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Market Integration and Forecasting in Sustainable Citrus Supply Chains in Türkiye

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Abstract

Sustainable fresh food supply chains depend heavily on effective coordination under uncertain market conditions. Citrus export systems are particularly sensitive to perishability, seasonality, and cold-chain constraints. Under these conditions, reliable price forecasts are important for export planning, logistics efficiency, and sustainable supply-chain management. This study examines the relationship between orange and mandarin export prices in Türkiye using monthly data from 2016 to 2025. Export prices are proxied by real unit values derived from official trade statistics. The analysis applies Augmented Dickey–Fuller tests, Johansen cointegration analysis, and Vector Error Correction Models (VECMs). Forecast performance is evaluated using a rolling-origin framework and compared with ETS, SARIMA, XGBoost, and a seasonal naïve benchmark. The results identify one cointegrating relationship between the two export markets. The estimated long-run coefficient is 0.92, indicating near one-to-one price co-movement. Adjustment toward equilibrium is asymmetric, with orange prices responding faster (ECT = −0.44) than mandarin prices (ECT = −0.21). Forecasting results show that VECM-based models outperform all alternative specifications. The robust VECM achieves the lowest forecast errors (MAPE = 8.3%), compared with 9.8% for XGBoost, 10.6% for SARIMA, 11.5% for ETS, and 14.1% for the seasonal naïve benchmark. Diebold–Mariano tests confirm that these improvements are statistically significant. The findings indicate that orange and mandarin export prices should be analyzed jointly rather than separately. In closely connected citrus supply chains, cointegration-based forecasting models provide more reliable forecasts and a stronger analytical basis for sustainable market coordination.

Keywords: sustainable supply chains; citrus export markets; export price forecasting; market integration; cold-chain coordination

Check for updates

Academic Editor: Koichi Murata

Received: 18 May 2026
Revised: 15 June 2026
Accepted: 16 June 2026
Published: 17 June 2026

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1. Introduction

Fresh fruit supply chains are highly sensitive to uncertainty. Perishability, seasonality, and logistics dependence increase this sensitivity [1–3]. Citrus products are among the most widely traded fresh fruits in the world [1,2]. These products require timely harvesting, proper storage, efficient transportation, and reliable cold-chain management [3–5]. When coordination is weak, product losses, energy use, and logistics costs may increase [4–6].

Sustainable food supply chains depend on coordination between production, storage, transportation, and markets [3,4]. Forecast uncertainty may weaken this coordination. In perishable horticultural markets, inaccurate price expectations may cause shipment mismatches, unnecessary storage, and inefficient resource allocation. These problems have

become more important under volatile market conditions and increasing sustainability concerns [7].

Türkiye is an important citrus producer and exporter in the Mediterranean region [1,3,8–10]. Citrus exports contribute to agricultural income and foreign exchange earnings [3,8–10]. Export competitiveness depends not only on production capacity. It also depends on logistics infrastructure, market coordination, and compliance with international food safety standards [3,8–11]. Recent evidence also shows that citrus production systems may involve considerable energy use and greenhouse gas emissions [7]. Therefore, efficient supply-chain management is important for the sustainability of citrus exports.

Orange and mandarin export markets in Türkiye are closely connected. Production regions overlap. Harvest calendars are similar. Packaging, cold storage, and transportation systems are commonly shared [2–4,9,12]. Export destinations are also largely similar [3,8–10]. Under these conditions, a shock in one citrus market may affect the other market. This may occur through substitution effects, common buyers, shared logistics systems, and joint export channels [7,13–17].

From a theoretical perspective, market integration may emerge when related products use similar production environments, logistics infrastructure, and export channels. In citrus supply chains, oranges and mandarins may compete for storage capacity, transportation services, packaging facilities, and export markets. A positive demand shock in one product may affect resource allocation and marketing decisions in the other product. Buyers may also purchase different citrus products from the same exporters. This creates substitution and portfolio effects within export transactions. These mechanisms provide a theoretical basis for long-run price co-movement.

This issue is important for export planning. Exporters must decide harvest timing, storage duration, shipment planning, and market allocation before final prices are fully known [4,5]. Inaccurate forecasts may reduce marketing efficiency and increase cold-chain costs. Forecast uncertainty may also contribute to unnecessary storage and inefficient transportation planning in perishable food systems [18–20]. Therefore, reliable forecasting is important not only for market efficiency but also for sustainable supply-chain coordination.

Previous studies have examined citrus competitiveness, trade performance, postharvest systems, supply chains, and regulatory constraints [4–11,13,16]. These studies provide important evidence. However, limited attention has been given to the joint dynamics of citrus export prices over time. This limitation is important for Türkiye. Oranges and mandarins operate within closely connected production, logistics, and export systems [7–11].

This study examines the joint dynamics of orange and mandarin export prices in Türkiye using monthly data from 2016 to 2025. Export prices are proxied by real unit values derived from official trade statistics [21]. The study addresses two questions. First, do orange and mandarin export prices share a stable long-run relationship? Second, does modeling this relationship improve forecast accuracy?

The study applies unit root tests, Johansen cointegration analysis, and Vector Error Correction Models. Forecast performance is evaluated using a rolling-origin framework. VECM-based models are compared with ETS, SARIMA, XGBoost, and a seasonal naïve benchmark. The study contributes to the literature by providing evidence on market integration and forecasting in Türkiye's citrus export system. It also offers an empirical framework for closely related perishable horticultural products operating under logistics and sustainability constraints.

2. Literature Review

Market integration and price transmission are central topics in agricultural economics. Related agricultural markets may move together when they share demand conditions,

trade channels, and supply-chain structures [14,15,17]. In such markets, price shocks may be transmitted from one product or location to another. Cointegration methods are widely used to test these long-run relationships [14,15,17,22,23]. These methods are useful because they distinguish short-run deviations from long-run equilibrium.

The literature shows that price transmission may be incomplete, delayed, or asymmetric [14,15,17]. This is important for agricultural markets. These markets often face transportation costs, product differentiation, information delays, and market power. In perishable products, these problems may be stronger. Storage time is limited. Logistics decisions are time-sensitive. Market actors must react quickly to price signals. Therefore, market integration in perishable supply chains is not only a price issue. It is also related to logistics coordination and operational timing [4,5,18–20].

Previous studies on citrus markets have mainly focused on production, competitiveness, trade performance, postharvest systems, and supply-chain constraints [4,6–13]. These studies show that citrus exports depend on product quality, food safety standards, cold-chain performance, and access to destination markets. However, they provide limited evidence on the joint price dynamics of related citrus products. This is an important gap. In Türkiye, oranges and mandarins use similar regions, logistics systems, and export channels [2,3,8–10,12]. Therefore, separate price models may ignore relevant cross-product information.

Forecasting studies in agricultural and food markets have expanded in recent years. Traditional statistical and econometric models remain widely used [24–27]. These models are transparent and suitable for relatively short time series. Machine-learning methods have also become more common in forecasting studies [24,28–31]. These models may capture nonlinear patterns and complex interactions. However, the literature does not show that one method is always superior [24,25,28–31]. Forecast performance depends on sample size, data structure, market conditions, and the strength of economic relationships.

This distinction is important for integrated markets. Univariate models such as ETS and SARIMA focus mainly on the internal dynamics of each series [25,26]. They may perform well when each market follows its own trend or seasonal pattern. However, they may lose information when related markets share a long-run equilibrium. Multivariate models can use cross-series information and capture long-run adjustment mechanisms [22,23,32,33]. For this reason, cointegration-based forecasting may be useful for closely connected agricultural markets.

Machine-learning models provide another benchmark. They can model nonlinear relationships and interactions [24,28–31]. However, they may require larger datasets. They may also fail to capture economic equilibrium directly unless the model structure includes this information. Therefore, in small or moderate monthly datasets, parsimonious econometric models may still provide competitive forecasting performance [24,25,31,34].

Sustainable supply-chain studies also emphasize the importance of coordination in fresh fruit and vegetable systems [18–20]. Cold-chain optimization, packaging performance, inventory management, real-time monitoring, and transportation planning are important for reducing losses and improving resource use [18–20]. Recent logistics studies also show that coordination across inventory, transportation, and facility networks can improve system-wide efficiency and sustainability outcomes [20,35]. Forecasting is linked to these issues because better price expectations may support more efficient storage, shipment, and market allocation decisions.

Overall, the literature suggests three points. First, related agricultural markets may share long-run price relationships [14,15,17]. Second, multivariate models may provide forecasting advantages when markets are integrated [22,23,32,33]. Third, forecasting accuracy may support better coordination in perishable and sustainable supply chains [18–20,35].

However, limited empirical evidence exists for citrus export markets in Türkiye. This study addresses this gap by jointly examining market integration and forecasting performance in orange and mandarin export prices.

3. Materials and Methods

Monthly export unit values for oranges and mandarins in Türkiye are used. The sample covers January 2016 to December 2025. Data are obtained from the Turkish Statistical Institute (TURKSTAT) and official trade statistics [21]. Export prices are proxied by unit values, defined as export value divided by export quantity. This measure reflects both prices and product composition. Changes in quality mix, destination structure, and exchange rates may affect the series. Results are interpreted with this limitation in mind.

This limitation is particularly relevant for cointegration analysis. Changes in export composition may induce common movements in unit values that do not fully reflect underlying transaction prices. Consequently, the estimated long-run relationship should be interpreted as cointegration between export unit values rather than pure market prices. Nevertheless, unit values remain widely used in international trade and agricultural export studies when transaction-level price data are unavailable. The results therefore provide evidence on the joint evolution of export values under actual market conditions, while acknowledging potential quality-composition effects.

Nominal unit values are deflated using the consumer price index (CPI). All series are expressed in real terms. The variables are transformed into natural logarithms. This transformation stabilizes variance and allows coefficient interpretation in proportional terms. Unit values are widely used in international trade studies when transaction-level export prices are unavailable.

Stationarity is examined using the Augmented Dickey–Fuller (ADF) test [36]. Tests are conducted for levels and first differences. Lag length is selected using the Schwarz Information Criterion (SIC) [37]. The integration order determines the suitability of cointegration analysis.

The lag structure of the system is determined prior to estimation. Alternative specifications with one to six lags are evaluated. The SIC is used as the primary criterion. Residual diagnostics are used to confirm the final specification. Seasonality is partially captured through the lag structure. Additional seasonal specifications were tested but were not included in the final model to preserve parsimony, as they did not materially affect the main results.

The long-run relationship between orange and mandarin export unit values is examined using the Johansen cointegration approach [22,23]. Both trace and maximum eigenvalue statistics are reported. The model includes an intercept restricted to the cointegration space. The number of cointegrating vectors is determined at the 5% significance level.

A Vector Error Correction Model (VECM) is estimated to capture both long-run equilibrium and short-run dynamics [32]. The specification includes lagged first differences and an error correction term derived from the cointegrating relationship. The error correction term measures the speed of adjustment toward equilibrium. All models are estimated as a two-equation system.

The VECM can be written as:

$$\Delta y_t = \alpha \beta' y_{t-1} + \Sigma \Gamma_i \Delta y_{t-i} + \varepsilon_t \quad (1)$$

where y_t is a vector containing the logarithms of orange and mandarin export prices, $\beta' y_{t-1}$ represents the cointegration relationship, α is the adjustment coefficient matrix, Γ_i captures short-run dynamics, and ε_t is a vector of error terms. The coefficients of α indicate the

speed at which each market adjusts toward long-run equilibrium following a deviation from the cointegrating relationship.

To account for extreme observations, a robust VECM is also estimated. The procedure follows an iteratively reweighted least squares approach with Huber-type weighting [34,38]. Initial residuals from the standard VECM are used to construct observation weights. Observations with large residuals receive lower weights. The model is re-estimated until parameter changes fall below a fixed tolerance level. Standard errors are computed from the final weighted system.

Model adequacy is evaluated using standard diagnostic tests. Residual autocorrelation is examined using the Ljung–Box Q statistic. Normality is assessed using the Jarque–Bera test. Conditional heteroskedasticity is tested using ARCH-type tests. Stability is evaluated based on the eigenvalue modulus condition.

Forecast performance is evaluated using a rolling-origin framework. An expanding window design is applied. The initial estimation period covers January 2016 to December 2022. The model is re-estimated at each step. One-step-ahead forecasts are generated recursively until December 2025. This procedure is applied consistently across all models.

The study focuses on one-step-ahead forecasts because export planning decisions in fresh citrus supply chains are updated frequently under changing market conditions. Short-horizon forecasts are therefore particularly relevant for shipment scheduling, storage management, and market allocation decisions. The objective is to evaluate operational forecasting performance rather than long-term scenario prediction.

Forecast accuracy is measured using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) [27]. All metrics are computed for each series and then averaged to provide a joint performance measure.

The VECM and robust VECM are compared with alternative forecasting models. ETS models are used to capture exponential smoothing dynamics [25]. SARIMA models account for autoregressive and seasonal structures [26]. XGBoost is employed as a machine learning benchmark. Lagged values of both series up to 12 months are used as predictors. The model is estimated in a recursive multi-output setting. Hyperparameters, including learning rate, tree depth, and number of estimators, are selected through grid search with time-series cross-validation. A seasonal naïve model is used as a baseline. Forecasts are set equal to the value observed in the same month of the previous year.

The XGBoost model is estimated using lagged values of orange and mandarin export prices up to 12 months. Hyperparameter tuning is conducted using a grid-search procedure combined with expanding-window time-series cross-validation. The search space includes learning rates between 0.01 and 0.30, maximum tree depths between 2 and 8, and between 100 and 500 estimators. Model selection is based on validation-set RMSE. To reduce overfitting, subsampling and regularization parameters are included in the tuning procedure, and model performance is evaluated only on observations not used during estimation. This approach ensures comparability with the forecasting framework used for the econometric models.

All models are estimated and evaluated under the same forecasting design to ensure comparability.

4. Results

Orange and mandarin export unit values show a clear upward trend over the sample period. The increase becomes more pronounced after 2021. Both series display similar long-run patterns, while short-run movements differ. Descriptive statistics of the export unit value series are presented in Table 1.

Table 1. Descriptive statistics of export unit values.

Variable	Mean	Std. Dev.	Min	Max
Orange	2.14	1.05	1.08	3.80
Mandarin	2.32	1.18	1.10	4.10

Notes: Values are expressed in natural logarithms of real export unit values. Export unit values are calculated as export value divided by export quantity and deflated using the Consumer Price Index (CPI). Std. Dev. = standard deviation.

Mandarin export prices exhibit higher variability than orange prices. The higher standard deviation indicates greater short-run fluctuations. The similarity in mean values suggests that both products operate within comparable price ranges.

Stationarity properties are examined using ADF tests. The results of the Augmented Dickey–Fuller unit root tests are reported in Table 2.

Table 2. ADF unit root test results.

Variable	Level (*p*-Value)	First Difference (*p*-Value)	Integration Order
Orange	0.41	0.01	I (1)
Mandarin	0.37	0.02	I (1)

Notes: ADF = Augmented Dickey–Fuller test. SIC = Schwarz Information Criterion. The test includes an intercept, and lag length is selected based on SIC. Reported *p*-values correspond to MacKinnon critical values.

Both series are non-stationary in levels and stationary in first differences. The results confirm that the variables are integrated of order one. This supports the use of cointegration analysis.

The long-run relationship between the two series is tested using the Johansen procedure. The results of the Johansen cointegration tests are presented in Table 3.

Table 3. Johansen cointegration test results.

Hypothesis	Trace Statistic	5% Critical Value	Result	Max-Eigen Statistic	5% Critical Value	Result
r = 0	28.24	15.49	Reject	27.99	14.26	Reject
r $\leq$ 1	0.25	3.84	Accept	0.25	3.84	Accept

Notes: The Johansen cointegration test is estimated with an intercept restricted to the cointegration space and no deterministic trend. Lag length is selected using SIC. Critical values correspond to the 5% significance level.

Both trace and maximum eigenvalue statistics indicate the presence of one cointegrating vector between orange and mandarin export prices. The null hypothesis of no cointegration (r = 0) is rejected at the 5% level, while the hypothesis of at most one cointegrating relationship (r $\leq$ 1) cannot be rejected. These results confirm a stable long-run relationship between the two series.

The estimated cointegrating vector can be expressed as follows (normalized on orange prices):

$$\log(\text{Orange}) = 0.92 \times \log(\text{Mandarin}) + c \quad (2)$$

This relationship indicates a strong positive linkage between the two export price series. In the long run, the prices move proportionally. The coefficient close to unity suggests that the two series exhibit near one-to-one co-movement.

The VECM captures both long-run equilibrium and short-run dynamics.

The VECM results are presented in Table 4. The error correction terms are negative and statistically significant in both equations. This indicates convergence toward long-run equilibrium. The magnitude of adjustment is larger for orange prices, suggesting faster correction, while mandarin prices adjust more gradually.

Table 4. VECM Estimation Results.

Dependent Variable	Error Correction Term (ECT)	t-Statistic	ΔOrange(-1)	t-Stat	ΔMandarin(-1)	t-Stat	Constant	t-Stat
ΔOrange	−0.44	−3.25	0.18	2.10	0.08	1.32	0.02	1.45
ΔMandarin	−0.21	−2.02	0.07	1.21	0.13	1.78	0.01	1.10

Notes: VECM = Vector Error Correction Model; ECT = Error Correction Term. The model includes one lag in first differences. t-statistics are reported for each coefficient. The ECT is derived from the estimated cointegration relationship.

Short-run coefficients are smaller in magnitude. This suggests that most of the adjustment occurs through the long-run equilibrium mechanism rather than short-term interactions. Cross-variable effects appear limited in magnitude, and their statistical significance is weak.

To account for potential outliers, a robust VECM is estimated (Table 5). Coefficient signs remain unchanged across specifications. The magnitude of the error correction terms is slightly reduced. This indicates that extreme observations influence parameter size but do not alter the underlying relationship.

Table 5. Robust VECM estimation results.

Dependent Variable	Error Correction Term (ECT)	t-Statistic	ΔOrange(-1)	t-Stat	ΔMandarin(-1)	t-Stat	Constant	t-Stat
ΔOrange	−0.41	−3.10	0.16	1.95	0.07	1.20	0.02	1.38
ΔMandarin	−0.19	−1.95	0.06	1.10	0.12	1.60	0.01	1.05

Notes: VECM = Vector Error Correction Model; ECT = Error Correction Term. Robust estimates are obtained using an iteratively reweighted least squares procedure with Huber-type weighting. Observations associated with large residuals receive lower weights. t-Statistics are reported for each coefficient.

The similarity between standard and robust estimates confirms the stability of the system. The long-run linkage between orange and mandarin export prices remains intact under alternative estimation approaches.

Coefficient signs remain unchanged across specifications. The magnitude of adjustment is similar, although the statistical strength of the error correction term is weaker in the mandarin equation under the robust specification. The robust model slightly reduces the size of coefficients, indicating lower sensitivity to extreme observations.

Model adequacy is evaluated using standard tests.

Model adequacy is assessed using standard diagnostic tests, and the results are reported in Table 6. The Ljung–Box test does not indicate residual autocorrelation at conventional significance levels. This suggests that the model captures serial dependence in the data.

Table 6. Diagnostic test results.

Test	Statistic	*p*-Value	Conclusion
Ljung–Box	9.8	0.36	No autocorrelation
Jarque–Bera	4.2	0.12	Mild deviation
ARCH	2.5	0.10	Weak heteroskedasticity
Stability	—	—	Stable system

Notes: The Ljung–Box statistic is reported for 12 lags. The ARCH statistic refers to the Lagrange Multiplier test for conditional heteroskedasticity. Stability is evaluated using the eigenvalue modulus condition.

The Jarque–Bera statistic does not reject the null of normality at the 5% level. This indicates that there is no strong evidence against normality in the residuals. The ARCH

test also does not provide statistically significant evidence of conditional heteroskedasticity at conventional levels, although the result is close to the threshold and may be considered borderline.

Stability diagnostics show that all eigenvalues lie within the unit circle. This indicates that the estimated system is dynamically stable. Overall, the diagnostic results do not point to major specification problems.

Forecast accuracy is evaluated under a rolling-origin framework.

Forecast performance results are reported in Table 7. Accuracy measures are computed separately for orange and mandarin series and averaged across the two products. VECM-based models produce the lowest forecast errors across all metrics. The robust specification performs slightly better, particularly in terms of RMSE and MAPE, indicating improved performance under volatile conditions.

Table 7. Forecast performance comparison.

Model	MAE (Avg)	RMSE (Avg)	MAPE (%) (Avg)	MAE (Orange)	MAE (Mandarin)
Robust VECM	0.20	0.28	8.3	0.19	0.21
VECM	0.21	0.30	8.7	0.20	0.22
XGBoost	0.25	0.34	9.8	0.24	0.26
SARIMA	0.27	0.36	10.6	0.26	0.28
ETS	0.29	0.38	11.5	0.28	0.30
Seasonal Naïve	0.35	0.45	14.1	0.33	0.37

Notes: MAE = Mean Absolute Error; RMSE = Root Mean Squared Error; MAPE = Mean Absolute Percentage Error. Forecast errors are calculated separately for orange and mandarin export prices under a rolling-origin forecasting framework and then averaged. MAE and RMSE are reported in logarithmic units.

Machine learning improves upon the naïve benchmark but does not outperform econometric specifications. Univariate models such as ETS and SARIMA show weaker performance, suggesting that ignoring cross-series dependence leads to a loss of predictive information. These results highlight the importance of modeling the joint dynamics of export prices in closely related agricultural markets. The Diebold–Mariano test results are reported in Table 8.

Table 8. Diebold–Mariano test results.

Comparison	DM Statistic	*p*-Value
Robust VECM vs. ETS	−2.61	0.009
Robust VECM vs. SARIMA	−2.23	0.026
Robust VECM vs. XGBoost	−1.98	0.048
Robust VECM vs. Seasonal Naive	−3.44	0.001

Notes: DM = Diebold–Mariano test. Negative DM statistics indicate lower forecast errors for the Robust VECM relative to the competing model. Statistical significance is evaluated using two-sided tests.

Diebold–Mariano test results confirm that the forecast accuracy improvements achieved by the robust VECM are statistically significant relative to ETS, SARIMA, and the seasonal naïve benchmark. The comparison with XGBoost is also significant at conventional levels. These findings indicate that the superior forecasting performance of cointegration-based models is not solely attributable to random variation in forecast errors.

The results indicate a stable long-run relationship between orange and mandarin export prices. Adjustment dynamics are asymmetric. Orange prices respond faster to disequilibrium.

Models that incorporate this relationship achieve better forecast accuracy. Univariate models fail to capture this structure.

As an additional robustness assessment, alternative lag specifications were examined during the model selection process. The evidence for a single cointegrating relationship remained unchanged across the alternative lag structures considered. Likewise, VECM-based models consistently outperformed the benchmark forecasting models, although minor differences in forecast error magnitudes were observed. These findings support the stability of both the cointegration results and the forecasting conclusions.

5. Discussion

The results indicate a stable long-run relationship between orange and mandarin export prices in Türkiye. This finding is consistent with the broader literature on market integration and price transmission in related agricultural markets [14,15,17]. However, the observed relationship extends beyond conventional spatial market integration. In the Turkish citrus sector, oranges and mandarins are embedded within interconnected export supply chains characterized by shared logistics infrastructure, common storage facilities, and overlapping export channels [2–4,9,12]. Under these conditions, market shocks may be transmitted through common operational constraints and commercial linkages, generating persistent co-movement between export prices.

The estimated cointegration relationship may also reflect substitution mechanisms within export markets. International buyers frequently source multiple citrus products from the same production regions and export networks [2,3,8,9,12,39]. Consequently, changes in demand conditions, shipment allocation, or export-market opportunities for one product may influence marketing decisions for the other. Similar mechanisms have been discussed in studies emphasizing market interdependence and price transmission across closely related agricultural products [14,15,17]. The results therefore suggest that the two export markets should not be viewed as independent pricing systems.

The adjustment process is asymmetric. Orange export prices respond faster to disequilibrium, while mandarin prices adjust more gradually. Differences in market structure, destination composition, and product differentiation may contribute to this pattern. Possible explanations include differences in product characteristics, export destinations, importer composition, and market organization. However, the present dataset does not contain destination-level trade information, product-specific quality indicators, or importer-level data required to directly evaluate these mechanisms. Similar asymmetric adjustment patterns have been documented in agricultural price transmission studies [14,15,17]. Therefore, the observed asymmetry should be interpreted as an empirical finding, while the underlying mechanisms remain a subject for future research.

The forecasting results provide additional support for the economic relevance of the cointegration relationship. If the long-run linkage merely reflected statistical correlation, incorporating it into the forecasting framework would not necessarily improve predictive accuracy. However, VECM-based specifications consistently outperform alternative models. This finding suggests that the equilibrium relationship contains economically meaningful information that can be exploited for forecasting purposes [32,33]. In closely connected agricultural markets, cross-series information may therefore represent an important source of predictive content.

Differences between forecasting methods are also informative. ETS and SARIMA models effectively capture trend and seasonal dynamics within individual series [25,26], yet they ignore the long-run interactions between related markets. Their weaker forecasting performance suggests that a substantial portion of export-price variation originates from cross-market linkages rather than isolated price movements. Although XGBoost is capable of capturing nonlinear relationships, it does not explicitly model equilibrium adjustment mechanisms. Consistent with previous forecasting studies, econometric models may out-

perform machine-learning approaches when economic structure and long-run relationships constitute the dominant source of predictability [24,25,28–31].

The robust VECM provides additional evidence regarding model stability and the nature of export-unit-value data. Export unit values may be influenced by temporary changes in shipment composition, destination-market structure, product quality, or exchange-rate conditions in addition to underlying market prices. These factors may generate extreme observations that are not fully representative of long-run market behavior. The robust estimation procedure reduces the influence of such observations while preserving the underlying equilibrium relationship [38]. The similarity between standard and robust estimates therefore increases confidence that the identified cointegration relationship is not driven by a limited number of atypical observations.

The findings also have implications for sustainable food supply chains. Citrus products are highly perishable. In export-oriented fresh fruit systems, forecasting accuracy is not only a market-efficiency issue but also a supply-chain sustainability issue. More accurate forecasts may contribute to improved capacity utilization in storage facilities, more efficient cold-chain operations, and better transportation planning. However, the present study does not directly quantify the resulting reductions in logistics costs, food losses, or carbon emissions [18–20]. The objective of the present study is not to estimate sustainability outcomes directly, but rather to evaluate whether improved forecasting can provide an informational basis for more efficient supply-chain decisions. Quantifying reductions in logistics costs, postharvest losses, and carbon emissions would require operational and facility-level data that are beyond the scope of the available dataset.

The results therefore suggest that jointly modeling related citrus products may support more sustainable supply-chain coordination. More reliable forecasts may improve inventory management, shipment scheduling, and market allocation decisions. This issue is particularly important in highly seasonal horticultural export systems characterized by perishability and timing constraints. Recent food supply-chain studies also emphasize that cold-chain optimization, packaging performance, real-time monitoring, and logistics coordination are critical for reducing losses and improving sustainability in fresh fruit and vegetable systems [18–20]. This perspective is consistent with recent logistics and supply-chain research emphasizing that coordination across inventory, transportation, and facility networks can substantially improve system-wide efficiency and sustainability outcomes in complex agri-food supply chains [20,35].

The results should also be interpreted together with the limitations of the data. Export prices are proxied by unit values. These measures reflect both prices and product composition. Quality differences, destination-market structures, and exchange-rate movements may influence observed values. The estimated relationship therefore captures co-movement in export unit values rather than fully standardized transaction prices.

The analysis also excludes several external variables that may influence export unit values. Exchange-rate movements, freight costs, and energy prices may affect both products simultaneously, particularly during periods of macroeconomic volatility. Consequently, part of the observed co-movement may reflect common external shocks rather than direct market interaction alone. However, the primary objective of this study is to evaluate whether a stable empirical relationship exists between the two export markets and whether this relationship improves forecasting performance. Future studies may extend the framework by incorporating additional macroeconomic and logistics variables within a multivariate system.

Future studies may compare cointegration-based models with additional machine-learning and deep-learning forecasting approaches using larger datasets. Future research may extend the framework in several directions. Destination-specific export data may

reveal heterogeneous market structures. Additional explanatory variables may improve forecasting performance. Nonlinear or regime-dependent approaches may better capture adjustment dynamics under stress conditions [14]. Higher-frequency data may also provide additional insight into short-run dynamics in sustainable perishable food supply chains.

Overall, the main implication is clear. Orange and mandarin export prices in Türkiye should not be evaluated independently. In closely connected citrus supply chains, models incorporating long-run relationships provide more reliable forecasts and a stronger analytical basis for sustainable market coordination than separate univariate approaches.

6. Conclusions

This study examined the relationship between orange and mandarin export prices in Türkiye using monthly data for 2016–2025. The results indicate a stable long-run linkage between the two citrus export markets. Orange and mandarin prices do not move independently. The two markets are connected through common production conditions, overlapping export destinations, and shared logistics systems.

The findings also show that models incorporating this relationship generate more accurate forecasts. VECM-based specifications outperform ETS, SARIMA, XGBoost, and the seasonal naïve benchmark under the same forecasting framework. This result highlights the importance of joint modeling in closely connected citrus supply chains.

The study contributes to the literature in two ways. First, it provides empirical evidence on market integration in Türkiye's citrus export system. Second, it demonstrates that cointegration-based forecasting approaches may improve forecasting performance in perishable horticultural supply chains operating under uncertainty and logistics constraints.

The findings also have implications for sustainability. Citrus exports depend heavily on cold-chain coordination, storage management, transportation efficiency, and shipment timing. Under these conditions, forecast quality becomes operationally important. More reliable forecasts may support more efficient inventory management, reduce logistical inefficiencies, and improve resource allocation in export systems. Improved coordination may also contribute to more sustainable food supply chains by reducing unnecessary storage periods and transportation inefficiencies. However, these sustainability-related benefits are inferred from the forecasting results and are not directly quantified in the present study.

These findings are particularly important for export-oriented perishable food systems operating under increasing market and climate uncertainty.

Some limitations should be acknowledged. Export prices are represented by unit values and may reflect quality composition and destination-market differences. The analysis also excludes several external factors, such as exchange rates, freight costs, and energy prices. In addition, the sample size remains moderate for machine-learning applications.

Future studies may extend the framework using destination-level trade data, additional explanatory variables, or nonlinear forecasting approaches. Comparative analyses across other perishable food markets may also provide broader evidence on market integration and forecasting performance in sustainable agricultural supply chains.

Overall, the main conclusion is clear. In Türkiye's citrus sector, orange and mandarin export prices should be evaluated within a common analytical framework. In closely connected perishable food systems, multivariate approaches provide a more reliable basis for sustainable supply-chain coordination and market forecasting than separate univariate models.

Author Contributions: Conceptualization, B.Ö.; Methodology, B.Ö.; Software, B.Ö.; Validation, B.Ö.; Formal analysis, T.K.; Investigation, T.K.; Resources, T.K.; Data curation, T.K.; Writing—original draft, B.Ö.; Writing—review & editing, T.K. and B.Ö.; Visualization, B.Ö.; Supervision, B.Ö.; Project

administration, B.Ö.; Funding acquisition, B.Ö. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments: During the preparation of this manuscript, the author used ChatGPT 5.0 for the purposes of English readability, grammar consistency, and structural clarity of the manuscript. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

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