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Global Competitiveness and Production Projection of Türkiye's Cherry Sector

Alptekin Mert Yılmaz [1], Rezzan Kasım [2,*] and Özge Can Niyaz Altınok [3]

[1] Department of Agricultural Economics, Faculty of Agriculture, Kocaeli University, Kocaeli 41285, Türkiye; alptekin.yilmaz@kocaeli.edu.tr
[2] Department of Horticulture, Faculty of Agriculture, Kocaeli University, Kocaeli 41285, Türkiye
[3] Department of Agricultural Economics, Faculty of Agriculture, Çanakkale Onsekiz Mart University, Çanakkale 17020, Türkiye; ozgecanniyaz@comu.edu.tr
* Correspondence: rkasim@kocaeli.edu.tr

Abstract

Türkiye is the world's largest cherry producer by volume, yet the value of its cherry exports has stagnated since the mid-2000s. This study tests whether growth in output translates into stronger export competitiveness. The Balassa RCA, Vollrath RXA and Laursen RSCA indices were computed annually for Türkiye and four reference exporters (Chile, the United States, Spain, and China including Hong Kong SAR) from FAO trade data for 1990–2023. Structural break tests, HAC-robust trend regressions, Mann–Kendall and Sen's slope tests, and a Box–Jenkins ARIMA(1,1,2) projection of domestic production to 2033 with rolling-origin validation were applied. Türkiye retained a revealed comparative advantage in every year (RSCA > 0), but a supremum-Wald test identified a break in 2006 (95% CI 2002–2009). Competitiveness rose over 1990–2004 (RSCA slope +0.026 yr^{-1}, $p < 0.001$) and declined over 2004–2023 (-0.023 yr^{-1}, $p < 0.001$), with RCA falling from 20.1 to 2.9. Production growth was positively associated with contemporaneous RSCA changes ($\beta = 0.33$, $p = 0.015$), yet the post-2004 period carried an independent decline of 0.051 index points per year ($p = 0.002$). Meanwhile, Chile consolidated dominance and China approached parity. Production is projected to reach 0.88–0.94 million t by 2033. The divergence between expanding output and weakening competitiveness is reported as an association, consistent with rising domestic absorption and limited post-harvest logistics and market diversification capacity.

Keywords: *Prunus avium*; cherry exports; revealed comparative advantage; box–Jenkins; export competitiveness; agricultural trade policy

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1. Introduction

Cherries (*Prunus avium* L.) are among the most valuable temperate fruits in international trade, commanding premium prices relative to other stone fruits and generating substantial export revenue for leading producers [1–3]. World output has expanded markedly over three decades, driven by rising demand in emerging economies, the diffusion of cold-chain logistics that made long-distance trade in a highly perishable fruit feasible, and continued investment in high-yielding cultivars [2,4]. According to FAOSTAT (the FAO Corporate Statistical Database), world cherry production exceeded 4.5 million t in 2023, with Türkiye, the United States, Chile, Uzbekistan, and Iran supplying most of it [1].

Türkiye occupies a structurally distinctive position. As the largest producer by volume it accounts for roughly 15–18% of world output in a given year, with production concen-

trated in İzmir, Afyonkarahisar, Konya, and Isparta, where conditions favour high-quality sweet cherry cultivation [5–7]. The sector supports hundreds of thousands of smallholder households [5,8]. Yet Türkiye's share of world cherry export value has not grown in step with its output, the central puzzle motivating this study.

Three features make the Turkish case worth analysing on its own terms rather than as one observation in a cross-country panel. First, the scale–position mismatch is unusually stark: no other leading exporter combines the world's largest harvested area and output with a mid-tier and declining share of world export value, which makes Türkiye an unusually clean setting in which to ask, 'What breaks the link between physical volume and traded value?' Second, the sector is dominated by smallholdings and by fragmented post-harvest infrastructure, in contrast to the vertically integrated, export-oriented models of Chile and the United States. The consequences of that organisational structure for export performance are of direct interest to the many Mediterranean and Central Asian producers whose sectors are similarly organised. Third, Türkiye's external trading environment was reshaped over the study period by a sequence of country-specific events—entry into the EU Customs Union in 1996, the currency crises of 2001 and 2018, and successive changes in access to the Russian and EU markets—that have no counterpart in most comparator countries and that a pooled analysis would average away.

We organise the analysis around this production–export paradox: Türkiye leads the world in cherry production while its export competitiveness has weakened. The guiding research question is whether output growth is being converted into export-market gains, and if not, what the evidence implies about where the binding constraint lies. We test the following working hypothesis:

H1. *Growth in Türkiye's cherry production does not translate proportionally into stronger export competitiveness.*

H1 is directly testable with the data assembled here. It implies that a period of sustained output growth should not be accompanied by a sustained rise in revealed comparative advantage. The mechanisms that might account for such a divergence are stated separately, as exploratory propositions rather than as components of the hypothesis, because the present design contains no direct measures of them and it would be misleading to present them as though they were being evaluated:

P1. *A growing share of incremental output is absorbed by domestic demand, reducing the exportable surplus relative to total supply.*

P2. *Post-harvest and cold-chain capacity constrains the set of high-value destinations that can be served reliably.*

P3. *Limited quality differentiation and certification restrict the price premia obtainable in those destinations.*

P4. *Concentration of export destinations leaves realised export value exposed to demand and policy shocks in a small number of markets.*

P1–P4 are assessed in this paper against descriptive evidence only, and no claim of testing is made for any of them. Testing them would require consistent annual measures of post-harvest losses, cold-chain capacity, certification uptake, destination concentration, and product quality, none of which is available for the whole of 1990–2023. Section 5.3 sets out the multivariate export performance model that such a test would require.

It is important to be explicit about what the indices used here can and cannot establish. Revealed comparative advantage measures describe a country's realised position in observed trade flows. They do not, on their own, identify the mechanisms that move that

position. Accordingly, H1 is confined to the relationship that the indices can adjudicate and the candidate mechanisms are stated separately as P1–P4, which the present design can illustrate but cannot test.

Several mechanisms could plausibly drive a wedge between production and export competitiveness, and we introduce them here to ground the later interpretation. First, where domestic demand grows faster than output, a rising share of incremental production is absorbed at home and the exportable surplus shrinks relative to total supply [9]. Second, for a fruit as perishable as cherries, competitiveness in high-value distant markets depends heavily on pre-cooling, controlled-atmosphere storage, and refrigerated transport; gaps in this chain raise post-harvest losses and narrow the set of reachable markets [10–12]. Third, product differentiation through geographical-indication and quality certification can insulate export prices from commodity competition [13]. Fourth, exchange rate volatility can disrupt pricing and contracting and divert buyers toward more stable-currency suppliers [8,14]. Finally, competitiveness is relative: the rapid rise of rival exporters can erode a country's standing even when its own fundamentals are unchanged.

Competitiveness in agricultural trade has been assessed since Balassa (whose RCA (revealed comparative advantage) index operationalised comparative advantage from observed trade [15]. Vollrath proposed the RXA (relative export advantage) [16] index to remove the double-counting in the original formulation, and Laursen [17] and Dalum et al. [18] introduced the RSCA (revealed symmetric comparative advantage) transformation to correct the right-skew of RCA and render it suitable for statistical comparison. These measures have since been applied across a wide range of agri-food sectors and country settings [19–26]. Their limitations are equally well established and bear directly on how the present results should be read. Because the indices are computed from realised export values, they are shaped simultaneously by prices, exchange rates, and destination demand. They are silent on the cost and productivity fundamentals that trade theory takes comparative advantage to be about [17,27]. A fall in the index is therefore consistent with several structurally distinct causes—loss of cost competitiveness, reallocation of supply to the domestic market, or faster growth by rivals—that the index alone cannot separate.

What the applied literature has established about the determinants of horticultural export performance can be grouped around the four propositions set out above. On domestic absorption (P1), demand studies in middle-income countries report income elasticities for fresh fruit high enough that domestic consumption claims a rising share of incremental output as incomes grow, mechanically compressing the exportable surplus even where production expands [9]. On post-harvest and logistics capacity (P2), work on perishable value chains identifies pre-cooling, controlled-atmosphere storage, and unbroken refrigerated transport as the binding technical constraints on reaching distant premium markets, with losses in weakly integrated chains large enough to alter realised export value materially [10–12,28,29]. On quality differentiation (P3), European evidence indicates that geographical indications and certification schemes can sustain price premia in fruit markets that would otherwise converge on commodity pricing [13,30]. On destination concentration (P4), studies of agri-food trade report that concentrated export portfolios raise the variance of realised export value and slow recovery from market-specific shocks [31–33]. Finally, the intermediating role of re-export and trade-hub entities in the East Asian fruit trade is a structural feature of the market rather than evidence of production capacity in the hub economy—a distinction that is essential to the comparator design adopted in Section 2.2.

Applied to cherries specifically, the evidence base is considerably thinner. Previous studies [3,34] report RCA-type indices for Turkish cherries over shorter windows and without a comparator set spanning the counter-seasonal, established Northern-Hemisphere, and

Mediterranean competitive models. Ninaquispe et al. [11] analyse the Peruvian and Chilean chains from a value-chain rather than an index perspective. None of these studies asks whether the movement in Turkish competitiveness is monotonic or phase-dependent, which is the question the structural break analysis of Section 2.4 addresses. Nor do any of the studies link the trade position to the theoretical chain running from production growth through domestic absorption to the exportable surplus that value-based RCA actually measures. A separate literature applies Box–Jenkins ARIMA (autoregressive integrated moving average) models to agricultural output [35–40]. A recurring criticism of that literature points out its reliance on in-sample information criteria rather than out-of-sample validation against simple benchmarks. Recent contributions argue for rolling-origin evaluation and forecast combination as minimum standards in agricultural forecasting [41,42]. Section 2.5 adopts that standard. The gap this study addresses is therefore specific: whether, over a horizon long enough to contain a full competitive cycle, Türkiye's revealed advantage in cherries has moved independently of its production expansion, and whether that movement is statistically distinguishable from a stable series once break-date selection and residual dependence are handled explicitly.

The contribution of this study is deliberately framed as descriptive and diagnostic. The two components are not estimated within a single empirical model: the indices characterise realised trade position, while the ARIMA model extrapolates production. Placing them side by side does not by itself demonstrate that production growth and export competitiveness are systematically disconnected. Earlier cherry-competitiveness work [3,11,34,43] reports RCA-type indices without a forward-looking supply benchmark, while ARIMA fruit-production studies [38,40] forecast output without linking it to trade position. What the pairing provides is narrower but, we would argue, still useful. It establishes the sign and the timing of the movement in revealed advantage, establishes that the supply base is not projected to contract, and thereby excludes one candidate explanation—insufficient production volume—for the observed weakening. We do not claim that the combination constitutes a test of the mechanisms in P1–P4. The remainder of the paper is organised as follows. Section 2 sets out data, the comparator framework, the indices, the trend-testing strategy, and the ARIMA procedure. Section 3 reports results. Section 4 discusses mechanisms and limitations, and Section 5 concludes with empirically anchored policy implications.

2. Materials and Methods

2.1. Data and Study Period

Two FAOSTAT series underpin the analysis: cherry (*Prunus avium*) production, and cherry export value and volume [1]. The competitiveness analysis covers 1990–2023, the longest interval for which complete trade data are available for all study countries. The year-on-year forecast extends production to 2033. To avoid the inconsistency of mixing series of different lengths, all index calculations and trend tests use 1990–2023 exclusively. Where the most recent FAOSTAT and national figures (2024) are reported, they are used only for the descriptive structural snapshot of the sector (Tables 1–4) and are clearly labelled as such; they are not included in the index series or the trend regressions. National structural indicators (tree numbers, orchard area, yield, per-capita consumption, self-sufficiency) are drawn from the Turkish Statistical Institute [44]. All monetary values are in current US dollars, consistent with standard RCA practice, in which currency effects cancel through the share ratios. Production is in metric tonnes. Computations were performed using Python 3.14 with the statsmodels 0.14.6 package [45].

Table 1. World cherry harvested area, leading countries, 2024.

Country	Harvested Area (ha)	Share (%)
Türkiye	77,528	16.38
Chile	76,447	16.16
United States	38,688	8.18
Syrian Arab Republic	30,358	6.42
Spain	28,920	6.11
Italy	28,290	5.98
Iran	19,484	4.12
Uzbekistan	17,264	3.65
Greece	16,140	3.41
Russian Federation	10,460	2.21
Rest of world	129,601	27.39
World	473,180	100.00

Source: Ref. [1].

Table 2. World cherry production, leading countries, 2024.

Country	Production (t)	Share (%)
Türkiye	726,500	23.41
Chile	596,968	19.24
United States	333,120	10.73
Uzbekistan	209,025	6.74
Iran	136,921	4.41
Greece	124,010	4.00
Spain	121,060	3.90
Syrian Arab Republic	98,449	3.17
Italy	80,670	2.60
Ukraine	55,700	1.79
Rest of world	621,094	20.01
World	3,103,517	100.00

Source: Ref. [1].

Table 3. Cherry export value by country, five-year period means, 2000–2024 (million USD—United States dollars).

Period	Chile	China †	United States	Türkiye	Spain
2000–2004	29.3	0.6	160.6	63.3	23.8
2005–2009	106.4	7.3	261.4	109.4	52.1
2010–2014	419.3	82.5	446.4	147.0	76.5
2015–2019	913.9	448.7	492.9	162.0	76.0
2020–2024	2300.7	931.2	446.7	192.9	116.9

† China (incl. Hong Kong SAR); reflects re-export/trade-hub activity (see Section 2.2). Source: authors' calculations from [1]. Full annual series in Supplementary Table S4.

Table 4. Türkiye cherry sector structural indicators, five-year period means, 2004–2024.

Period	Bearing Trees (Million)	Orchard Area (da)	Yield (kg/Tree)	Production ('000 t)	Per-Capita Cons. (kg)	Self-Suff. (%)
2004–2008	10.67	489,545	29.4	314.4	3.4	120.7
2009–2013	15.74	700,724	28.6	447.9	4.5	117.2
2014–2018	20.70	829,367	27.4	569.5	5.3	117.3
2019–2024	21.76	809,326	32.2	699.7	6.2	115.9

Per-capita consumption averages exclude years not reported in the source. Source: Ref. [44]. Full annual series in Supplementary Table S5.

2.2. Selection of Comparator Countries

Four reference exporters were selected on transparent, pre-specified criteria rather than convenience. Chile and the United States are the two largest cherry exporters by value over the study period and represent, respectively, the Southern-Hemisphere counter-seasonal supplier and a long-established Northern-Hemisphere exporter. Spain is included as a comparable Mediterranean producer whose competitive trajectory offers an instructive contrast to Türkiye. Together, these three span the principal competitive models against which Türkiye is benchmarked. The fourth entity, reported in FAOSTAT as "China, Hong Kong SAR," requires specific clarification because it functions primarily as a trade and re-export hub rather than as a production competitor: a large share of the cherries it re-exports are physically grown elsewhere and transit Hong Kong en route to mainland and regional markets. We therefore retain it for two reasons—first, because it is the single most consequential node in the East Asian cherry trade that historically absorbed Turkish exports, and second, because its revealed-advantage trajectory captures the structural reorientation of global cherry trade toward Asian demand. Throughout, we read this entity as a trade/re-export position and label it "China (incl. Hong Kong SAR)" to distinguish it from mainland Chinese domestic production; readers should not interpret its indices as those of a primary production competitor. This distinction directly conditions the interpretation in Sections 3 and 4. Two further points support retaining this entity. Its export value is very large relative to any plausible domestic harvest—at its 2020–2024 average of USD 931 million it far exceeds what its area under cherry cultivation could generate—which is itself the clearest internal evidence that the flows are predominantly re-exports rather than domestic output. Furthermore, excluding it would remove from the comparator set precisely the node through which the reorientation of world cherry demand toward Asia has been intermediated, leaving the competitive pressure on mid-tier suppliers such as Türkiye invisible.

Two large producers that appear prominently in the descriptive tables—Uzbekistan and Iran—are deliberately excluded from the comparator set, and the reason is a data constraint rather than a substantive judgement. Both are significant by production volume (Table 2), but neither reports a cherry export-value series to FAOSTAT that is continuous and comparably compiled across the whole of 1990–2023. Because RCA-type indices are ratios of a country's commodity export share to its total export share, years in which either the numerator or the denominator is missing or compiled on a different basis produce index values that are not comparable over time, and a comparator with a discontinuous series would weaken rather than strengthen the trend tests of Section 2.4. We therefore retain both countries in the production tables, where coverage is complete, and exclude them from the index analysis. Section 5.3 identifies their inclusion, once continuous trade series become available, as a specific extension.

2.3. Competitiveness Indices

Three complementary indices are used; employing more than one mitigates the known weaknesses of any single measure and allows cross-validation. The Balassa RCA [15] is

$$RCA_{ij} = (X_{ij}/X_{it})/(Xw_j/Xw_t) \quad (1)$$

where X_{ij} is country i's export value of cherries, X_{it} its total exports, X_{vj} world cherry exports, and X_{vt} total world exports. RCA > 1 indicates a revealed comparative advantage. The Vollrath (RXA [16] index removes the country-and-commodity double-counting by

excluding i and j from the reference totals; values above unity indicate a relative export advantage. The Laursen RSCA [17] rescales RCA to a symmetric, bounded interval

$$RSCA_{ij} = (RCA_{ij} - 1)/(RCA_{ij} + 1) \quad (2)$$

with RSCA $\in (-1, +1)$; positive values denote advantage. The symmetry and boundedness remove the right-skew of raw RCA, making RSCA the preferred series for cross-country comparison and for the trend tests below [17,18].

In plain terms, the three indices answer three slightly different questions about the same trade flows. RCA asks whether cherries account for a larger share of a country's exports than it does of world exports: a value of 5 means cherries are five times as prominent in that country's export basket as in the world's. RXA asks the same question but removes the country itself and the commodity itself from the world benchmark, so that a large exporter is not partly compared against its own contribution. This adjustment matters most for countries that dominate the commodity and is why Chile's RXA exceeds its RCA. RSCA rescales RCA onto the interval $(-1, +1)$ with zero as the neutral point, so that advantage and disadvantage become symmetric. On the raw RCA scale, a move from 1 to 2 and a move from 1 to 0.5 are equal and opposite in economic terms but very different in numerical magnitude, whereas on the RSCA scale they are equal and opposite in both. That symmetry is what makes RSCA, rather than RCA, the appropriate series for the regression-based trend tests reported below.

Interpretive status of the indices—These are descriptive measures of realised trade position. They are computed from monetary trade values and therefore reflect prices, exchange rates, and demand conditions as well as underlying competitiveness. They do not directly capture production costs, productivity, product quality, logistics performance, contract structure, trade barriers, or market access. We treat them as diagnostic, not causal, and frame all mechanism-level statements accordingly.

2.4. Trend Estimation and Structural Break

To resolve the apparent tension between a flat long-run trend and a post-peak decline, we estimate time trends for Türkiye over the full sample and over sub-periods defined by a break date. The break date is not selected by inspection. The sample was split at 2004 because that year is the observed maximum of the RCA and RSCA series. Choosing the extremum of a series and then estimating separate trends on either side of it will, however, tend mechanically to produce an inverted-U pattern, and the resulting *p*-values do not account for the fact that the break date was itself estimated from the same data. We therefore replace that procedure with a formal one.

The break date is estimated by the supremum-Wald or Quandt likelihood-ratio test [46] in the form developed by Andrews [47]) applied to the trend regression, trimming 15% of the observations at each end of the sample and using the Andrews asymptotic critical values [47], which are constructed precisely for the case in which the break date is unknown and estimated. This is complemented by the Bai and Perron) multiple-break procedure [48,49], which allows for more than one break and selects the number of breaks by the Schwarz Bayesian Information Criterion (BIC) [50] and by the LWZ (Liu–Wu–Zidek) criterion [51]. The confidence interval for the break date is obtained by a residual bootstrap with 1000 replications, in which the sup-Wald date is re-estimated on each resampled series. A Chow test at the estimated date, following [52], is reported as supplementary evidence only. Three robustness checks follow: the sub-period regressions are re-estimated at alternative break dates within the Bai–Perron confidence interval; the sample is re-estimated with the peak observation deleted; and the analysis is repeated with 2022, the observed trough, deleted.

The trend regressions themselves are estimated with Newey–West heteroskedasticity- and autocorrelation-consistent standard errors, the lag truncation being set by the Newey and West automatic bandwidth rule [53], because annual trade indices are serially dependent and conventional OLS standard errors would be understated. Residual diagnostics are reported for every trend regression in Supplementary Table S7: Breusch–Godfrey [54] for serial correlation, Breusch and Pagan [55] and White [56] for heteroskedasticity, Jarque and Bera [57] for normality, and Cook distance [58] for influential observations. Because RSCA is bounded on $(-1, +1)$, a linear trend is not appropriate near the boundaries. Alongside the linear specification we therefore report a fractional-logit specification estimated by quasi-maximum likelihood on the rescaled series $(\mathrm{RSCA} + 1)/2$ following [59], which respects the bounds by construction. Finally, because all of the foregoing are parametric, we report the non-parametric Mann–Kendall trend test [60,61] and the associated Sen slope estimator [62], which require no functional form for the trend and are robust to non-normality and to individual outliers.

Finally, we estimate directly whether movements in production are statistically associated with movements in competitiveness, rather than inferring a disconnect from the two analyses being reported side by side. Both series are first tested for unit roots with the augmented Dickey–Fuller [63] and KPSS tests [64] and for a cointegrating relationship with the Engle and Granger procedure [65]. Because they prove to be integrated of order one and not cointegrated, the association is estimated in first differences, regressing the annual change in RSCA on the contemporaneous growth rate of production, on that growth rate with two lags, and on both together with an indicator for the post-break regime and its interaction with production growth. All specifications use Newey–West standard errors with two lags. This is a bivariate reduced-form relationship, not a structural model of export performance. Its purpose is to establish whether the production series carries any explanatory content for the index series once non-stationarity, the structural break, and lagged effects are accounted for.

2.5. Production Forecasting: Role and Specification

The Box–Jenkins ARIMA model is applied to Türkiye's annual cherry production over 1990–2023. Its role in this study is deliberately limited: it forecasts production, that is, the supply-side base, and is not a model of export competitiveness. It provides a forward-looking benchmark against which the supply-constraint reading of the paradox can be assessed—if output is projected to keep rising while competitiveness has fallen, supply volume is unlikely to be the binding constraint, but it cannot by construction explain trade performance, and it cannot incorporate climate shocks, disease outbreaks, price movements, or trade-barrier changes. These limitations are made explicit in Section 4.

Identification followed the standard four stages. Stationarity was assessed with the augmented Dickey–Fuller (ADF) [63], Phillips–Perron (PP) [66], and KPSS tests [64], the first two testing a unit-root null and the third a stationarity null so that their joint use is robust to conflicting single-test inferences. Orders p and q were selected by a grid search over all ARIMA(p, 1, q) with $p, q \in \{0, 1, 2, 3\}$, ranked primarily by the Akaike Information Criterion (AIC) [67] with BIC and HQIC as supplementary criteria, subject to residual adequacy (Ljung–Box at lag 10, $p > 0.05$). The selected model was estimated by maximum likelihood and residuals were checked for autocorrelation (Ljung–Box) [68], normality (Jarque–Bera), and stability [69]. Out-of-sample forecasts for 2024–2033 were generated with 95% confidence intervals. Because annual ARIMA forecasts of a single series are sensitive to specification, the selected model is not reported on the strength of in-sample criteria alone. Computations used Python's statsmodels [45].

Minimum AIC and a residual portmanteau test establish only that a model fits the data it was estimated on; they are not evidence that it will forecast well. The specification is therefore validated out of sample using a rolling-origin (expanding-window) design: the model is re-estimated at every origin from 2008 to 2022 and used to forecast one, two, and three years ahead, yielding 42 out-of-sample forecasts per model. Accuracy is summarised by mean absolute error, root mean square error, and mean absolute percentage error. Interval quality by the empirical coverage of the nominal 95% forecast intervals. ARIMA(1,1,2) is benchmarked against a random walk, a random walk with drift, a deterministic linear trend, simple exponential smoothing, Holt's linear trend, a damped-trend specification, and the lower-order ARIMA(1,1,1) and ARIMA(0,1,1) alternatives. Pairwise differences in squared-error loss are tested with the Diebold and Mariano statistic [70]. We also report the equal-weighted combination of the three best-performing specifications, since forecast combinations are frequently more accurate than, and always less exposed to selection error than a single chosen model [71,72]. Model stability is assessed from the moduli of the estimated autoregressive and moving-average roots, from re-estimation over alternative windows beginning in 1961, 1980, 1995, and 2000, and from a leave-one-year-out influence analysis of the ten-year projection. Because FAOSTAT has since published the 2024 observation, which was not used in estimation, that year additionally serves as a genuine real-time hold-out.

3. Results

3.1. Competitiveness in Comparative Perspective

Türkiye leads the world in both cherry area and output. In 2024, it held the largest harvested area (77,528 ha; 16.4% of the world total of 473,180 ha), marginally ahead of Chile (76,447 ha; 16.2%), and the largest production (726,500 t; 23.4% of 3.10 million t), ahead of Chile (596,968 t; 19.2%) (Tables 1 and 2). Türkiye's production share exceeds its area share, which is consistent with above-average yields per hectare, whereas Chile's area and production shares are closely matched. The two countries together supply about 43% of world output. This near-parity in physical supply is the essential backdrop to the paradox: as shown below, it coincides with a wide and widening gap in export competitiveness.

Five-year averages of export value (Table 3) show a fundamental reordering of the market. Chile's average export value rose from about USD 29 million in 2000–2004 to USD 2.30 billion in 2020–2024, and China (incl. Hong Kong SAR) from under USD 1 million to USD 931 million, the latter consistent with its role as the principal Asian trade node. Over the same span, the United States plateaued near USD 0.45–0.49 billion and Spain remained modest. Türkiye's average export value grew far more slowly—from USD 63 million to USD 193 million—despite its production leadership, the clearest monetary expression of the pattern this study examines.

Five-year means of the national structural indicators (Table 4) clarify how output has grown and where it has gone. Bearing-tree numbers roughly doubled from about 10.7 million (2004–2008) to 21.8 million (2019–2024) and orchard area expanded correspondingly, while yield per bearing tree was essentially flat (27–32 kg). Output growth has therefore come mainly from the extensive margin—more trees and area—rather than the intensive margin of higher productivity per tree, a pattern less likely to deliver the quality gains that underpin premium export prices. Meanwhile, per-capita consumption rose from 3.4 to 6.2 kg and the self-sufficiency rate eased from about 121% to 116%, both consistent with a growing share of incremental output being absorbed domestically rather than exported.

Table 5 summarises the three indices over 1990–2023. Chile records the highest means and significant positive trends across all indices. China (incl. Hong Kong SAR) shows the largest variability, reflecting its transition from near-zero values before 2008 to high values thereafter. The United States and Spain show significant negative trends. For Türkiye,

the full-sample trend slopes are statistically insignificant (RCA $p = 0.31$; RXA $p = 0.34$; RSCA $p = 0.17$), which on its own might suggest a stable competitive position.

Table 5. Descriptive statistics and OLS (ordinary least squares) trend slopes of the indices, 1990–2023.

Country	RCA Mean	RCA Slope	RXA Mean	RXA Slope	RSCA Mean	RSCA Slope	*n*
Türkiye	8.44	−0.087 ns	9.51	−0.101 ns	0.728	−0.003 ns	34
Chile	27.68	+2.123 ***	42.01	+4.086 ***	0.872	+0.007 ***	34
China †	10.55	+1.229 ***	13.56	+1.776 ***	−0.011	+0.073 ***	34
United States	2.58	−0.068 ***	3.62	−0.128 ***	0.411	−0.013 ***	34
Spain	1.46	−0.038 ***	1.53	−0.040 ***	0.133	−0.012 **	34

Slopes are per-year OLS coefficients. *** $p < 0.001$; ** $p < 0.01$; ns: not significant at 10%. † China (incl. Hong Kong SAR). Source: authors' calculations from [1].

The insignificant full-sample slope is, however, an artefact of two opposing phases that cancel, and the break separating them is now dated formally rather than by inspection. The supremum-Wald statistic for a break of unknown date in the RSCA trend regression is 74.69 in F form, far above the Andrews 1% critical value of 7.78 for two restrictions under 15% trimming [47]. The break is located at 2006, meaning that 2005 is the last year of the first regime, with a residual bootstrap 95% confidence interval of 2002–2009 for that date. For RCA and RXA, the statistics are 90.77 and 80.49, both significant at 1%, with break dates of 2002 and confidence intervals of 2001–2007. Under the LWZ criterion, the Bai–Perron procedure selects a single break at 2006 for RSCA and 2002 for RCA and RXA. Under BIC, it selects two, the later of which falls in 2008. The 2004 date used below therefore lies inside the estimated 95% confidence interval for all three indices rather than being an arbitrary selection of the series maximum. A Chow test at that date returns F = 74.13 ($p < 0.001$) for RSCA. The full set of break tests is reported in Table 6. We retain 2004 for continuity with the descriptive narrative and with Table 3, and we verify below that no conclusion depends on it. Splitting the series at 2004 reveals two strong and statistically significant trends in opposite directions (Table 7). Between 1990 and 2004, competitiveness rose sharply (RSCA slope = +0.026 yr^{-1}, $p < 0.001$, $R^2 = 0.82$; RCA slope = +1.11 yr^{-1}, $p < 0.001$). Between 2004 and 2023, it fell just as clearly (RSCA slope = −0.023 yr^{-1}, $p < 0.001$, $R^2 = 0.86$; RXA slope = −0.98 yr^{-1}, $p < 0.001$). The series is thus not trendless but inverted-U shaped with a break around 2004. This reconciles the descriptive language of "post-2004 decline" with the statistics: the decline is real and significant within the post-peak window, even though no monotonic trend spans the whole period. We therefore confine claims of erosion to 2004–2023 and avoid describing the full 1990–2023 span as a secular decline.

Table 6. Formal structural break tests, Türkiye competitiveness indices, 1990–2023.

Index	sup-Wald F	Break Date	Bootstrap 95% CI	Bai–Perron (LWZ)	Chow at 2004
RSCA	74.69 ***	2006	2002–2009	1 break: 2006	F = 74.13 ***
RCA	90.77 ***	2002	2001–2007	1 break: 2002	F = 80.29 ***
RXA	80.49 ***	2002	2001–2007	2 breaks: 2000, 2005	F = 72.85 ***

sup-Wald is the Quandt likelihood-ratio statistic in F form for a break of unknown date in both the intercept and the trend coefficient (q = 2), with 15% trimming; Andrews critical values are 5.00 (10%), 5.86 (5%) and 7.78 (1%) [47]. Break dates are the first year of the second regime. The confidence interval is the 2.5–97.5th percentile of the estimated break date across 1000 residual bootstrap replications. Bai–Perron allows up to three breaks with a minimum segment of five observations. The Chow test is conditional on 2004. *** significant at 1%. Source: Authors' calculations from [1].

Table 7. Türkiye competitiveness trend by phase, with HAC (heteroskedasticity- and autocorrelation-consistent) standard errors and non-parametric tests.

Series and Phase	OLS Slope	HAC SE	HAC p	R^2	MK Z (p)	Sen's Slope
RCA 1990–2023	−0.0869	0.1353	0.525	0.032	−1.39 (0.164)	−0.1274
RCA 1990–2004	+1.1147	0.1716	<0.001	0.829	+3.86 (<0.001)	+1.1240
RCA 2004–2023	−0.7948	0.0700	<0.001	0.863	−5.42 (<0.001)	−0.6854
RXA 1990–2023	−0.1014	0.1629	0.538	0.028	−1.36 (0.173)	−0.1573
RXA 1990–2004	+1.3937	0.2420	<0.001	0.811	+3.86 (<0.001)	+1.4410
RXA 2004–2023	−0.9750	0.1028	<0.001	0.840	−5.42 (<0.001)	−0.8185
RSCA 1990–2023	−0.0033	0.0047	0.484	0.058	−1.41 (0.159)	−0.0043
RSCA 1990–2004	+0.0256	0.0025	<0.001	0.822	+3.86 (<0.001)	+0.0248
RSCA 2004–2023	−0.0233	0.0032	<0.001	0.857	−5.42 (<0.001)	−0.0211

Slopes are per-year coefficients; n = 34 for the full sample, 15 for 1990–2004, and 20 for 2004–2023, the break year appearing in both sub-periods. HAC = Newey–West heteroskedasticity- and autocorrelation-consistent standard errors, lag truncation by the Newey–West automatic rule [53]. MK = Mann–Kendall; Sen's slope is the Theil–Sen median slope. Fractional-logit estimates for RSCA on (RSCA + 1)/2: +0.1204 ($p < 0.001$) for 1990–2004, −0.1042 ($p < 0.001$) for 2004–2023, −0.0142 ($p = 0.235$) for the full sample. Residual diagnostics are in Supplementary Table S7.

These sub-period results survive every robustness check the estimation raises. Newey–West standard errors leave the sub-period conclusions intact—the RSCA slope is +0.0256 (HAC SE 0.0025, $p < 0.001$) before 2004 and −0.0233 (HAC SE 0.0032, $p < 0.001$) after it—while for the full sample they weaken an already insignificant slope further, the p-value rising from 0.168 to 0.484. That contrast is what the residual diagnostics predict: serial correlation is severe in the full-sample regression (Breusch–Godfrey LM = 23.1, $p < 0.001$) and absent in both sub-periods ($p = 0.70$ and $p = 0.09$), so the dependence in the full-sample residuals is itself a symptom of the unmodelled break rather than an independent defect. The non-parametric tests agree with the parametric ones: Mann–Kendall gives Z = +3.86 ($p = 0.0001$, $\tau = +0.72$) before 2004 and Z = −5.42 ($p < 0.0001$, $\tau = -0.87$) after it, against Z = −1.41 ($p = 0.159$) for the full sample, and Sen's slopes of +0.0248 and −0.0211 bracket the corresponding OLS estimates. The fractional-logit specification, which respects the (−1, +1) bounds of RSCA by construction, returns a time coefficient of +0.120 ($p < 0.001$) in the first phase, −0.104 ($p < 0.001$) in the second, and an insignificant −0.014 ($p = 0.235$) over the full sample.

Sensitivity to individual observations and to the break date is equally reassuring. Residual normality is rejected in the post-2004 RSCA regression (Jarque–Bera $p < 0.001$) and the 2022 trough carries a Cook's distance above unity, which is precisely why the non-parametric results matter. Excluding 2022 nevertheless leaves the post-2004 slope at −0.0206 ($p < 0.001$), and excluding the peak year 2004 gives slopes of +0.0262 and −0.0241, both significant at the 1% level. Most directly relevant to the concern about endogenous break selection, re-estimating at every alternative break date between 2002 and 2010 leaves the pre-break slope between +0.0156 and +0.0268 and the post-break slope between −0.0212 and −0.0295, each significant at 1%. The inverted-U pattern is therefore not produced by selecting the extremum. It appears wherever the sample is divided within the plausible range. The full set of alternative break date estimates is reported in Supplementary Table S8 and the residual diagnostics for all nine trend regressions in Supplementary Table S7.

The dating also has an interpretation independent of the series itself, which matters because a break that can only be found in the data is weaker evidence than one coinciding with an identifiable change in market conditions. The mid-2000s are the point at which Chile's export expansion moved from incremental to exponential—its five-year mean export value rose roughly fourfold between 2000–2004 and 2005–2009, and again between 2005–2009 and 2010–2014 (Table 3)—and the point at which air-freight and controlled-

atmosphere capacity into East Asia was scaled up, opening the counter-seasonal window that Türkiye cannot serve. On the domestic side, it is also the period in which Turkish bearing-tree numbers began the sustained extensive margin expansion visible in Table 4, so the divergence between rising volume and stagnant value begins where the volume expansion itself begins. We do not claim that these coincidences establish causation; we report them because a break date that is both statistically estimated and institutionally interpretable is more credible than one resting on either alone.

Table 8 condenses the RSCA series for all five entities. Chile climbed from 0.80 to 0.97 and China (incl. Hong Kong SAR) reversed from −0.75 to 0.95, while the United States declined toward zero and Spain turned negative. Türkiye's RSCA stayed positive throughout but slipped from a 2000–2004 peak of 0.87 to 0.50 in 2020–2023—persistently advantaged, yet increasingly outpaced by the two leaders and squeezed in the middle tier. The RCA and RXA five-year means for Türkiye (Table 9) move in close parallel, confirming that the dynamics are export-driven rather than artefacts of the import side. Full annual values for all indices and countries are provided as Supplementary Tables S1–S3.

Table 8. RSCA index, five-year period means by country, 1990–2023.

Period	Chile	China †	United States	Spain	Türkiye
1990–1994	0.80	−0.75	0.51	0.10	0.59
1995–1999	0.79	−0.83	0.52	0.41	0.78
2000–2004	0.80	−0.70	0.51	0.19	0.87
2005–2009	0.88	−0.22	0.49	0.24	0.86
2010–2014	0.94	0.76	0.44	0.19	0.78
2015–2019	0.95	0.90	0.31	−0.08	0.68
2020–2023	0.97	0.95	0.01	−0.18	0.50

† China (incl. Hong Kong SAR). Source: Authors' calculations from [1].

Table 9. Türkiye RCA, RXA, and RSCA, five-year period means, 1990–2023.

Period	RCA	RXA	RSCA
1990–1994	3.90	4.03	0.59
1995–1999	8.42	9.22	0.78
2000–2004	15.17	17.97	0.87
2005–2009	13.75	15.91	0.86
2010–2014	8.32	9.20	0.78
2015–2019	5.30	5.66	0.68
2020–2023	3.16	3.30	0.50

Source: Authors' calculations from [1].

Figure 1 makes the relative dynamics visible: Chile high and rising, China (incl. Hong Kong SAR) crossing from deep disadvantage to near-parity around 2012 and overtaking Türkiye, the United States drifting down, Spain volatile and turning negative, and Türkiye positive but on a post-2004 downward path. Figure 2 traces all three indices for Türkiye, with the 2004 peak and 2022 trough clearly marked and the four descriptive phases shaded.

3.2. Production Projection (Supply-Side Background)

This section projects the supply base only; it does not model competitiveness. The question it addresses is narrow but decisive for the paradox: Is Türkiye's production likely to keep rising, so that any future weakness in export competitiveness cannot be attributed to a shrinking supply base?

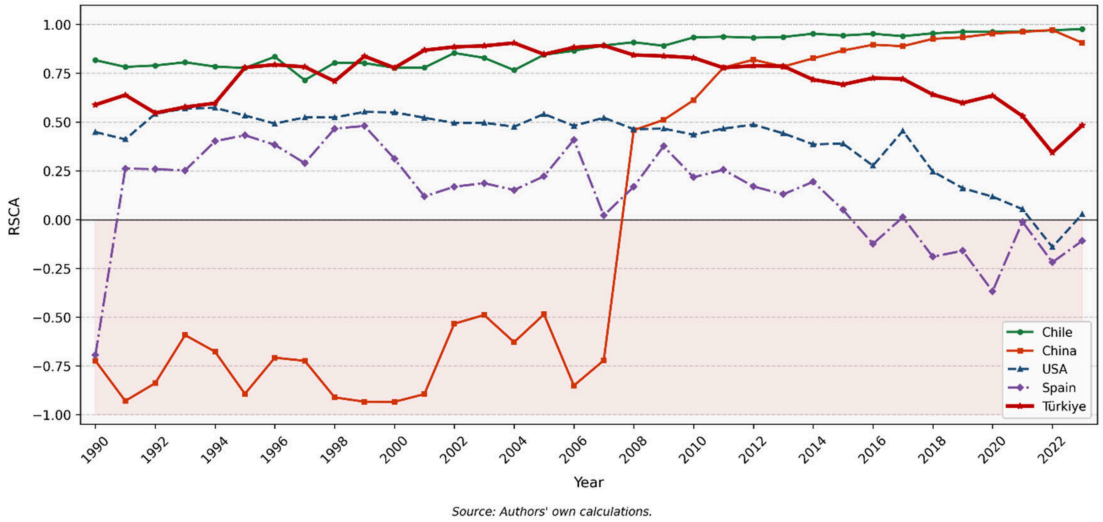


Figure 1. RSCA index values, Türkiye and reference exporters, 1990–2023. Values above zero indicate revealed comparative advantage. The red-shaded band below the zero line marks the zone of comparative disadvantage (RSCA < 0) Türkiye is the bold red line. Source: Authors' calculations. Main message: Türkiye stays above zero throughout, but is overtaken by Chile and by the Asian trade node after 2012.

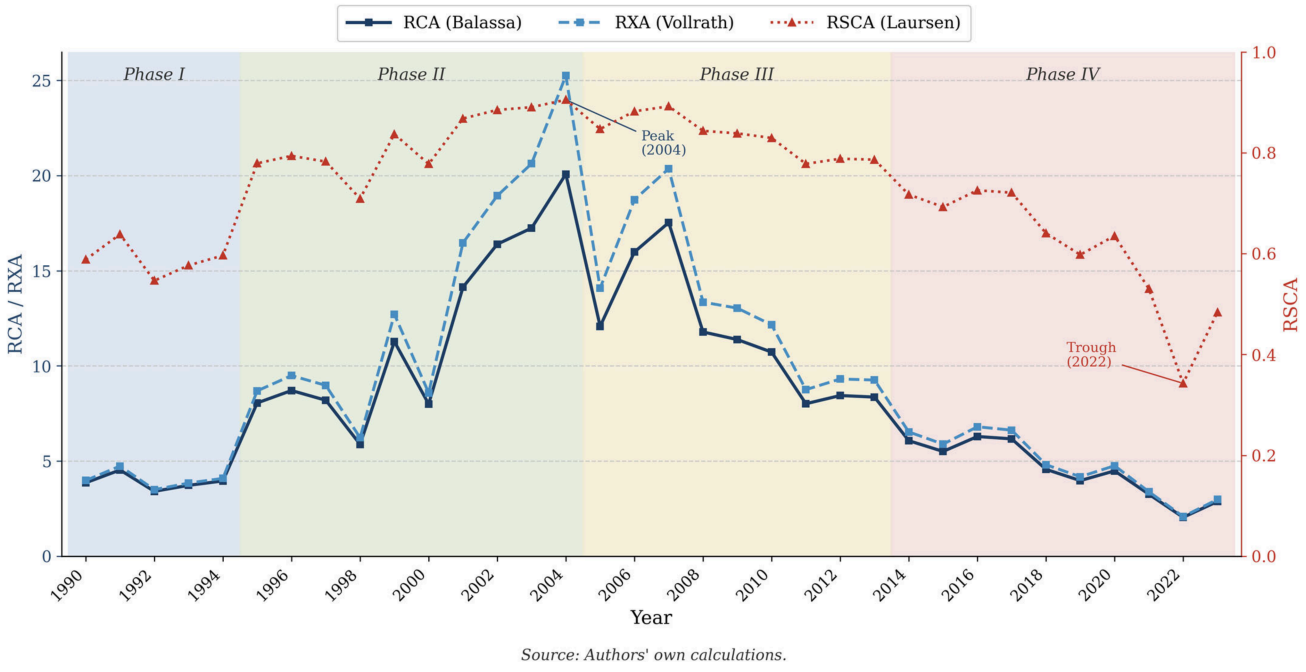


Figure 2. RCA, RXA, and RSCA for Türkiye, 1990–2023. Left axis: RCA and RXA; right axis: RSCA. Shaded bands denote descriptive phases. Source: authors' calculations. Main message: All three indices peak in the mid-2000s and decline thereafter, so the result does not depend on which index is used.

All three unit-root tests agree that the production level is non-stationary and becomes stationary after first differencing (Table 10), so the series is integrated of order one and d = 1. The grid search identified ARIMA(1,1,2) as the preferred specification on minimum AIC (339.5) and with residuals free of autocorrelation (Ljung–Box p = 0.91) (Table 11). All parameters are significant. The near-unit autoregressive term (0.98) indicates strong but bounded persistence and the MA terms capture short-run correction following supply shocks (Table 12). The Jarque–Bera test shows only a mild departure from normality that, given n = 34, does not materially affect the forecast intervals. The estimated autoregressive

root has modulus 1.019 and the two moving-average roots moduli of 1.41 and 1.47, so the differenced process is both stationary and invertible; the proximity of the autoregressive root to the unit circle nevertheless means that over long horizons the model behaves very much like a random walk with drift, which is precisely the comparison made in Section Forecast Validation and Model Comparison.

Table 10. Unit-root tests, Türkiye cherry production, 1990–2023.

Specification	ADF (*p*)	PP (*p*)	KPSS Stat
Level (constant)	0.72 (0.990)	1.35 (0.997)	0.758 ***
Level (constant + trend)	−2.75 (0.218)	−2.63 (0.266)	—
First difference	−8.45 (<0.001)	−8.78 (<0.001)	0.316 ns

ADF/PP null: Unit root. KPSS null: stationarity (critical value 0.739 at 1%; 0.347 at 10%). *** rejects at 1%. ns: not significant (null not rejected). Source: Authors' calculations.

Table 11. Candidate ARIMA models (selected: lowest AIC).

Model	Log-Lik.	AIC	BIC	HQIC	Ljung–Box *p*
ARIMA(1,1,2) *	−165.77	339.54	345.52	341.55	0.908
ARIMA(2,1,3)	−164.66	341.32	350.30	344.34	0.989
ARIMA(0,1,3)	−167.21	342.41	348.40	344.42	0.879
ARIMA(2,1,2)	−166.43	342.86	350.34	345.38	0.939
ARIMA(1,1,1)	−168.82	343.63	348.12	345.14	0.944

* Selected model. All models estimated with d = 1. Source: Authors' calculations.

Table 12. ARIMA(1,1,2) estimation results.

Parameter	Coefficient	Std. Error	z	*p*
ar.L1 (φ_1)	0.981	0.127	7.71	<0.001
ma.L1 (θ_1)	−1.389	0.226	−6.15	<0.001
ma.L2 (θ_2)	0.482	0.191	2.52	0.012
σ^2	1297.4	427.0	3.04	0.002

AIC 339.5; Ljung–Box Q (10) = 4.75 (p = 0.908); Jarque–Bera p = 0.039; n = 34. Source: Authors' calculations.

The forecast indicates continued but moderating growth, from 737,000 t in 2023 to about 893,000 t by 2033, with annual increments easing from roughly 2.4% to 1.8% (Table 13, Figure 3 panels, Figure 4). The 95% interval widens to about 685,000–1,102,000 t by 2033, reflecting the historical volatility of an annual agricultural series; even its lower bound stays above early-2020s levels. The key inference for this study is simple and robust to the wide bands: The supply base is not contracting. A shrinking supply therefore cannot explain weakening competitiveness, which is consistent with—though it does not by itself prove—the hypothesis that the binding constraints lie downstream of production.

Table 13. ARIMA(1,1,2) production forecast, 2024–2033 ('000 t).

Year	Forecast	95% Lower	95% Upper	Change (%)
2024	742.9	672.3	813.5	+0.8
2026	778.6	683.8	873.5	+2.3
2028	813.0	689.3	936.7	+2.1
2030	846.1	690.2	1001.9	+2.0
2033	893.4	684.7	1102.1	+1.8

Selected interim years shown; full annual forecast in Supplementary Table S6. Source: Authors' calculations from [1].

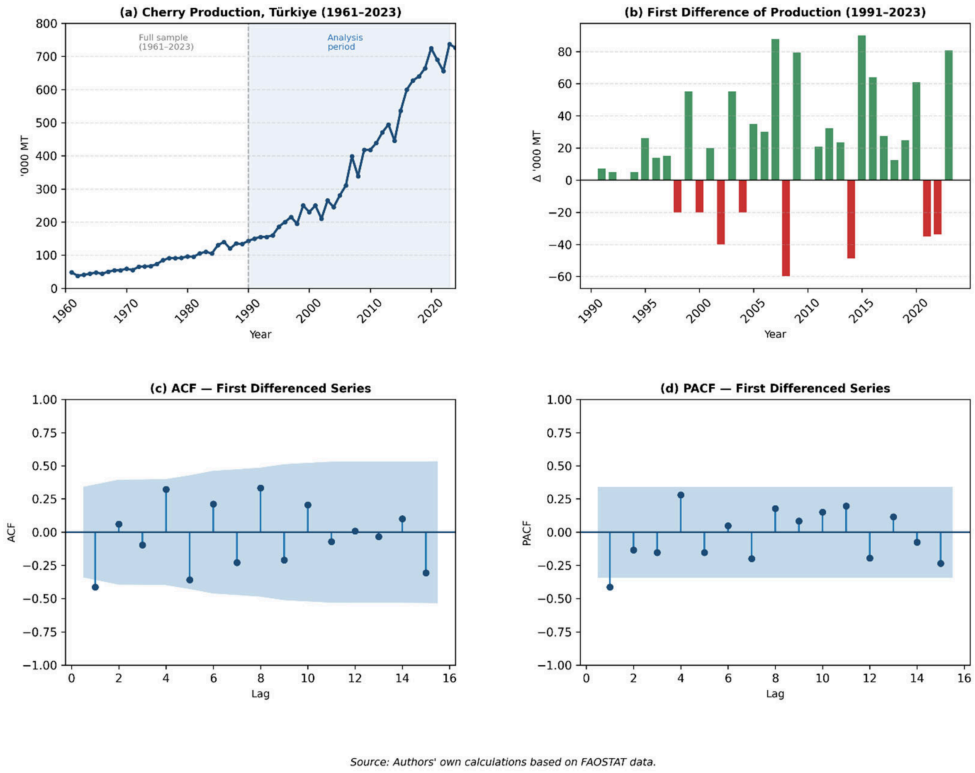


Figure 3. Box–Jenkins identification: (**a**) Production level; (**b**) First difference; (**c**) ACF (autocorrelation function); (**d**) PACF (partial autocorrelation function). Source: Authors' calculations from [1]. Main message: The level series is non-stationary while its first difference is stationary with no strong residual structure.

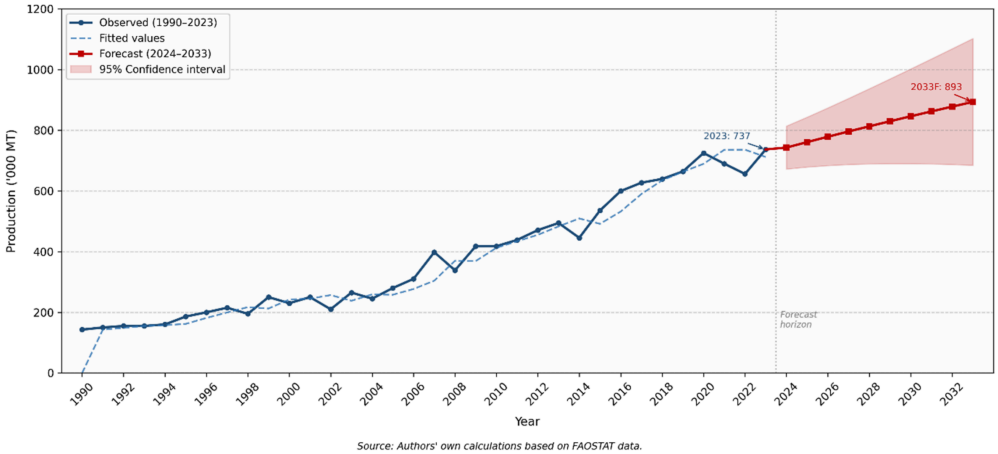


Figure 4. ARIMA(1,1,2) out-of-sample forecast of Türkiye cherry production, 2024–2033. Shaded band: 95% confidence interval. Source: Authors' calculations from [1]. Main message: Production continues to rise under the selected model, but the interval widens quickly, so the projected level should be read as indicative rather than precise. Figure S1 in the Supplementary Material compares this projection with the benchmark models of Section Forecast Validation and Model Comparison.

Forecast Validation and Model Comparison

Table 14 reports the rolling-origin evaluation, and it does not favour the specification selected on in-sample criteria. Across the 42 out-of-sample forecasts, ARIMA(1,1,2) records an RMSE of 65.0 thousand t and a MAPE of 9.7%, whereas a random walk with drift records 52.4 thousand t and 7.1%, with the damped-trend and Holt specifications falling between them. Diebold–Mariano tests confirm that the differences in squared-error loss relative to ARIMA(1,1,2) are statistically significant for the random walk with drift (DM = 3.36,

$p = 0.002$), the damped trend (DM = 2.70, $p = 0.010$), and Holt's linear trend (DM = 2.54, $p = 0.015$), while the deterministic linear trend is significantly worse (DM = −2.07, $p = 0.044$) and the remaining ARIMA alternatives are not distinguishable from it. Empirical coverage of the nominal 95% intervals is 73.8% for ARIMA(1,1,2), so its intervals are somewhat too narrow at short horizons, against 88.1% for the random walk with drift. We report these results in full rather than restricting the comparison set to alternatives that would flatter the original choice.

Two considerations bear on how far this changes the substantive reading. First, the models are close where it matters for this study. Estimated on 1990–2023, the 2033 projection is 893 thousand t under ARIMA(1,1,2), 917 under the random walk with drift, 929 under the damped trend, 940 under Holt's linear trend, and 883 under a deterministic linear trend, with the equal-weighted combination of the three best performers giving 913 thousand t. Every specification therefore implies a 2033 supply base between roughly 0.88 and 0.94 million t, that is, 21–29% above the 2020–2024 mean. Second, the 2024 observation published after estimation provides a real-time check: ARIMA(1,1,2) projected 742.9 thousand t against an outturn of 726.5 thousand t, an error of 2.3% and comfortably inside its 95% interval of 672–814 thousand t, while the random walk with drift over-predicted by 3.9%.

Sensitivity to the estimation window turns out to be more consequential than sensitivity to model class. Windows beginning in 1980 or 1995 leave the 2033 projection essentially unchanged, at 894 and 882 thousand t, but windows beginning in 1961 or 2000 return an autoregressive coefficient near 0.61 rather than 0.98 and a 2033 projection near 704 thousand t—broadly flat rather than rising. The 1961 window spans two structurally different growth regimes, and the 2000 window is short enough for the post-2020 plateau to dominate estimation. We retain 1990–2023 for consistency with the trade analysis, but we report the alternatives because they qualify the strength of the growth claim. The leave-one-year-out analysis identifies 2014, the frost-affected year in which output fell by about 10% [73], as the single most influential observation: excluding it lowers the 2033 projection by 196 thousand t.

Taken together, this evidence supports a narrower claim than the one made previously. What is robust across model classes, estimation windows, and influential observations is that the projected supply base does not contract and the point estimate of how far it rises is not robust and should not be read as a precise forecast. That narrower claim is nonetheless sufficient for the argument of this paper, which requires only that insufficient production volume can be excluded as an explanation of weakening competitiveness.

Table 14. Rolling-origin forecast evaluation and ten-year projections, Türkiye cherry production.

Model	MAE	RMSE	MAPE (%)	95% Coverage (%)	2033 Forecast
Random walk with drift	40.4	52.4	7.13	88.1	916.7
Damped trend	42.1	54.5	7.32	83.3	929.0
Holt linear trend	45.1	55.0	7.98	83.3	940.2
Combination of best three	44.0	55.1	7.72	—	913.0
ARIMA(1,1,2) *	54.5	65.0	9.72	73.8	893.4
Random walk	56.8	68.4	9.93	90.5	—
ARIMA(1,1,1)	57.8	69.2	10.10	71.4	—
ARIMA(0,1,1)	60.4	70.6	10.56	81.0	—
Simple exponential smoothing	60.5	70.6	10.58	78.6	—
Deterministic linear trend	70.2	78.1	12.13	45.2	882.7

* Model selected on in-sample AIC. Errors in '000 t from 42 rolling-origin forecasts (origins 2008–2022, h = 1–3), ranked by RMSE. The 2033 column reports the ten-year projection from each model estimated on the full 1990–2023 sample. Source: Authors' calculations.

3.3. Is Production Growth Associated with Competitiveness?

H1 asserts that output growth does not translate proportionally into stronger competitiveness. Rather than leave that proposition to be inferred from two analyses reported side by side, we estimate the association directly. Both series are non-stationary in levels—the augmented Dickey–Fuller statistic for RSCA is −0.57 ($p = 0.878$) in levels and −6.40 ($p < 0.001$) in first differences, and log production is likewise integrated of order one—and an Engle–Granger test finds no cointegrating relationship between them (statistic −1.60, $p = 0.90$), so the association is estimated in first differences with Newey–West standard errors (Table 15).

Three results follow. First, in the short run production and competitiveness move together rather than apart: a 10% increase in output is associated with a same-year rise in RSCA of about 0.032 index points ($\beta = 0.312$, $p = 0.030$, $R^2 = 0.222$), which is what one would expect if a larger harvest enlarges the exportable surplus. Second, much of that effect is transitory. With two lags included, the contemporaneous coefficient rises to 0.383 ($p = 0.026$) while the second lag is −0.242 ($p = 0.025$), so roughly three-fifths of the initial gain is reversed within two years. Third, and decisively for H1, adding an indicator for the post-2004 regime leaves the contemporaneous coefficient positive and significant ($\beta = 0.333$, $p = 0.015$) while the indicator itself takes a value of −0.051 index points per year ($p = 0.002$); the interaction between production growth and the post-2004 regime is indistinguishable from zero ($p = 0.995$). The relationship between output and competitiveness therefore did not change after 2004. What changed was the appearance of an independent downward drift alongside it.

Table 15. Production growth and competitiveness: First-difference regressions.

Regressor	(1)	(2)	(3)	(4)
Constant	−0.0187 (0.0122)	−0.0091 (0.0195)	+0.0099 (0.0136)	+0.0178 (0.0157)
Δln(Production), t	+0.3120 ** (0.1375)	+0.3833 ** (0.1622)	+0.3326 ** (0.1289)	+0.4160 *** (0.1325)
Δln(Production), t − 1	—	+0.0018 (0.1181)	—	+0.0497 (0.1172)
Δln(Production), t − 2	—	−0.2420 ** (0.1023)	—	−0.1919 (0.1210)
Post-2004 indicator	—	—	−0.0513 *** (0.0152)	−0.0545 *** (0.0161)
n	33	31	33	31
R^2	0.222	0.356	0.344	0.486
Breusch–Godfrey(2) *p*	0.471	0.978	0.026	0.030

Dependent variable: Annual change in Türkiye's RSCA. Newey–West standard errors with two lags in parentheses. *** $p < 0.01$, ** $p < 0.05$. Adding an interaction between Δln(Production) and the post-2004 indicator to specification (3) gives a coefficient of +0.0015 ($p = 0.995$). Unit-root tests: augmented Dickey–Fuller for RSCA −0.57 ($p = 0.878$) in levels and −6.40 ($p < 0.001$) in first differences; for ln(Production) $p = 0.206$ in levels and $p < 0.001$ in first differences. Engle–Granger cointegration statistic −1.60 ($p = 0.90$). Source: Authors' calculations.

The accounting implied by this specification is stark. Over 2004–2023 Türkiye's RSCA fell by 0.421 index points. Within the estimated model, cumulative production growth over the same span contributed +0.366 points and the regression constant a further +0.187, while the post-2004 drift contributed −0.974. Output growth thus pushed measured competitiveness upward across the period and the observed erosion occurred despite that contribution rather than because of any weakness on the supply side. This is a direct test of the relationship asserted in H1 rather than a juxtaposition of two separate analyses, and the evidence is consistent with H1: growth in production did not translate into stronger competitiveness, because the force producing the post-2004 drift was some three times larger than the production effect working in the opposite direction. What that drift represents is not identified here—P1 to P4 name the candidates—and the specification remains bivariate and reduced-form, so it cannot be read as a structural model of export

performance. It does, however, establish that the production series carries no explanatory content for the post-2004 decline once non-stationarity, the break, and lagged effects are accounted for.

4. Discussion

The results document a clear association: Türkiye's production has risen continuously and is projected to keep rising, while its export competitiveness rose to a 2004 peak and then declined significantly through 2023. We discuss the candidate mechanisms below, but emphasise at the outset that the indices establish co-movement, not causation; the mechanism-level statements that follow are interpretations consistent with the descriptive evidence, advanced as hypotheses rather than demonstrated results.

4.1. Interpreting the Production–Export Paradox

Output rose almost fivefold between 1990 (143,000 t) and 2023 (737,000 t), yet RCA fell from 20.1 in 2004 to 2.9 in 2023. Two features of the domestic data are consistent with part of this divergence being absorption-driven rather than competitiveness-driven. First, per-capita consumption rose from 2.5 to 6.5 kg over 2004–2024, and the self-sufficiency rate eased from its mid-2000s peak; together, these suggest that a growing share of incremental output has been consumed at home, reducing the exportable surplus relative to total production [9]. Second, the flat yield per tree against sharply rising tree numbers indicates extensive margin growth: more area planted rather than higher productivity or quality per tree. Volume added in this way may be less likely to command the price premia that lift value-based competitiveness, which may help explain why a rising tonnage has coincided with a falling RCA. These readings are consistent with the data but are not directly tested here. Disentangling absorption from competitiveness effects would require a demand-system or export-supply decomposition, which we identify as a priority for future work.

Other plausible contributors cannot be assessed with the present indices and are therefore stated cautiously. Higher post-harvest losses relative to Chile, where cold-chain and controlled-atmosphere capacity were built out over two decades, would narrow the set of high-value markets Türkiye can reliably serve [10,11]. The marked depreciation of the Turkish lira after 2018 may have introduced pricing and contracting volatility that diverted buyers toward more stable-currency suppliers [8,14]. Because the indices are value-based, currency movements also enter the measure directly, a point we return to under limitations. Each of these is consistent with the observed pattern, and none is established by it.

4.2. Relative Decline: The Repositioning of Rivals

The erosion of Türkiye's standing is partly relative. Chile's RSCA rose to 0.98 by 2023, and China (incl. Hong Kong SAR) reversed from −0.94 around 2000 to 0.91 by 2023. The latter must be read in light of Section 2.2. This entity is largely a re-export and trade hub serving Asian demand, so its trajectory reflects the reorientation of cherry trade toward Asia and the growing intermediation of that trade, rather than the rise of a mainland production rival. For Türkiye, the practical implication is the same—the competitive space in the destination markets that historically absorbed Turkish cherries has been compressed from both ends by Chile's counter-seasonal dominance and by the consolidation of Asian trade flows. Spain's slide into negative RSCA after 2016 offers a cautionary parallel: A Mediterranean producer that did not sustain investment in productivity and export logistics was displaced relatively quickly [30,32]. Türkiye's still-positive but declining RSCA places it between these outcomes.

These patterns are broadly consistent with what the wider empirical literature on horticultural export competitiveness reports, though with one instructive difference. Studies of Central and Eastern European agri-food exporters find that a revealed advantage in fruit and vegetable lines is typically unstable and prone to reversal, with persistence markedly lower than in bulk commodity lines [31–33]. Mediterranean evidence points the same way, with [30] documenting the erosion of the Italian and Spanish positions in fresh fruit as counter-seasonal and lower-cost suppliers entered. Türkiye's trajectory differs from these cases in one respect that is central to this paper: Its revealed advantage remained positive throughout. Its decline occurred alongside rather than instead of sustained output growth. In the European cases, the loss of position accompanied stagnant or falling production. That difference is what makes the Turkish case a production–export paradox rather than a straightforward competitiveness decline, and it is why the propositions P1–P4 concern the conversion of supply into traded value rather than the adequacy of supply itself.

4.3. What Could Türkiye Realistically Adopt?

Not every rival's advantage is transferable. Chile's counter-seasonal position is structural and cannot be replicated, but several of the practices that underpin its and China's performance are within reach. The most transferable is systematic cold-chain and controlled-atmosphere investment, which directly addresses the post-harvest-loss channel and is the element most clearly linked to the post-2004 export-value gap in Table 3. A second is product differentiation through geographical-indication and quality certification, which other Mediterranean producers have used to defend price premia [13] and which is well suited to Türkiye's distinctive regional varieties. A third is varietal and seasonal repositioning toward late-ripening cultivars that extend the supply window beyond the crowded June–July peak. The counter-seasonal scale of Chile and the trade-hub function of Hong Kong are, by contrast, not realistically adoptable. Recognising this keeps the policy discussion grounded in the empirical findings rather than in aspiration.

4.4. The Forecast and Export Strategy

The projection implies that the raw-material base for an export recovery will remain ample through 2033. But the model forecasts supply only; it cannot anticipate the climate shocks, disease pressure, price swings, or trade policy changes that drive the largest single-year movements in the series, and the widening confidence band reflects exactly this. The wide band is itself relevant to competitiveness: Buyers under multi-year procurement contracts value a predictable supply, so volatility can erode market position independently of price [28]. The strategic reading is that volume is a necessary but not sufficient condition—the constraints most consistent with the evidence sit downstream of production, in storage, logistics, certification, and market diversification.

4.5. Limitations

Several limitations bound the inferences. First and most important, RCA, RXA, and RSCA are descriptive measures of realised trade position. They capture neither the determinants of competitiveness—production costs, productivity, quality, logistics performance, contract structure, trade barriers, brand strength, or market access—nor the direction of causation. The mechanism-level claims in Sections 4.1–4.3 are therefore interpretations, not findings. Second, being value-based, the indices absorb price and exchange rate effects, so in years of sharp depreciation they may understate volume-based performance [17,27]. Third, the "China, Hong Kong SAR" entity conflates production and re-export. Its indices should be read as a trade position signal, not a production benchmark. Fourth, the ARIMA model assumes structural stability and excludes climate, disease, price, and policy shocks. The comparisons reported in Section Forecast Validation and Model Comparison show

that its point accuracy is inferior to that of a random walk with drift and that its ten-year projection is sensitive to the estimation window, so the projection should be used only for the qualitative inference it supports—that the supply base does not contract—and not as a production target. Fifth, the comparator set is limited to four reference exporters. Adding emerging suppliers such as Uzbekistan and Iran would map the competitive landscape more fully. These limitations define a clear agenda for confirmatory analysis rather than undermining the central, well-supported descriptive result: Rising production has coincided with significant post-2004 competitive erosion.

5. Conclusions

5.1. Summary of Findings

Using three revealed-advantage indices and an ARIMA production projection, this study examined the production–export paradox of Türkiye's cherry sector. Four findings are firmly supported by the data. (i) Türkiye held a positive revealed comparative advantage in every year of 1990–2023, distinguishing it from Spain, which turned negative after 2016. (ii) That advantage was not static. It rose significantly to a 2004 peak and then declined significantly through 2023 (RCA 20.1 $\rightarrow$ 2.9), a structural break that resolves the earlier apparent contradiction between a flat full-sample trend and a visible post-peak fall. (iii) The global market was reordered over the period, with Chile reaching near-total dominance and the Asian trade hub captured by "China (incl. Hong Kong SAR)" rising to near-parity, compressing the mid-tier. (iv) Production is projected to remain on an expanding path, reaching roughly 0.88–0.94 million t by 2033 depending on the specification adopted, so the supply base is not the constraint. The direction of this result is robust across model classes and estimation windows, whereas the level is not, and only the direction is relied on here. The further claim—that the binding constraints lie in domestic absorption, post-harvest and logistics capacity, certification, and market diversification—is consistent with the descriptive evidence but is advanced as an interpretation requiring confirmatory testing, not as a demonstrated result.

A fifth finding was added in this revision and bears directly on the hypothesis. Estimated in first differences with Newey–West standard errors, annual production growth is positively and significantly associated with contemporaneous movements in RSCA, yet conditional on that growth, the post-2004 period carries an independent decline of 0.051 index points per year. Decomposing the observed fall of 0.421 points between 2004 and 2023, production growth contributed +0.366 and the post-2004 drift -0.974. Output growth was therefore working to raise measured competitiveness throughout the period of decline, which is the strongest available evidence that the binding constraint lies downstream of production.

The role of the production forecast in this argument should not be overstated. It complements the competitiveness analysis but does not explain it. An ARIMA model of output predicts production alone and carries no information about export value, prices, market share, or the indices themselves. Its function here is strictly eliminative—it removes one candidate explanation for the post-2004 erosion—and none of the policy implications set out below rests on the projected level of production, only on the fact that production is not projected to fall.

5.2. Policy Implications

Each implication is tied to a specific empirical observation and should be read as conditional on the interpretive caveats above. Cold-chain and post-harvest investment, prioritised in the main producing provinces, follows most directly from the widening export-value gap with Chile in Table 3 and from the post-harvest-loss channel. Public–

private models akin to Chile's offer an implementation route that does not place the full burden on smallholders. Geographical-indication and quality certification for distinctive regional varieties follows from the extensive margin, flat-yield pattern in Table 4, which implies that value rather than volume must be the next source of gains, and from Spain's displacement as a warning. Varietal upgrading and season extension toward late-ripening cultivars follows from the relative-decline finding in Table 8 and Figure 1. Occupying a lower-competition supply window is one of the few rival advantages Türkiye can realistically adopt. Market diversification, including positioning as a premium supplier into Asian demand rather than treating that demand only as a competitor, follows from the reordering of export value in Table 3 and the rise of the Asian trade node. Production-stability and climate-resilience measures follow from the wide ARIMA confidence band and the series' historical volatility, since unreliable supply can erode market position independently of price. Institutional coordination—a dedicated cherry export council linking producers, exporters, logistics providers, and authorities—follows from the core paradox itself, which reflects a gap between successful production policy and lagging export-promotion policy.

Table 16 summarises these implications together with the specific empirical observation each rests on, the actor best placed to act, and an indicative time horizon. The final row is addressed to the evidence base itself. The propositions that the sector's policy debate turns on cannot presently be evaluated because the necessary annual series have not yet been compiled, and remedying that would do more for the quality of future analysis than any single intervention listed above.

Table 16. Practical recommendations, their empirical basis, and the actors responsible.

Recommendation	Empirical Basis in This Study	Primary Actor	Horizon	Relates to
Invest in pre-cooling, controlled-atmosphere storage, and refrigerated transport in the main producing provinces	Widening export-value gap with Chile (Table 3) despite near-parity in volume (Table 2)	Ministry of Agriculture and Forestry; producer unions; private operators	3–7 years	P2
Extend geographical-indication registration and quality certification to distinctive regional varieties	Extensive margin growth with flat yield per tree (Table 4) implies value, not volume, is the remaining source of gains	Turkish Patent and Trademark Office; exporter associations	3–5 years	P3
Support varietal renewal toward late-ripening cultivars to extend the supply window beyond the June–July peak	Relative decline against counter-seasonal supply (Tables 6 and 8; Figure 1)	Research institutes; nursery sector; producers	5–10 years	P2, P3
Diversify destinations, including positioning as a premium supplier into Asian demand rather than treating it only as competition	Reordering of world export value toward the Asian trade node (Table 3)	Ministry of Trade; exporter associations	1–5 years	P4
Strengthen producer organisation and pooled marketing among smallholders	Fragmented supply base is the structural contrast with Chile and the United States (Section 4.3)	Producer unions; cooperatives	3–7 years	P2, P4
Build production-stability and climate-resilience capacity, including frost protection and irrigation reliability	Wide forecast intervals and the influence of the 2014 frost year on the projection (Section Forecast Validation and Model Comparison)	Ministry of Agriculture and Forestry; TARSİM	3–7 years	—

Table 16. *Cont.*

Recommendation	Empirical Basis in This Study	Primary Actor	Horizon	Relates to
Establish a cherry export council coordinating producers, exporters, logistics providers, and regulators	The paradox itself reflects a gap between production policy and export-promotion policy	Ministry of Trade; sector bodies	1–3 years	P1–P4
Compile and publish annual statistics on post-harvest losses, cold-chain capacity, certification uptake, and destination concentration	These are exactly the variables P1–P4 require and that are currently unavailable (Sections 2.1 and 5.3)	TurkStat; Ministry of Agriculture and Forestry	1–3 years	P1–P4

Recommendations are conditional on the interpretive caveats in Section 4.5; the propositions they relate to are exploratory and are not tested in this paper. Horizons are indicative. Source: Authors' compilation.

5.3. Future Research

Priorities follow directly from what the present design still cannot do. Section 3.3 establishes a bivariate association between production growth and competitiveness. The natural next step is a multivariate export performance model in which competitiveness is the dependent variable and production, domestic consumption, export unit values, the real effective exchange rate, destination concentration, and a cold-chain capacity proxy enter as regressors, estimated with explicit attention to non-stationarity, structural breaks, and lagged effects. This is the specification under which the association asserted in H1 could be tested rather than described, and under which P1–P4 could be evaluated jointly. The second is a demand-system or export-supply decomposition separating domestic absorption from competitiveness effects, which is what P1 requires on its own. The third is a gravity-model analysis of bilateral cherry flows to identify destination-level drivers and to quantify the concentration effect in P4. The fourth is farm- and firm-level data on costs, productivity, and post-harvest losses, without which P2 and P3 cannot be evaluated at all; the absence of a consistent annual series on these variables is the single most important data constraint on this literature. The fifth is extension of the comparator set to Uzbekistan, Iran, and other emerging suppliers as continuous trade series become available, and of the forecast comparison to a wider set of specifications and to estimated rather than equal combination weights.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agriculture16161776/s1, Figure S1: Forecast validation for Türkiye cherry production; Table S1: Revealed Comparative Advantage (RCA) Index Values for Türkiye and Selected Competitor Countries, 1990–2023; Table S2: Revealed Export Advantage (RXA) Index Values for Türkiye and Selected Competitor Countries, 1990–2023; Table S3: Relative Symmetric Comparative Advantage (RSCA) Index Values for Türkiye and Selected Competitor Countries, 1990–2023; Table S4: Cherry Export Values of Leading Countries, 2000–2024 (thousand USD); Table S5: Cherry Production, Yield, Consumption, and Self-Sufficiency Rate in Türkiye, 2004–2024; Table S6: ARIMA (1,1,2) Forecast of Türkiye Cherry Production, 2024–2033; Table S7: Residual diagnostics for the trend regressions; Table S8: Sensitivity of the sub-period slopes to the break date and to influential observations.

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Abbreviations

The following abbreviations are used in this manuscript

ACF	Autocorrelation Function
ADF	Augmented Dickey–Fuller (test)
AIC	Akaike Information Criterion
ARIMA	Autoregressive Integrated Moving Average
BIC	Bayesian Information Criterion
CI	Confidence Interval
da	Decare (1 da = 1000 m^2 = 0.1 ha)
DM	Diebold–Mariano (test)
FAO	Food and Agriculture Organization of the United Nations
FAOSTAT	Food and Agriculture Organization Corporate Statistical Database
ha	Hectare
HAC SE	Heteroskedasticity- and Autocorrelation-Consistent Standard Errors (Newey–West)
Hong Kong SAR	Hong Kong Special Administrative Region of China
HQIC	Hannan–Quinn Information Criterion
kg	Kilogram
KPSS	Kwiatkowski–Phillips–Schmidt–Shin (test)
LWZ	Liu–Wu–Zidek Criterion
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MK	Mann–Kendall (trend test)
OLS	Ordinary Least Squares
PACF	Partial Autocorrelation Function
PP	Phillips–Perron (test)
RCA	Revealed Comparative Advantage (Balassa Index)
RMSE	Root Mean Square Error
RSCA	Revealed Symmetric Comparative Advantage
RXA	Relative Export Advantage
t	Tonne (metric ton)
TARSİM	Agricultural Insurance Pool of Türkiye (Tarım Sigortaları Havuzu)
TurkStat	Turkish Statistical Institute (Türkiye İstatistik Kurumu)
USD	United States Dollar

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