Table Appendix B.17) corroborate the regression findings. For cotton T-shirts and cotton shirts, the F-statistics (4.38 and 2.09, respectively) yield p-values below the 5% threshold, confirming that price means are not equal across classifications. Pairwise comparisons show that specific manufacturing processes (e.g., striped patterns) introduce structural price shifts. However, for T-shirts or vests of textile fibers, the near-zero F-statistic (0.01) validates the use of the 6-digit aggregate.

Table Appendix B.17: *Textile Sector: One-way ANOVA and Pairwise Comparisons*

	Cotton T-shirts (6109.10)	Cotton shirts (6105.10)	Textile vests (6109.90)
Pairwise Comparisons (Diff.)			
Striped (.32) vs. Uniform (.31)	0.2526**		
(p-value)	(0.0380)		
Others (.39) vs. Striped (.32)	-0.2539**		
(p-value)	(0.0370)		
Boys' w/ collar (.91) vs. Men's Striped (..42)		-0.2909**	
(p-value)		(0.0300)	
Men's Others cuffs (.49) vs. Men's Striped (.42)		-0.2647*	
(p-value)		(0.0850)	
Other textile fibers vs. Acrylic			0.0100
(p-value)			(0.9170)
Variance Components			
$SS_{Between}$	1.0691	1.6665	0.0012
SS_{Within}	8.7971	21.3125	5.4554
F-statistic	4.38	2.09	0.01
$Prob > F$	0.0161	0.0315	0.9170

Notes: Shading identifies product-specific subheadings.

Non-significant pairs ($p > 0.10$) are omitted for brevity.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Overall, the analysis of the Textile sector reveals a significant presence of price heterogeneity in high-value-added categories. The empirical evidence confirms that cotton T-shirts and cotton shirts exhibit structural price decoupling across their 10-digit subheadings. This phenomenon is largely driven by manufacturing complexities and specific fabric treatments; for instance, striped (yarn-dyed) garments consistently command a statistical premium over piece-dyed or uniform color alternatives.

Steel and Metallurgy sector. The variance decomposition analysis for the Steel and Metallurgy sector (Table Appendix B.18) indicates that raw silver (7106.91) exhibits a behavior characterized by high idiosyncratic volatility. Unlike the structural heterogeneity found in textile products and some agribusiness products, the results show a low intraclass correlation ($\rho = 3.33\%$), suggesting that the vast majority of price fluctuations are driven by exogenous market shocks ($\sigma_e = 1.1389$) rather than systematic differences between its component subheadings.

Table Appendix B.18: *Steel and Metallurgy Sector: Estimates of Variance Components*

	Raw silver (7106.91)
σ_u	0.2115
σ_e	1.1389
ρ	0.0333
Obs. (N)	50
Subheadings	2

To complement the analysis, the DVLS model (Table Appendix B.19) confirms the absence of statistically significant price gaps between subheadings. The joint significance test (F-test) fails to reject the null hypothesis of price equality ($p = 0.3578$), indicating that the two tariff codes within raw silver share a common price dynamic.

Table Appendix B.19: *Steel and Metallurgy Sector: Heterogeneity Analysis (DVLS)*

	Raw silver (7106.91)
Reference Category	*7106.91.10*
Subheadings (vs. Base)	
7106.91.20	-0.2991
(p-value)	(0.3578)
Constant (Mean Base)	6.1125***
(p-value)	(0.0000)
F-test (Equality)	0.86
$Prob > F$ (Heterog.)	0.3578
Observations	50

Notes: Robust standard errors applied.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The one-way ANOVA results are omitted since they are identical to those obtained from the DVLS model when the analysis is restricted to a single product of just two subheadings.

Chemicals sector. The analysis of the Chemicals sector (Table Appendix B.20) reveals a stark contrast in price dynamics. Dyes (3203.00) represents one of the most heterogeneous categories in the study, with an intraclass correlation (ρ) of 65.22%, indicating that structural differences between its nine subheadings drive the variance. Conversely, polypropylene films (3920.20) presents a ρ parameter of 17.71% which, while non-negligible, lacks the statistical backing to be classified as heterogeneous in subsequent tests.

Table Appendix B.20: *Chemicals Sector: Estimates of Variance Components*

	Dyes (3203.00)	**Poly. Films** (3920.20)
σ_u	0.9219	0.0648
σ_e	0.6732	0.1397
ρ	0.6522	0.1771
Obs. (N)	200	18
Subheadings	9	2

As shown in Table Appendix B.21, the DVLS model confirms the extreme heterogeneity in dyes ($F = 68.75$, $p - value < 0.01$). For polypropylene films, however, the F-test fails to reject the null hypothesis of price equality ($p - value = 0.1830$), reinforcing its behavior as a homogeneous commodity despite its moderate ρ parameter.

Table Appendix B.21: *Chemicals Sector: Heterogeneity Analysis (DVLS Model)*

	Dyes (3203.00)	**Poly. Films** (3920.20)
Reference Category	*3203.00.11*	*3920.20.10*
Subheadings (vs. Base)		
3203.00.12	-0.6409**	
(p-value)	(0.0126)	
3203.00.14	-0.8609***	
(p-value)	(0.0003)	
3203.00.15	-2.4863***	
(p-value)	(0.0000)	
3203.00.17	-1.5421***	
(p-value)	(0.0000)	
3203.00.19	-1.8271***	
(p-value)	(0.0000)	
3203.00.29	-0.7952***	
(p-value)	(0.0060)	
3920.20.90		0.0917
(p-value)		(0.1830)
Constant (Mean of Base)	3.9997***	0.9321***
F-test (Equality)	68.75	1.94
$Prob > F$ (Heterogeneity)	0.0000	0.1830
Observations	200	18

Notes: Standard errors are robust. Shading identifies product-specific subheadings.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, the ANOVA results (Table Appendix B.22) confirm that dyes will proceed to second stage of the ETCI heterogeneity diagnosis. The structural variation between its subheadings ($SS_{Between} = 162.67$) overwhelms the idiosyncratic noise, a condition not met by polypropylene films.

Table Appendix B.22: *Chemicals Sector: One-way ANOVA and Pairwise Comparisons*

	Dyes (3203.00)	**Poly. Films** (3920.20)
Pairwise Diff.		
.15 vs .11	-2.4862***	
(p-value)	(0.0000)	
.16 vs .15	2.6551***	
(p-value)	(0.0000)	
.90 vs .10		0.0917
(p-value)		(0.1830)
Variance Comp.		
$SS_{Between}$	162.6795	0.0378
SS_{Within}	86.5648	0.3122
F-statistic	44.87	1.94
$Prob > F$	0.0000	0.1830
Observations	200	18

Notes: Shading identifies product-specific comparisons. Pairwise comparisons use Bonferroni adjustment. Dyes displays only a selection of significant pairs ($p < 0.01$).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Fishing sector. The variance decomposition for frozen shrimps and prawns (0306.13) reveals a notable contribution of the subheading-specific effect to the total unit value variance. With an intraclass correlation (ρ) of 24.13%, the data suggests that structural differences between subheadings are a non-negligible driver of price dispersion, over and above idiosyncratic market shocks.

Table Appendix B.23: *Fishing Sector: Estimates of Variance Components*

	Frozen shrimps and prawns (0306.13)
σ_u	0.3521
σ_e	0.6243
ρ	0.2413
Obs. (N)	126
Subheadings	7

Analysis through the DVLS model (Table Appendix B.24) provides further evidence against the homogeneity assumption. Although not all subheadings exhibit individual statistical significance, the presence of specific highly significant categories triggers the rejection of the null hypothesis of price equality ($F = 11.66, p - value = 0.0000$). This indicates that the internal composition of the 6-digit heading significantly distorts the aggregate unit value.

Table Appendix B.24: *Fishing Sector: Heterogeneity Analysis (DVLS Model)*

	Frozen shrimps and prawns (0306.13)
Reference Category	*0306.13.11*
Subheadings (vs. Base)	
0306.13.12.00	0.4004***
(p-value)	(0.0000)
0306.13.13.00	0.2826***
(p-value)	(0.0000)
0306.13.14.00	-0.6588
(p-value)	(0.1436)
Constant (Mean of Base)	1.6921***
F-test (Equality)	11.66
$Prob > F$ (Heterogeneity)	0.0000
Observations	126

Finally, the results of one-way ANOVA (Table Appendix B.25) confirm the global significance of the model ($F = 4.94, p - value = 0.0002$). This analysis identifies two specific significant differences at the 5% level involving subheading 0306.13.14 (cooked shell-on tails) versus subheadings 0306.13.12 (peeled tails) and 0306.13.13 (raw shell-on tails). The negative signs of these differences indicate that cooked frozen prawns exhibit a systematically lower unit value than their raw counterparts. This price break likely reflects a market segmentation where raw, larger-sized specimens command a premium for high-end culinary use, whereas cooked presentations are often associated with industrial food services.

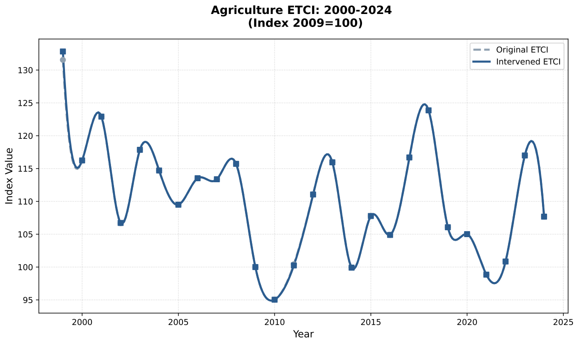
Table Appendix B.25: *Fishing Sector: One-way ANOVA and Pairwise Comparisons*

	Frozen shrimps and prawns
Pairwise Diff.	
0306.13.14 vs 0306.13.12	-1.0591***
(p-value)	(0.0000)
0306.13..14 vs 0306.13..13	-0.9413***
(p-value)	(0.0010)
Variance Comp.	
$SS_{Between}$	11.5583
SS_{Within}	46.3776
F-statistic	4.94
$Prob > F$	0.0002
Observations	126

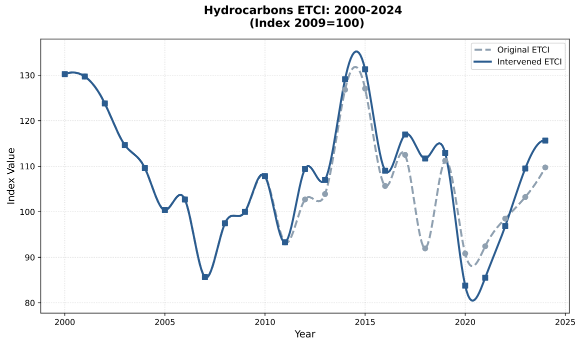
Appendix C Supplementary Figures on ETCI Corrections

The following figures present the complete evolution of the original and corrected ETCIs for traditional and non-traditional exports. These graphical representations reinforce the evidence summarized in Table 7, confirming that the adjustments have only minor implications for traditional exports while leading to more noticeable, though not transformative, changes in non-traditional sectors.

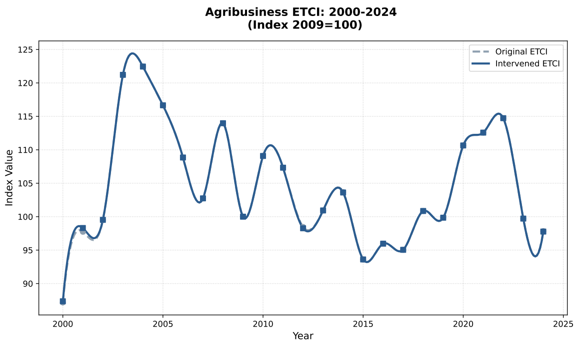
Figure 10: *Comparison between the original and corrected sector-level ETCIs after heterogeneity adjustments at the product level.*



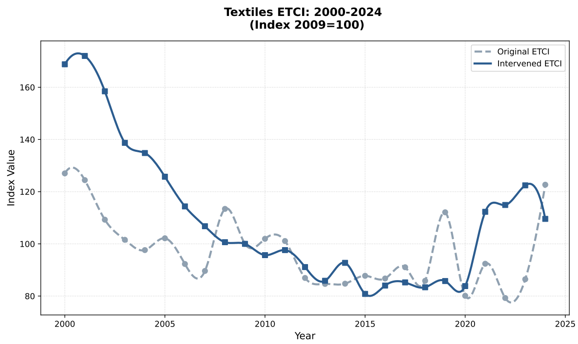
(a) *Agricultural sector*



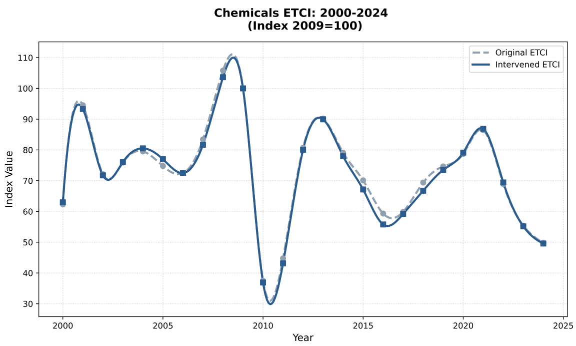
(b) *Hydrocarbon sector*



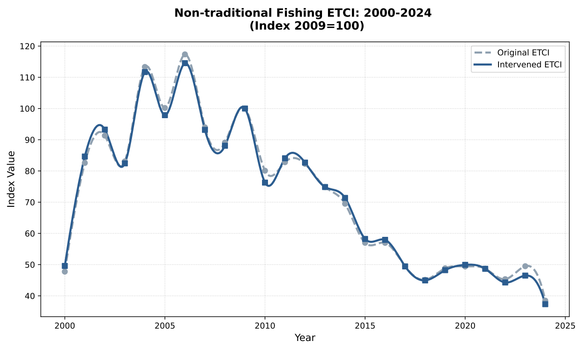
(c) *Agribusiness sector*



(d) *Textile sector*

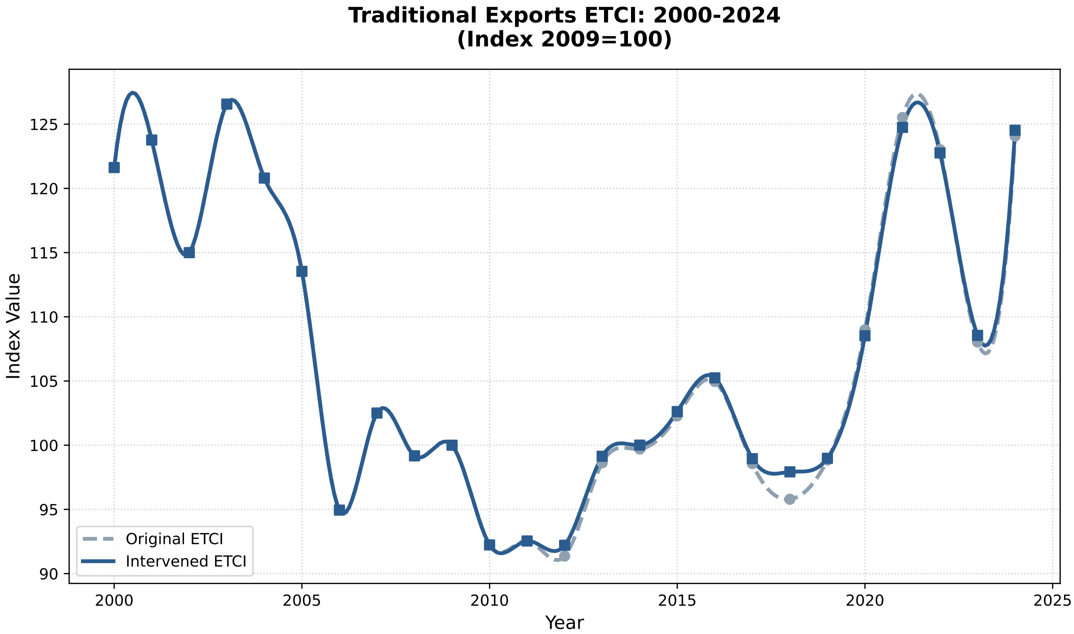


(e) *Chemical sector*

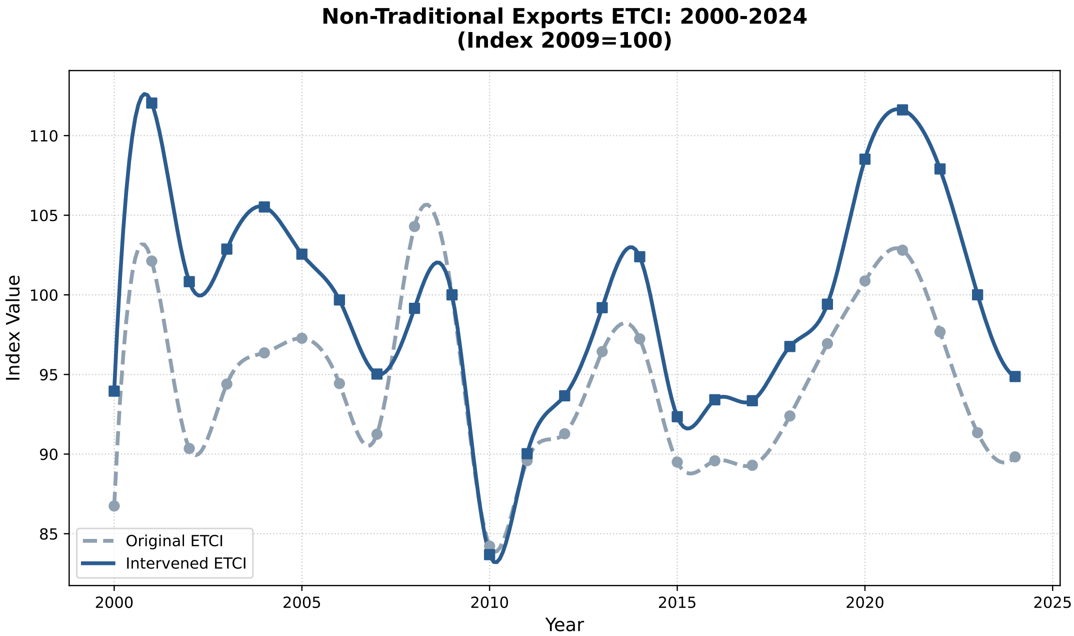


(f) *Non-traditional fishing sector*

Figure 11: *Comparison between the original and corrected ETCIs for traditional and non-traditional exports after heterogeneity adjustments.*



(a) *Traditional exports*



(b) *Non-traditional exports*

Appendix D Sectoral Transmission of Product-Level Historical Coherence

In a complementary exercise, we examine whether the product-level responses that were found to be historically coherent appear sufficiently broad to be reflected in the evolution of aggregate sectoral competitiveness. The results indicate that this transmission is not universal. In some cases, the effects identified at the product level seem to remain concentrated within a subset of export activities and therefore do not translate into noticeable changes at the sectoral level. By contrast, the episode associated with the Agricultural Promotion Regime, at the beginning of the century, exhibits evidence of a more generalized impact within agribusiness. Similarly, most episodes related to productive capacity expansion and export diversification (Panel B in Table 11) display sectoral manifestation, with the exception of one of the irrigation-related episodes, whose effects appear to be more localized, and the particular case of blueberries, which seems to represent a highly product-specific competitiveness gain. These findings suggest that some historical episodes were sufficiently pervasive to influence aggregate sectoral competitiveness, whereas others remained confined to a narrower set of products.

Table Appendix D.1: *Transmission of Product-Level Historical Coherence to the Sectoral Level*

Event	Sector	Expected	Period	Growth Window	Relative Performance	Sectoral Manifestation
EA1	Agribusiness	Positive	2000–2005	0.336	0.066	Yes
EA4	Agribusiness	Positive	2012–2017	-0.033	-0.023	No
EA4	Agriculture	Positive	2012–2017	0.051	0.019	Yes
EA5	Agribusiness	Controversial	2020–2024	-0.116	-0.041	Yes
EB2	Hydrocarbons	Positive	2009–2014	0.291	0.068	Yes
EB3	Mining	Positive	2012–2020	0.236	0.025	Yes
EB4	Agribusiness	Positive	2000–2005	0.336	0.066	Yes
EB4	Agribusiness	Positive	2013–2018	-0.001	-0.009	No
EB5	Agribusiness	Positive	2012–2017	-0.033	-0.023	No
EC2	Agribusiness	Negative	2016–2019	0.040	0.007	No
EC2	Fishing	Negative	2016–2019	0.032	0.039	No
EC3	Agribusiness	Negative	2022–2024	-0.148	-0.092	Yes
EC3	Fishing	Negative	2022–2024	-0.119	-0.039	Yes
EC5	Agribusiness	Negative	2015–2020	0.182	0.028	No
ED1	Textiles	Negative	2011–2016	-0.139	-0.017	Yes

Appendix E ETCI response to the Pandemic Episode

Although the pandemic was excluded from the historical coherence validation exercise due to the absence of a clear ex ante competitiveness response, the ETCI provides useful insights into the heterogeneous patterns observed across sectors and products during this episode. Sector-level evidence indicates that Mining, Agribusiness, Fishing, Steel and Metallurgy, and Textile sectors exhibited improvements according to both metrics, whereas Hydrocarbons, Chemicals, Agriculture, and Non-traditional Fishing sectors displayed deteriorations. These patterns are broadly coherent with the characteristics of the period. Sectors more closely linked to manufacturing supply chains and industrial demand tended to exhibit weaker competitiveness performance, consistent with the disruptions in production networks, logistics constraints, and the slowdown in global economic activity observed during the pandemic years. Likewise, the deterioration observed in Hydrocarbons is coherent with the substantial adjustment experienced by global energy markets during the pandemic, reflected in unprecedented movements in oil prices and potentially differentiated effects on the export dynamics of hydrocarbon-producing countries. In contrast, sectors associated with favorable commodity price developments, resilient food demand, or greater adaptability to changing consumption patterns generally displayed stronger competitiveness outcomes over the same period.

At the product level, the ETCI reveals substantial heterogeneity within sectors, highlighting that aggregate indicators may conceal important differences in the way export activities evolved throughout the pandemic episode. Taken together, these findings suggest that the ETCI captures economically meaningful patterns that are broadly consistent with the historical narrative surrounding this complex external shock.

Table Appendix E.1: *Pandemic Responses Across Export Sectors (2019–2022)*

Sector	**Growth**	**Relative**	**Products with Improved Competitiveness**	**Products with Deteriorated Competitiveness**
Agribusiness	+	+	Paprika, tangerines, grapes, onions, avocados, preserved asparagus, bananas.	Fresh asparagus, cocoa butter, cocoa beans, mangoes, blueberries, ginger.
Agriculture	–	–	Cotton	Coffee, sugar
Chemicals	–	–	None	Lacquers, colorants, zinc peroxide, sulfuric acid, polypropylene films.
Fishing	+	+	Fishmeal, fish oil	None
Hydrocarbons	–	–	None	Oil derivatives, crude oil, natural gas.
Mining	+	+	Copper concentrates, refined copper, lead, gold	Iron, zinc concentrates, refined zinc.
Non-Traditional Fishing	–	–	Fish roe, frozen shrimps and prawns	Mackerel, frozen fish, frozen squid, preserved squid.
Steel and Metallurgy	+	+	Copper wire rods, silver, copper plates and sheets	Jewellery, unwrought zinc.
Textiles	+	+	Cotton shirts, cotton T-shirts	Cotton jerseys, T-shirts/vests of other textile fibers.

Notes: The “Growth” column summarizes the sign of the cumulative ETCI change between 2019 and 2022, whereas “Relative” refers to the sign of the relative performance metric, defined as the difference between the average annual ETCI growth during the pandemic period and the corresponding historical average outside the pandemic window. Products listed under deteriorated competitiveness correspond to those exhibiting either a negative cumulative change or a deterioration in relative performance.

Appendix F Robustness Checks by Export Segment

Figure 12: *Robustness of the Traditional ETCI under Alternative Weighting Schemes*

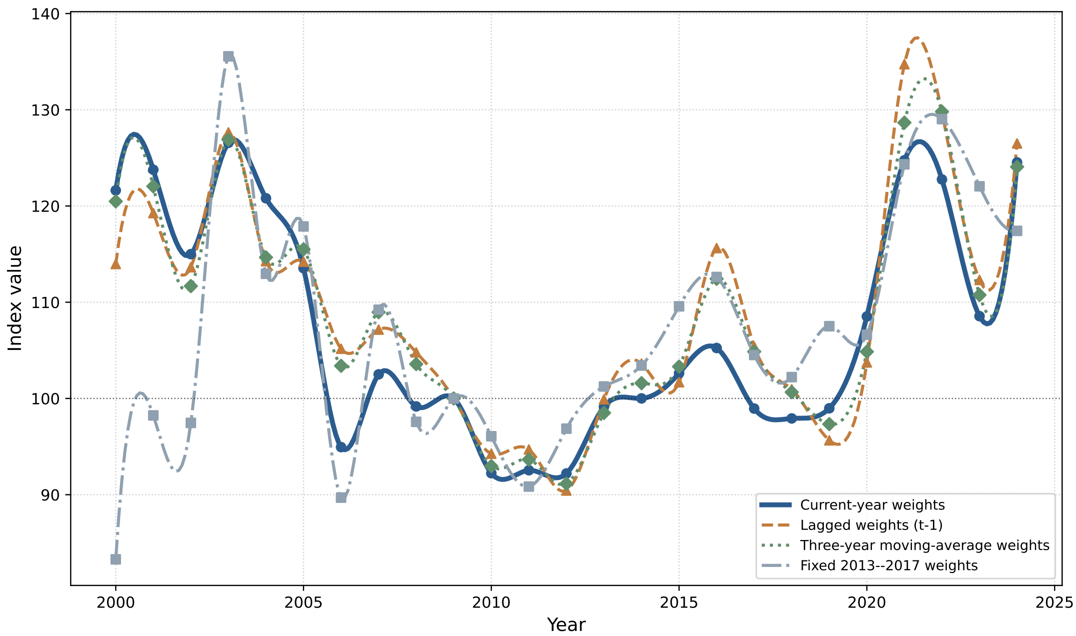


Figure 13: *Robustness of the Non-Traditional ETCI under Alternative Weighting Schemes*