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Article

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Links between US and Turkish agricultural commodity Markets: Nonlinear dependence and tail risk

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Abstract

In these unprecedented times, marred by the effects of the Covid-19 pandemic, global warming, and the war in Ukraine that began in February 2022, new approaches such as tail dependence have attracted more interest than conventional market dependence methodologies in analyzing time series in order to evaluate market linkage. In this study, we use the tail-restricted integrated regression function (IRF), introduced as a new methodology for nonlinear tail-mean dependence analysis. The IRF approach has several advantages over the existing tail-dependence measures focused solely on the occurrence of single tail events. To examine market dependence and tail risk, we analyze the nexus between the US and Turkish agricultural commodity markets over the period January 5, 2016–May 31, 2022. In addition to the daily prices of barley, corn, and wheat on agricultural commodity markets, we use Brent oil as a representative for the energy market, interest, and foreign exchange rates for financial markets as variables in our study. The results of upside and downside asymmetric risk spillovers show the direction of impact from the US agricultural market to the Turkish agricultural market. The findings suggest that, following the launch of a spot market in Türkiye, the launch of an agricultural commodity futures market will enhance the completeness and the link between the spot and derivatives markets there.

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Keywords: Contagion; Mean dependence; Nonlinear dependence; Spillovers; Tail dependence; Tail risk

1. Introduction

In recent years, several contagion events that disrupted supply chains (e.g., Covid-19, drought due to global warming) have moved the water, energy, and food security nexus to the forefront of the agenda for world economies. Discussions on deglobalization and self-sufficiency in the food and energy sectors entered a new phase in February 2022 after the war in Ukraine began. As markets become more interdependent, measuring and managing local market dynamics become more challenging. Furthermore, energy and commodity markets are closely linked to financial markets, as their financial inclusion in most developed economies has been completed, particularly

with derivatives based on relevant underlying assets. In this regard, studies that measure interdependence among markets to manage the deteriorating impact and to develop policies and measures are important (Table 1).

The possibility that extreme prices in one market will exacerbate prices in others, or the joint collapse of different markets, has garnered significant attention in tail-dependence studies. Therefore, numerous tail-dependence measures have been developed in addition to traditional correlation-based measures in order to examine price comovement and dependence structures between different markets under extreme market conditions. However, traditional measures have major drawbacks, such as estimating tail dependence symmetrically and using linear models with nonlinear data sets, which may lead to biased estimates (Lahiani et al., 2021). Moreover, the majority of time series have nonlinear characteristics, such as nonnormality, asymmetric cycles, bimodality, and nonlinearity

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Table 1
Literature review summary.

Author/Date	Data set	Methods	Findings
Wang (2023)	Daily data set for US and Chinese stock markets and China's commodity markets from January 10, 2008 to October 26, 2021.	DCC-FIGARCH model is applied in investigating tail dependence.	The results show similar downward trend contagion, where return spillovers are strong at the extreme lower quantile.
Erdogan et al. (2022)	WilderHill Clean Energy Index, gold, silver, platinum, and palladium daily data from January 1, 2001, to December 12, 2021.	Nonparametric Granger causality in the distribution test developed by Candelon and Tokpavi (2016).	The results suggest unidirectional causality from clean energy stock index to precious metals for left tail and the center of the distribution, and bidirectional causality between variables for the right tail.
Hanif et al. (2021)	West Texas Intermediate (WTI) crude oil benchmark and world food price index subcategories for the period January 1990 to February 2018.	Value-at-risk (VaR) and conditional VaR (CoVaR) methods are applied.	Oil and aggregate food price indexes move independently during market upturns and downturns. However lower- and upper-tail dependence is observed between oil prices and food commodities.
Kumar et al. (2021)	Global daily futures prices of WTI oil and agricultural commodities. Data set from January 3, 2002 to June 29, 2017.	VaR and CoVaR methods are applied.	The study results imply significant dependence in the left tail, indicating a contagion effect between markets that is dominant under negative market conditions.
Lahiani et al. (2021)	Leading cryptocurrencies, selected stock markets, oil market, and gold market for 2016–2019.	Mean and tail dependence analysis via newly developed nonlinear model-free tail dependence measure.	Bidirectional and unidirectional volatility spillovers are observed. Mean and tail dependence between cryptocurrency and stock market returns are reshaped by the introduction of Bitcoin futures contract.
Yousef et al. (2021a)	Hourly data set before Covid-19 from May 21, 2019, to December 31, 2019, and after Covid-19 from January 1, 2020, to May 20, 2020, for crude oil-gold and crude oil-Bitcoin pairs.	DCC-GARCH.	Return spillovers indicate different patterns during pre- and post-Covid-19 in the asset pairs. Gold serves as a strong hedge, and Bitcoin acts as a diversifier for the oil market during Covid-19.
Yousef et al. (2021b)	Brazil, Chile, Mexico, and Peru stock market indexes and gold daily values for the full period January 2000–June 2018 as well as two subperiods that represent US financial crises (August 2007–July 2010) and Chinese stock market crash (June 2015–May 2018).	VAR-AGARCH model is employed for spillover estimate.	Return and volatility spillovers depict different patterns across crises and markets between gold and Latin American stock markets. The study confirms gold's safe haven characteristics during financial crises and stock market crashes.
Albulescu et al. (2020)	The Rogers International Commodity Index (RICI). Daily index data set for January 3, 2005–August 1, 2018.	Copula-based local Kendall's tau is used for investigating dependence.	The dependence level is asymmetric, with both high- and low-level tail dependence observed, with particularly strong low-level dependence.
Yuan et al. (2020)	Price data set for six major grain commodities traded in the US market from January 1, 2000, to September 30, 2018.	GARCH.	The results confirm the presence of strong contagion effects in agricultural markets, with stronger comovement after the food crisis.
Escanciano and Hualde (2021)	S&P 500/USA, FTSE/UK, DAX/Germany and CAC/France stock market indexes from 2005 to February 2018.	The tail-restricted integrated regression function (IRF), the marginal expected shortfall functions (MESF) are used.	Fundamentally, the US S&P 500 and European stock indexes exhibit different dependence structures. There is a negative expectation of dependence between the S&P 500 and its lagged values, but positive dependence between European stocks and lagged values of S&P 500.
Hau et al. (2020)	Weekly data set for crude oil and China's agricultural market from future contract listing until December 2019.	Quantile regression (QR) and quantile-on-quantile regression (QQR) techniques are applied.	The empirical results reveal absolute volatility spillovers with an increasing trend in higher quantiles.
Liu et al. (2019)	The crude oil (WTI) and Chinese agricultural commodity market prices from listing until 2018.	Markov-switching GRG copula is applied.	The results show that among 12 kinds of agricultural commodity futures, 11 have varying levels of positive correlation with WTI.
Naeem et al. (2019)	Volume–return dependence in Bitcoin, Ethereum and Litecoin for 2014–2018.	GARCH-copula models.	There is a significant relationship between extreme returns and extreme trading volumes. However, tail dependence tends to be weaker when returns and volumes are low.
Dey and Sampath (2019)	Gold, realty, banking, IT sector indexes and rupee/USD exchange rate for July 2010 to March 2017.	Modeling dynamic interactions via VAR model.	External events from the US and decisions made by the US Federal Reserve contributed to the Indian economy through gold and foreign exchange (FX) markets. The IT sector also acts as a transmitter of volatility shocks.
Kondoz et al. (2019)	WTI crude oil price to US S&P 500 stocks for 2006–2016.	Test volatility spillover via BEKK-GARCH model.	Change in the US stock returns should be taken into consideration when forecasting volatility in crude oil.

(continued on next page)

Table 1 (continued)

Author/Date	Data set	Methods	Findings
Davis et al. (2018)	S&P 500 and Procter & Gamble stock price 1990–2009.	GARCH and APARCH models.	Significant serial external dependence in P&G daily log-returns triggered by the negative shocks and high asymmetry in volatility are observed. APARCH model captures the asymmetry that the GARCH model cannot.
Jiang et al. (2018)	Energy, agriculture, and metal commodity market indexes monthly data set for 1986–2017.	Wavelet squared coherence model.	The result showed higher dependence at the lower tails.
Kumar et al. (2018)	Asian selected stock markets (indexes from China, S. Korea, Taiwan, India, and Malaysia) for 2011–June 2016.	ARCH-GARCH models.	The study illustrates a positive and significant relationship between returns and volatility in all markets in the study.
Al Rahahle et al. (2017)	US, UK, and Asian market data for 15-year period, 1993 to June 2008.	DCC-GARCH models.	DCC model captures unidimensional dynamic correlation between UK-Taiwan and Taiwan-US markets in the left tail direction, as well as bidirectional spillover effects between the US and Hong Kong and US-Australia markets.
Hamadi et al. (2017)	Daily prices in US markets from December 30, 1999, to May 5, 2015.	DARCH, ICSS, and 3SLS models.	Significant bidirectional volatility spillovers are observed among the four commodities in the study.
Mensi et al. (2017)	OVX crude oil index, WTV wheat volatility index, and CIV corn volatility index daily data set from July 27, 2017, to May 20, 2016.	Wavelet squared coherence.	The result supported time-varying asymmetric tail dependence between pairs in different time horizons.
Trabelsi (2017)	Weekly data on Saudi, United Arab Emirates, and Russian stock indexes (at aggregated and desegregated levels) and oil prices are used for February 23, 2007, to July 15, 2016.	DCC-MGARCH approach and CoVaR measure are employed.	There is significant tail dependence from oil to stock indexes of major oil-exporting countries, which depends on the origin of the oil price shocks. The intensity of the dependence varies among countries and across different sectors.
Islam (2016)	Daily returns on S&P 500 and Shanghai Composite Index for May 2008–June 2016.	ARMA-GARCH models are used to measure spillovers.	Significant and positive return and volatility spillovers from the US S&P 500 Index stocks to Chinese Shanghai Composite Index stocks.
Candelon and Tokpavi (2016)	12 European daily stock market indexes from January 1, 2007, to May 6, 2011.	The nonparametric test for Granger causality in distribution.	The findings show a higher downside risk, supporting the presence of contagion.
Joudeau (2015)	US equities listed on NYSE and Nasdaq, divided into five portfolios based on market cap, book-to-market ratio, and momentum.	A parametric model is developed to measure tail dependence and test asymmetry.	Most of the time, tail dependence is significantly higher on the downside for market cap size, the book-to-market ratio, and momentum portfolios.

between lagged variables (Fan & Yao, 2005). Additionally, because joint tail analysis is incompatible with the multivariate normality assumption made by classical multivariate approaches, the conclusions drawn using those techniques can be problematic for tail-risk analysis (Krupskii & Joe, 2019). Therefore, nonparametric measures, which provide a better fit to data and are more flexible for modeling tail dependence, should be used, instead of parametric measures, which are insufficient for exploring nonlinear dependence structures in nonlinear time series.

Therefore, we use a nonparametric tail-dependence measure developed by Escanciano and Hualde (2021) to capture the nonlinear dependence linkage between markets. Instead of looking at whether a market is above or below a specific threshold (i.e., just one quantile value), this measure takes into consideration a continuum of quantiles, providing more information about tail events. Accordingly, it offers a richer view of how outliers trigger extreme events in other markets and financial contagion. The measure also enables us to deal with large variances and limited information on the tail risk of marginal expected shortfalls and exceedance correlations. Furthermore, as it is a model-free approach, it does not require model estimation and assumptions concerning the distribution of model residuals, and it is more flexible at capturing different

parts of the distribution of the time series. The other advantages of the measure are its simplicity for estimation and interpretation. It also avoids smoothing by considering the integrated regression function (IRF) (Escanciano & Hualde, 2021).

Our research primarily investigates the price dynamics of basic food products between the US and Türkiye. However, we also include asset classes in the energy and financial markets to evaluate information transmission between these markets. Our study covers the periods before and after July 26, 2019, the spot national agricultural commodity market at the Turkish Mercantile Exchange (TMEX) was launched. Because Türkiye has no agricultural commodity derivatives market, we include prices from both the Turkish spot market and the international derivatives market. In general, in terms of information transmission between markets, the spot and derivatives markets contribute jointly to price discovery. Evidence on spillovers during periods of stress indicates a possible contagion effect that increases volatility and worsens tension in the financial system. However, the major source of information spillovers appears to be the direction of price changes, that is, return spillover (Milunovich & Joyeux, 2010).

Furthermore, we investigate the tail dependence between agricultural commodity markets in the periods before and after February 24, 2022, when Russia invaded Ukraine, initiating

an ongoing conflict. Russia and Ukraine are leading suppliers of wheat, corn, and barley, and this war led to an increase in the price of agricultural commodities. To examine the effect of this structural change, we divide the dataset into two subsets using February 24, 2022, at the threshold to conduct the analysis.

We compare the Turkish and US agricultural commodity markets, as the US market is a global leader and a significant benchmark. The US agricultural commodity market has already undergone its financialization phase through the derivatives market. Price discovery in this market is influenced by various factors, including international benchmarks, local and global agricultural production conditions, and transportation costs. Due to its size and depth, the US market provides a good reflection of all these parameters and expectations.

However, the Turkish agricultural industry is dependent on the international market because of the limited supply in the local market. Türkiye mostly imports agricultural commodities, primarily from the Black Sea Region, in US dollar terms. Therefore, when local market prices are compared to those on foreign markets, the cost of freight and insurance should also be taken into consideration. Furthermore, if the level of financialization and integration is high, local prices may be greatly affected by international markets. However, an understanding of market price dynamics needs to consider the local regulatory authorities' interventions and incentives to support local agricultural production. They can interfere with the local market by buying from farmers at above-market prices or selling to the milling and animal feeding industries at below-market prices in order to stabilize food prices. During these periods, importing from cheaper foreign markets might be preferred by the local industry because of excess demand or for reserve purposes by the local regulatory authorities (e.g., the Turkish Grain Board). In the private sector, export decisions are heavily influenced by US dollar rates in terms of local currency (FX rates) as well as funding (interest) rates. Therefore, local and international financial market conditions, the foreign exchange market, and regulatory regimes play an important role in pricing.

Our goal in this study is to explore whether the US and Turkish markets demonstrate dependence and comovement, or whether the Turkish market is primarily influenced by local or regional market dynamics. The implications of our findings might not only help market participants with their portfolio management and hedging activities but also inform policy makers' intervention pricing and subsidy packages aimed at stabilizing food prices.

We divide our analysis into two periods based on the TMEX launch for the following reasons. Before the introduction of TMEX, Türkiye had separate local markets, with limited regional supply and demand. Most trades in these local markets were bilateral negotiated deals, reported to local exchanges as being off-exchange. However, after the TMEX was launched as a national exchange, these separate regional markets were closed, and the trades were aggregated into one order book at TMEX. This consolidation of liquidity in one order book significantly increased the share of continuous auction deals,

which made price discovery more efficient and supported the formation of benchmark prices. By dividing the analysis into two distinct periods, before and after the launching of TMEX, we can observe whether this structural change affected the market dynamics.

To the best of our knowledge, this paper is the first to apply the tail-restricted IRF to spot and derivatives markets for agricultural commodities. Although the spot market is crucial for price discovery, insights obtained from the interconnection between spot and futures markets can yield significant outcomes for policy makers.

The study examines the interdependence and contagion risks between various markets and highlights the need for a sustainable and efficient agricultural market. The study also investigates the impact of past and present prices of US agricultural futures contracts on the current TMEX spot agricultural market prices and suggests the potential benefits of launching a local derivatives market in the Turkish agricultural market for price discovery and risk management purposes.

The study provides empirical evidence on the impact of US barley, wheat, and corn futures contract prices on the TMEX spot market prices in the Turkish agricultural market. This contributes to the literature on price discovery and risk management in agricultural markets by examining the dynamics between local spot markets and international derivative markets.

The study emphasizes the importance of diversifying risk management strategies to account for differences in tail dependence and mean dependence between markets. This contributes to the literature on risk management in agricultural markets by suggesting the use of a combination of traditional risk management tools and exploring new risk management techniques, such as weather derivatives or index-based insurance, to effectively manage risks associated with market interdependencies.

Overall, this study contributes to the literature by providing empirical evidence, policy implications, and risk management strategies for the Turkish agricultural market and by emphasizing the importance of sustainability and efficiency in agricultural markets.

The remainder of the paper is organized as follows. Section 2 provides a literature review, Section 3.2 describes the methodology used in the study, Section 3.1 presents information about the data set, and Section 4 summarizes and evaluates the empirical results. Section 5 provides a discussion and policy suggestions based on the findings, and the final section, Section 6, summarizes the main findings of the study in our conclusion.

2. Literature review

This section reviews the literature on financial market linkages and the relationship between instruments' returns. Academics and researchers have also studied the relationship between energy and commodity markets. Developments in bioenergy has increased the focus on interconnectedness between energy and agricultural commodity markets.

The literature review highlights the predominant use of autoregressive conditional heteroskedasticity (ARCH) models and its various extensions, such as GARCH (generalized ARCH) copula, BEKK-GARCH (Baba-Engle-Kraft-Kron-GARCH), VaR-AGARCH (Value at Risk-Asymmetric GARCH), and APARCH (Asymmetric Power ARCH), in the analysis of financial and commodity markets. Trabelsi (2017), Yousef et al. (2021a), Wang (2023), Al Rahahleh et al. (2017), Hamadi et al. (2017), Yousef et al. (2021b), Davis et al. (2018), Islam (2016), Joudeau (2015), Kondo et al. (2019), Kumar et al. (2018), Lahiani et al. (2021), and Yuan et al. (2020) have employed these models to investigate the relationship between different financial and commodity markets.

Trabelsi (2017) uses the DCC-MGARCH (Dynamic Conditional Correlation - Multivariate GARCH) approach and conditional value at risk (CoVaR) measurement to examine the negative tail dependence between oil and stocks of major oil-exporting countries, finding significant spillover effects. Yousef et al. (2021a) applies the DCC-GARCH model to crude oil-gold and crude oil-Bitcoin pairs, concluding that return spillovers have different patterns during before and after Covid-19, with gold acting as a strong hedge and Bitcoin as a diversifier for the oil market during Covid-19. Wang (2023) uses the DCC-FIGARCH (DCC-Fractionally Integrated GARCH) model to investigate tail dependence between stocks and Chinese commodity markets, finding a contagious strong downward trend at the extreme lower quantile. Al Rahahleh et al. (2017) also employ the DCC-GARCH model and observe a bidirectional information flow between the US and Hong Kong markets as well as the US and Australian markets.

Hamadi et al. (2017) apply a combination of ICSS, 3 SLS, and GARCH models to measure volatility spillovers in US agricultural commodities, finding significant bidirectional volatility spillovers. Yousef et al. (2021b) uses high-frequency data on return and volatility spillover in Latin American stock markets and gold via VaR-AGARCH, with results showing variations across different stock markets. Davis et al. (2018) analyze the persistence of negative and positive shocks in the equity market using GARCH and APARCH models. Islam (2016) measures the volatility spillover between US and Chinese financial markets via ARMA-GARCH (auto-regressive moving average - GARCH) and concludes that there are significant and positive return and volatility spillovers from the US to China. Joudeau (2015) establishes a multivariate noncentral *t*-distribution model to study the US stock market, and the results reveal higher tail dependence on the downside than the upside.

Kondo et al. (2019) tests for volatility spillover between oil prices and the US equity market using BEKK-GARCH, finding that crude oil investors should use data on US equity market returns for more effective prediction of oil market return volatility. Kumar et al. (2018) also study the equity market and test for volatility spillover using ARCH-GARCH models. Lahiani et al. (2021) employ a new measure of nonlinear dependence introduced by Escanciano and Hualde (2021) on cryptocurrency-stock markets. Yuan et al. (2020) model six major grain commodity price comovements using GARCH,

finding strong contagion effects and stronger comovement after the food crisis.

Overall, the literature review supports the widespread use of ARCH models and its extensions in studying financial and commodity markets, as well as the interconnectedness of different markets.

Candelon and Tokpavi (2016) develop a kernel-based nonparametric approach to test for Granger causality in distribution and examine causalities for the left tail, right tail, and center of the distribution for a set of 12 European daily stock market indexes. By employing this proposed test, Erdogan et al. (2022) investigate the dependence between clean energy stock index and precious metals prices, resulting in unidirectional causality from clean energy to precious metals for the left tail and the center of the distribution, and bidirectional causality for the right tail.

In addition, the above-mentioned methodologies, wavelet squared coherence (WSC) is a methodology used to analyze the lead-lag relationship between markets. Jiang et al. (2018) use WSC along with a wavelet-based copula to study the dependence structure of energy, agriculture, and metal commodity market indexes. They conclude that higher dependencies are more significant at the lower tails than at the upper tails, indicating asymmetric tail dependence. Similarly, Mensi et al. (2017) apply WSC to examine the dependence structure of oil, wheat, and corn commodities and find time-varying asymmetric tail dependence between pairs in different time horizons. These studies highlight the use of WSC as a method for analyzing the dependence structure and lead-lag relationships among different markets.

Albulescu et al. (2020) uses the copula-based local Kendall's tau approach to measure nonlinear local dependence in energy, agriculture, and metal commodities using the Rogers International Commodity Index subindexes. They find stronger dependence between energy and other commodity markets at the lower tail, indicating that extreme events can have higher dependence. Hau (2020) investigates the linkage between crude oil and China's agricultural market using conventional quantile regression (QR) and quantile-on-quantile regression (QQR) techniques. The results show absolute volatility spillovers with an increasing trend in higher quantiles, indicating that extreme events may lead to higher volatility spillovers. Hanif et al. (2021) use static and dynamic bivariate copula value-at-risk (VaR) and conditional VaR (CoVaR) methods to study the relationship between the West Texas Intermediate (WTI) crude oil benchmark and world food price index subcategories. The findings indicate that oil and aggregate food prices move independently during market upturns and downturns, but lower- and upper-tail dependencies are observed between oil prices and food commodities, indicating potential contagion effects during extreme events. Kumar et al. (2021) apply VaR and CoVaR to investigate the dependence between oil and agricultural commodity markets and find significant dependence in the left tail, suggesting that contagion among markets dominates during negative market conditions. These studies demonstrate the use of different methods, such as copula-based local Kendall's tau, QR, and VaR/CoVaR

approaches, to analyze the dependence structure and spillover effects in financial and commodity markets.

Liu et al. (2019) use a Markov-switching GRG (Gaussian Random Graphs) copula to analyze dependence between crude oil (WTI) and Chinese agricultural commodity market prices. The findings indicate that eleven of the twelve different agricultural commodity futures have varying degrees of positive correlation with WTI. This suggests that significant positive dependence or comovement exists between WTI crude oil prices and Chinese agricultural commodity market prices, implying potential linkages or spillover effects between these markets.

3. Data and methodology

3.1. Data

The underlying dataset in the study consists of daily agricultural commodity prices from Chicago Mercantile Exchange (CME)/USA, Chicago Board of Trade (CBOT)/USA, National Commodity and Derivatives Exchange (NCDEX)/India, Turkish Mercantile Exchange (TMEX)/Türkiye (Fig. 1), and Brent oil prices from Intercontinental Exchange (ICE) as representative of the energy market, foreign exchange, and overnight interest rates in the financial market. We use major food-related futures contracts, for barley, corn, and wheat from advanced economies and their spot market equivalents in TMEX (Table 2). The dataset other than TMEX comes from the Bloomberg terminal, and the TMEX dataset is obtained from TMEX. The period covered is January 5, 2016, to May 31, 2022. Because we conduct our analysis for two scenarios, we divide the dataset into subsample for the periods before and after the TMEX launch (July 26, 2019) and before and after the war in Ukraine war (February 24, 2022) for each scenario.

Table 3 shows descriptive statistics for the returns of both dependent variables and conditional variables. The Jarque-Bera normality test indicates the nonnormality of the variables. Additionally, the BDS (Brock-Dechert-Scheinkman) test rejects the linearity of most variables and lends support to the nonparametric analysis.

Table 2
Data set.

Series	Details	Data period
TMEX Barley	TMEX Barley spot	January 13, 2016–May 31, 2022
TMEX Wheat	TMEX Wheat spot	January 5, 2016–May 31, 2022
TMEX Corn	TMEX Corn spot	January 5, 2016–May 31, 2022
CBOT Corn	CBOT Corn futures	January 5, 2016–May 31, 2022
CME Wheat	CME Wheat	January 5, 2016–May 31, 2022
NCDEX Barley	NCDEX Barley	January 5, 2016–May 31, 2022
Brent Oil	ICE Brent futures	January 5, 2016–May 31, 2022
USDTRY	CBRT USD/TRY	January 5, 2016–May 31, 2022
TRLIBOR	TRLIBOR O/N	January 5, 2016–May 31, 2022

Notes: CBOT: Chicago Board of Trade; CME: Chicago Mercantile Exchange; ICE: Intercontinental Exchange; NCDEX: National Commodity and Derivatives Exchange/India; TMEX: Turkish Mercantile Exchange; CBRT: Central Bank of Türkiye; TRLIBOR: Turkish Lira Interbank Offer Rate.

3.2. Methodology

The measures of dependence calculate the covariance or correlation between two random variables over their entire distribution or specific parts of the distribution, indicating the comovement of the variables. The measures that exploit the entire distribution, that is, mean dependence, do not capture the link between the extremes of random variables. However, tail-dependence measures provide information about the dependence of the upper or lower parts of the distribution. In this regard, in a bivariate distribution, tail-dependence measures give the covariance or correlation between random variables at which the marginal distribution of one variable exceeds a certain threshold, provided that the margin of the other variable exceeds the same threshold (AghaKouchak et al., 2013), and refers to extreme events that occur simultaneously.

In order to assess the magnitude and persistence of both mean and tail dependence, we employ the newly developed nonlinear measure of tail dependence introduced by Escanciano and Hualde (2021) because of its several advantages over methods in the existing literature. This measure is different from copula-based tail-dependence measures as it extends the linear correlation measures in the literature to a nonparametric framework. Unlike other tail-dependence measures, it does not require model estimation and assumptions concerning the distribution of model residuals and is more flexible in handling different parts of the distribution of the time series. Furthermore, it enables the handling of large variances and limited information on the tail risk of marginal expected shortfalls and exceedance correlations, in addition to its simplicity of estimation and interpretation. Accordingly, the proposed measure can account for a continuum of tail market events, instead of just focusing on the occurrence of single-tail market events, providing a more complete overview of tail dependence and systemic risk. It also avoids smoothing by considering the IRF. In the following, we briefly explain the methodology of the nonlinear tail-dependence measure.

Let $(Y_t, X_t)_{t \in \mathbb{Z}}$, where $Y_t \in \mathbb{R}$ and $X_t \in \mathbb{R}^p$, be a time-series vector. Under the regular conditions mentioned by Escanciano and Hualde (2021) when the interest in the joint distribution or quantile dependence of (Y_{t+h}, X_t) , the cumulative measure or so-called IRF is as follows:

$$\varphi_{t,h}(y, x) = \text{Cov}(1(Y_{t+h} \leq y), 1(X_t \leq x)) = K_{t,h}(y, x) - L_{t+h}(y)F_t(x), \quad (1)$$

where $K_{t,h}(y, x)$, $L_{t+h}(y)$ and $F_t(x)$ are the joint and marginal cumulative distribution functions of Y_{t+h} and X_t , respectively, and $1(A)$ denotes the indicator function of event A . In order to consider different parts of the distribution, $\varphi_{t,h}(y, x)$ can be adjusted to specific values of y and x . Let $y \leq y_{tail}$ and $x \leq x_{tail}$; then, the covariances $\varphi_{t,h}(y, x)$ measure the distributional tail dependence, which can be defined as

$$\|\varphi_{t,h}\|_{y_{tail}, x_{tail}} = \sup_{y \leq y_{tail}} \sup_{x \leq x_{tail}} |\varphi_{t,h}(y, x)|. \quad (2)$$

As shown, this measure offers more information on distributional tail dependence, because it considers a continuum of values of y and x , rather than focusing on only a single value of them.

For strictly stationary time series, the estimation of the distributional measures of dependence based on a sample $\{Y_t, X_t\}_{t=1}^n$ is

$$\hat{\varphi}_h(y, x) = \frac{1}{n-h} \sum_{t=1}^{n-h} 1_c(Y_{t+h}, y) 1_c(X_t, x), \quad (3)$$

where $1_c(Z_t, x) = 1(Z_t \leq x) - (n-h)^{-1} \sum_{s=1}^{n-h} 1(Z_s \leq x)$, for a generic series $\{Z_t\}_{t=1}^n$.

To measure persistence, functions such as $\|\varphi_{t,h}(x)\|_\infty$ or its scaled version with Kolmogorov-Smirnov (KS)-type tests can be estimated. Then, fix a lag $h \geq 1$ and $\bar{x} \in \mathbb{R}^p$ and calculate the KS statistic and

$$KS_{n,\bar{x}}(h) := \|\hat{\varphi}_h\|_{\bar{x}} \quad (4)$$

To determine the bootstrap p -values, first, we calculate the bootstrap test statistics $KS_{n,\bar{x}}^{(r)}(h) := \|\hat{\varphi}_h^{(r)} - \hat{\varphi}_h\|_{\bar{x}}$ for $r = 1, \dots, R$, based on R bootstrap samples from the moving block bootstrap (for details, see the appendix to [Escanciano and Hualde, 2021](#)); then, the bootstrap p -values are as follows:

$$\hat{p}_{n,\bar{x}(h)} = \frac{1}{R} \sum_{r=1}^R 1(KS_{n,\bar{x}}^{(r)}(h) \geq KS_{n,\bar{x}}(h)). \quad (5)$$

The hypothesis of $\bar{x}$ -tail independence at lag h (i.e., $\|\hat{\varphi}_h\|_{\bar{x}} = 0$) and significance level α is rejected if $\hat{p}_{n,\bar{x}(h)} < \alpha$.

To sum up, the suggested tail-mean dependence measure calculates the covariance between two variables when the threshold values are satisfied for both variables, regardless of whether they are higher or lower. Because this measure

Table 3
Descriptive statistics.

Variable	Number of Obs.	Mean	Std. Dev.	Min	Max	Skew	Kurt	JB	BDS	ADF	ABP
Panel A: Before TMEX Launch											
TMEX Barley	419	−0.05	6.44	−31.79	29.51	−0.28	9.29	695.4832***	9.04***	−7.25***	0.00***
TMEX Wheat	694	−0.04	8.07	−40.73	25.38	−0.27	5.01	125.1747***	11.65***	−8.03***	0.00***
TMEX Corn	695	0.01	4.64	−20.31	19.99	−0.14	5.63	202.0354***	7.89***	−22.92***	0.00***
NCDEX Barley	419	0.08	1.87	−19.42	12.91	−2.71	45.72	32377.47***	0.29	−20.38***	0.80
CME Wheat	694	0.01	2.13	−13.43	16.80	0.45	12.28	2513.281***	1.93*	−27.44***	0.34
CBOT Corn	695	0.03	1.49	−8.30	6.89	−0.45	7.09	506.9963***	4.18***	−8.76***	0.67
Brent Oil	695	0.04	1.88	−7.18	10.42	0.03	6.26	308.4715***	3.40***	−27.58***	0.21
USDTRY	695	0.07	1.25	−8.07	14.74	2.02	34.82	29788.68***	7.92***	−18.62***	0.23
TRLIBOR	695	0.09	1.36	−10.29	22.15	8.16	127.44	456164.7***	−0.64	−25.89***	0.40
Panel B: After TMEX Launch											
TMEX Barley	710	0.08	1.65	−23.35	11.64	−5.79	97.96	270708.7***	11.06***	−8.95***	0.01***
TMEX Wheat	710	0.09	4.38	−26.97	30.84	0.22	12.96	2939.27***	9.75***	−9.69***	0.00***
TMEX Corn	710	0.11	2.20	−11.30	19.70	0.78	14.52	3999.81***	6.52***	−12.2***	0.00***
NCDEX Barley	710	0.07	6.27	−42.69	39.22	−0.45	15.66	4765.27***	7.52***	−12.46***	0.02***
CME Wheat	710	0.08	3.17	−16.81	23.58	0.41	9.91	1429.61***	7.24***	−13.3***	0.48
CBOT Corn	710	0.08	1.97	−20.57	6.21	−2.45	26.96	17664.39***	4.63***	−28.04***	0.25
Brent Oil	710	−0.04	1.80	−17.79	13.24	−4.08	53.77	78096.91***	7.86***	−7.82***	0.39
USDTRY	710	0.15	1.49	−20.81	11.90	−3.09	68.30	127099.7***	14.7***	−6.26***	0.39
TRLIBOR	710	0.06	3.29	−27.98	19.08	−1.50	20.94	9777.81***	2.43***	−24.6***	0.00***
Panel C: Before the War in Ukraine											
TMEX Barley	1064	0.01	5.30	−31.79	30.84	−0.12	11.87	3488.89***	14.37***	−8.02***	0.00***
TMEX Wheat	1339	0.00	6.93	−40.73	39.22	−0.08	7.79	1283.08***	15.95***	−11.63***	0.00***
TMEX Corn	1339	0.02	4.03	−20.31	23.58	0.00	7.10	938.53***	11.05***	−16.04***	0.00***
NCDEX Barley	1064	0.04	1.70	−23.35	12.91	−5.37	81.92	281244.5***	2.73***	−32.14***	0.32
CME Wheat	1339	0.05	1.95	−13.43	16.80	0.37	10.31	3015.35***	1.83*	−27.73***	0.33
CBOT Corn	1339	0.05	1.73	−20.57	6.89	−2.06	25.59	29429.19***	4.88***	−37.56***	0.62
Panel D. After War											
TMEX Barley	65	0.56	4.15	−13.75	15.76	−0.06	6.93	41.80***	3.16***	−12.66***	0.04**
TMEX Wheat	65	0.34	11.59	−42.69	21.23	−1.50	6.93	66.02***	2.68***	−6.13***	0.00***
TMEX Corn	65	0.47	2.10	−4.48	6.58	0.60	4.04	6.88**	1.04	−7.35***	0.62
NCDEX Barley	65	0.71	2.18	−2.43	11.64	2.73	12.12	306.08***	4.96***	−2.77***	0.00***
CME Wheat	65	0.33	4.82	−11.30	19.70	0.59	6.24	32.32***	3.63***	−6.92***	0.45
CBOT Corn	65	0.15	2.11	−5.24	5.88	0.03	3.70	1.33	5.60***	−10.95***	0.07*

Notes: This table reports number of observations, the mean, median, standard deviation (Std. dev), minimum and maximum values, skewness (Skew), kurtosis (Kurt), and test statistics of the Jarque-Bera (JB) normality test and the BDS test of nonlinearity. ABP denotes the p -value of the Data Driven Box Pierce test of [Escanciano and Lobato \(2009\)](#) for testing serial correlation with the null hypothesis of serial uncorrelation. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

considers a continuum of quantiles, the size of the covariance is measured by the uniform (sup-) norm.

4. Empirical results

We measure both tail and mean dependence from the US agricultural market, Brent oil, currency rates, and overnight interest rates to the Turkish agricultural market. This analysis enables us to evaluate upside and downside asymmetric risk spillovers in terms of tail dependence. Because we consider a continuum of quantiles, we use all quantiles between 1 percent

and 5 percent for the lower tail and all quantiles between 95 percent and 99 percent for the upper tail. For mean dependence, we consider the entire distribution. We conduct our analyses based on 300 moving block bootstraps.

Figs. 2–25 depict the nonlinear correlograms that show the magnitude and persistence of tail and mean dependence from conditioning variables to Turkish agricultural commodities. In other words, they display the IRF cross-coefficients $K_n(h) = \|\hat{\varphi}_h\|_\infty$ which are the size $\hat{\varphi}_h$ of a function of h with 5 percent marginal bootstrap critical values. Although we set h to 300 lags, when $1(A)$ is zero, the algorithm stops.

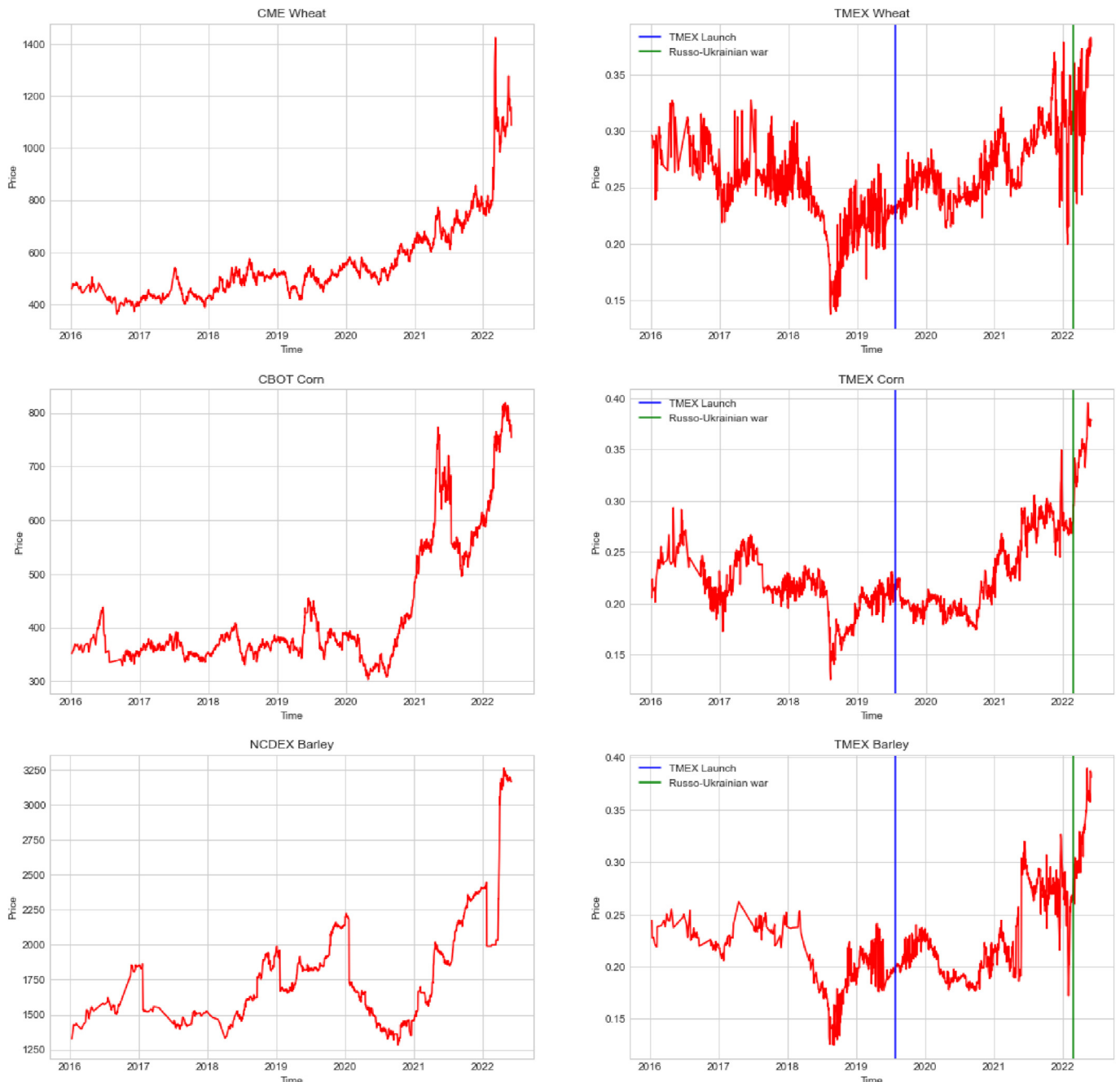


Fig. 1. Time series of commodity prices in terms of US dollars.

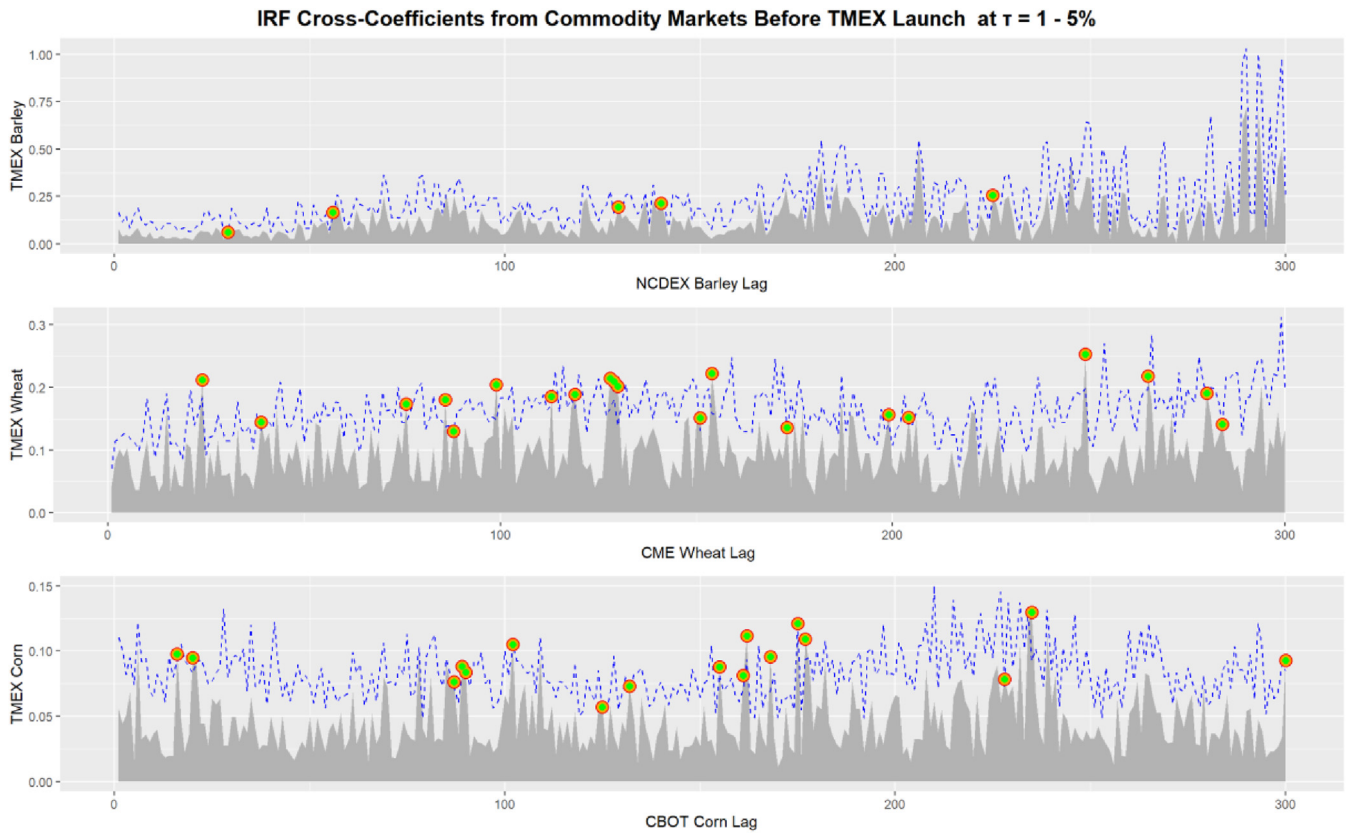


Fig. 2. IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 1%–5% (block 95% bootstrap critical values represented by dashed lines).

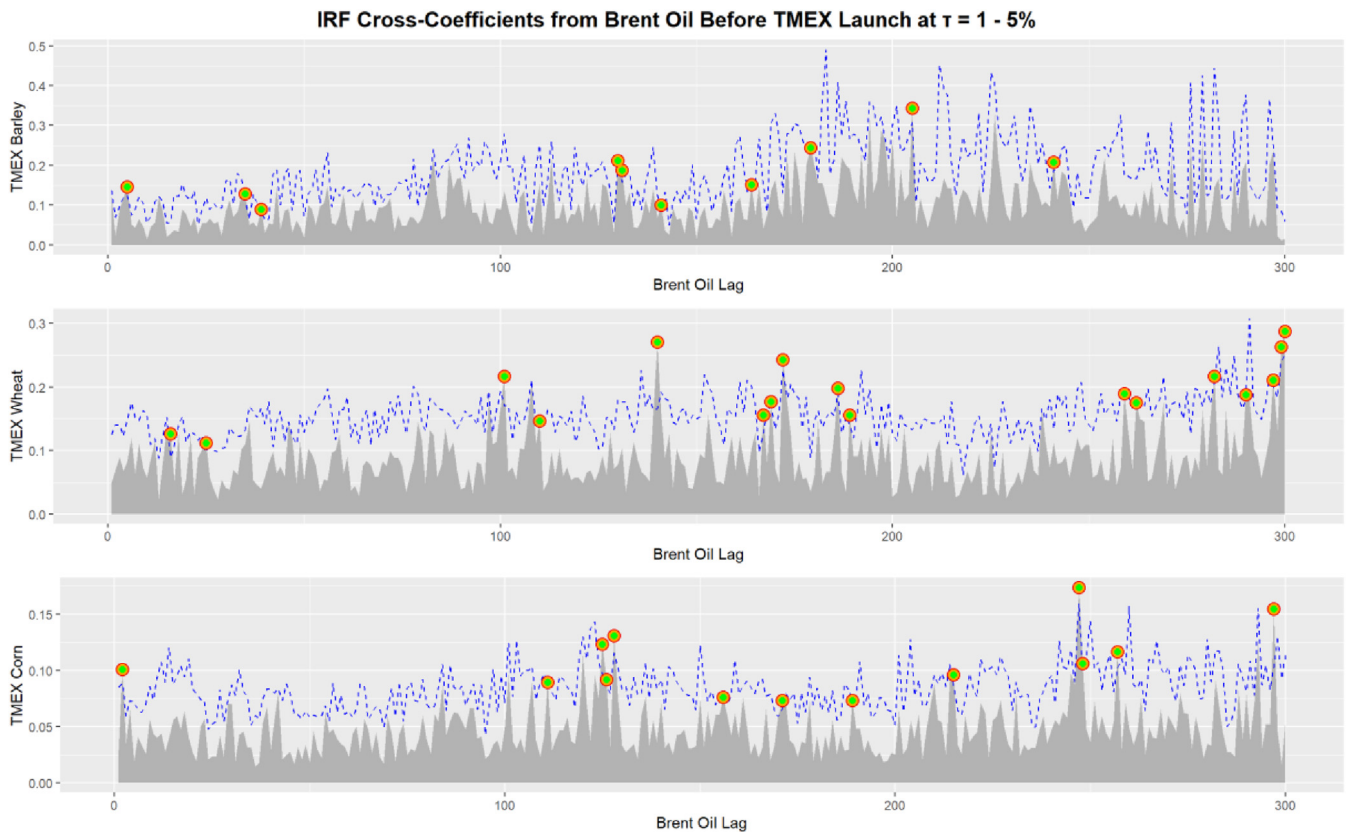


Fig. 3. IRF cross-coefficients from lagged Brent Oil to Turkish agricultural commodities market measured at quantiles 1%–5% (block 95% bootstrap critical values are represented by dashed lines).

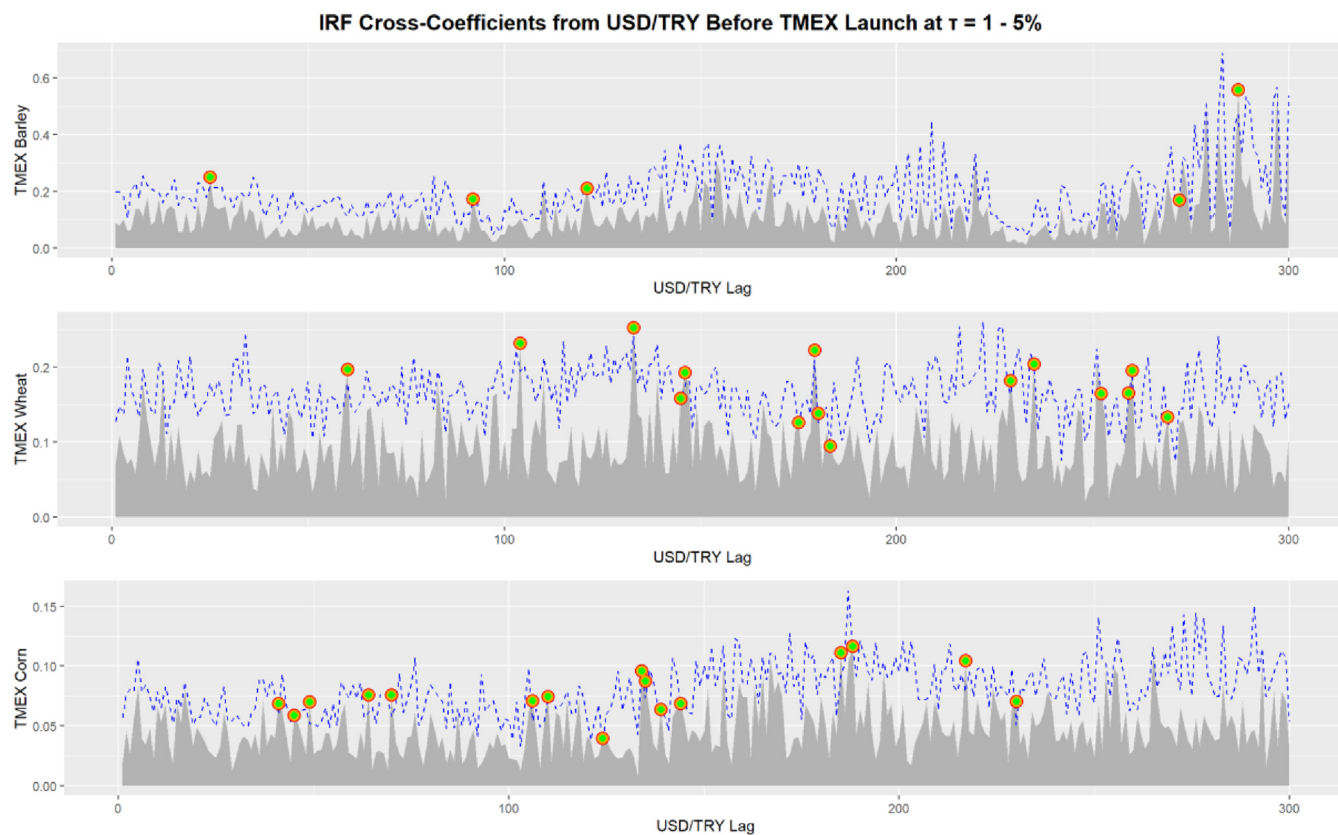


Fig. 4. IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 1%–5% (block 95% bootstrap critical values are represented by dashed lines).

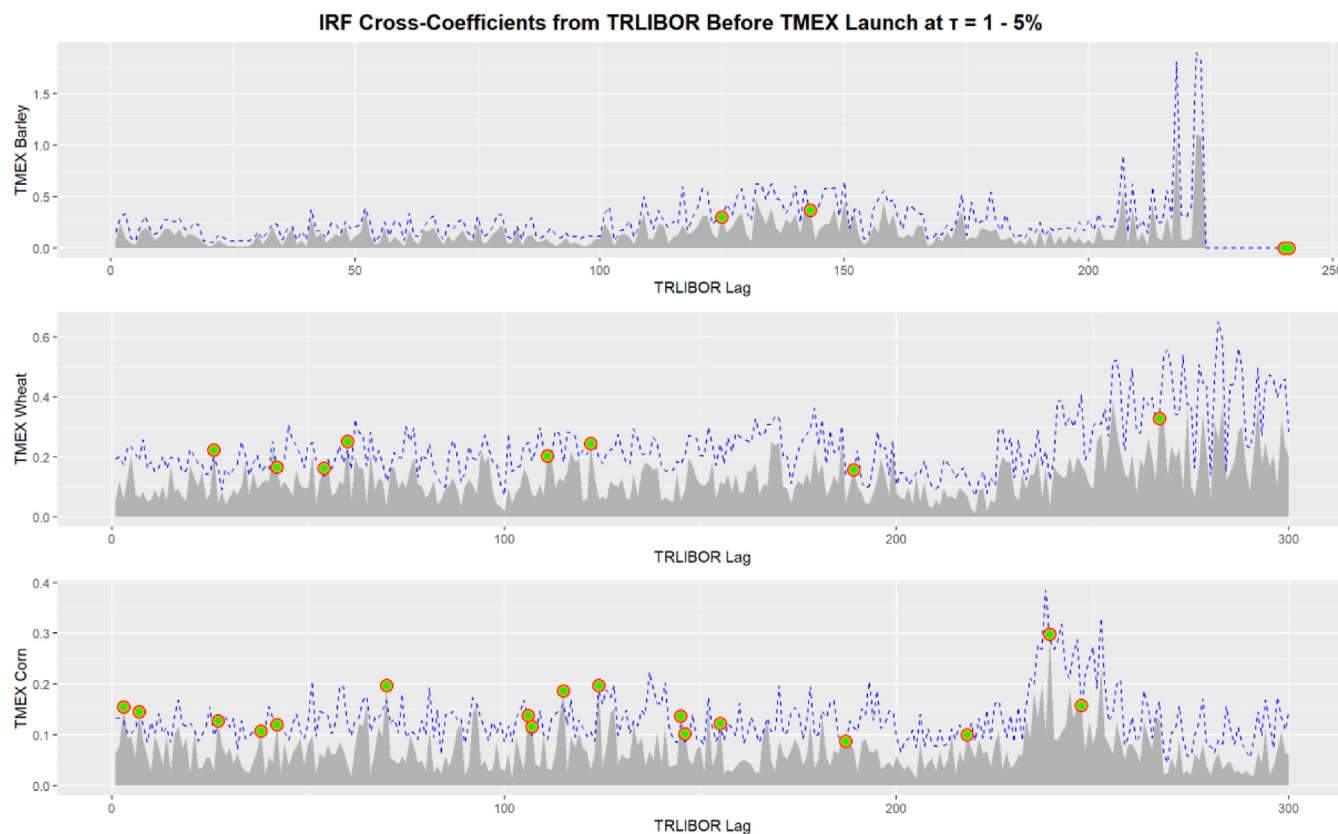


Fig. 5. IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 1%–5% (block 95% bootstrap critical values are represented by dashed lines).

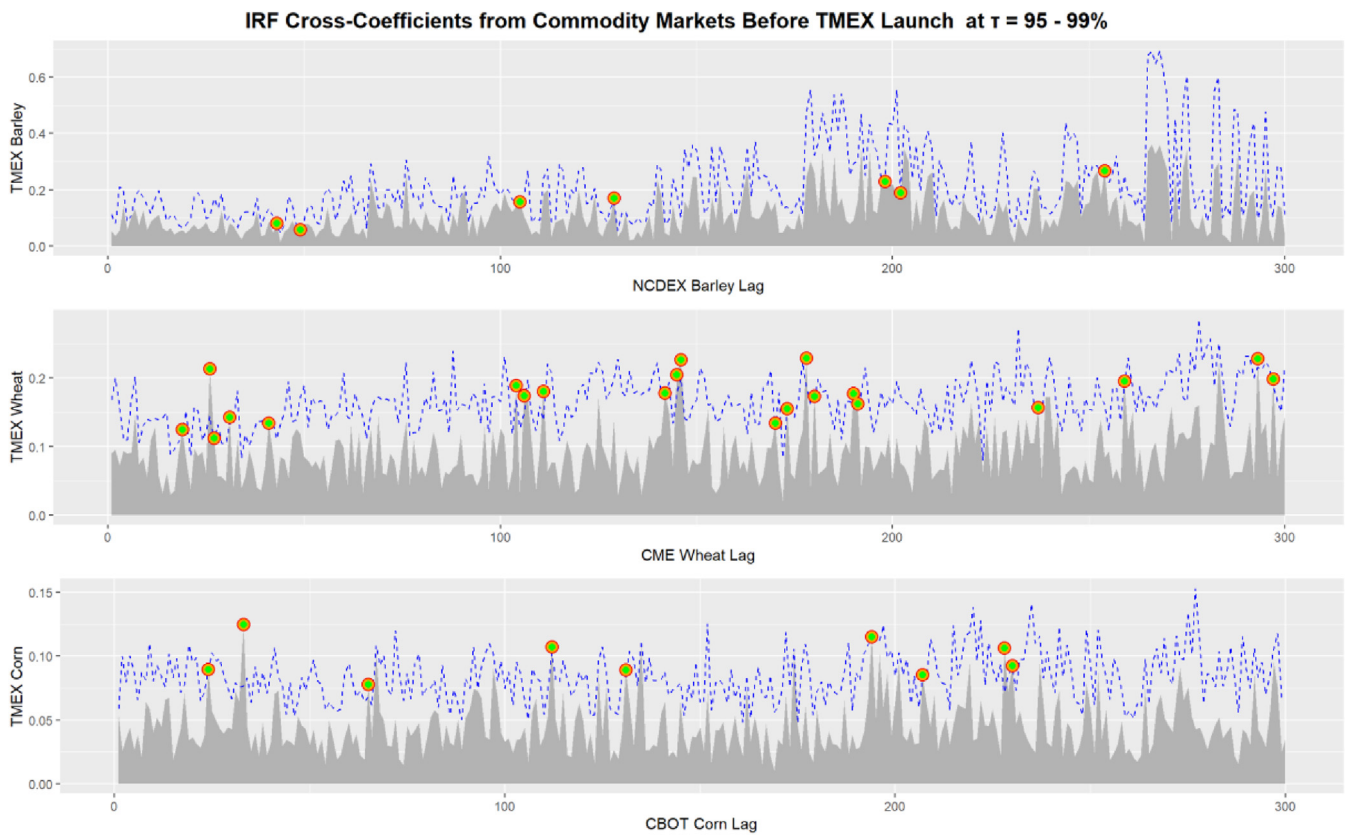


Fig. 6. IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 95%–99% (block 95% bootstrap critical values are represented by dashed lines).

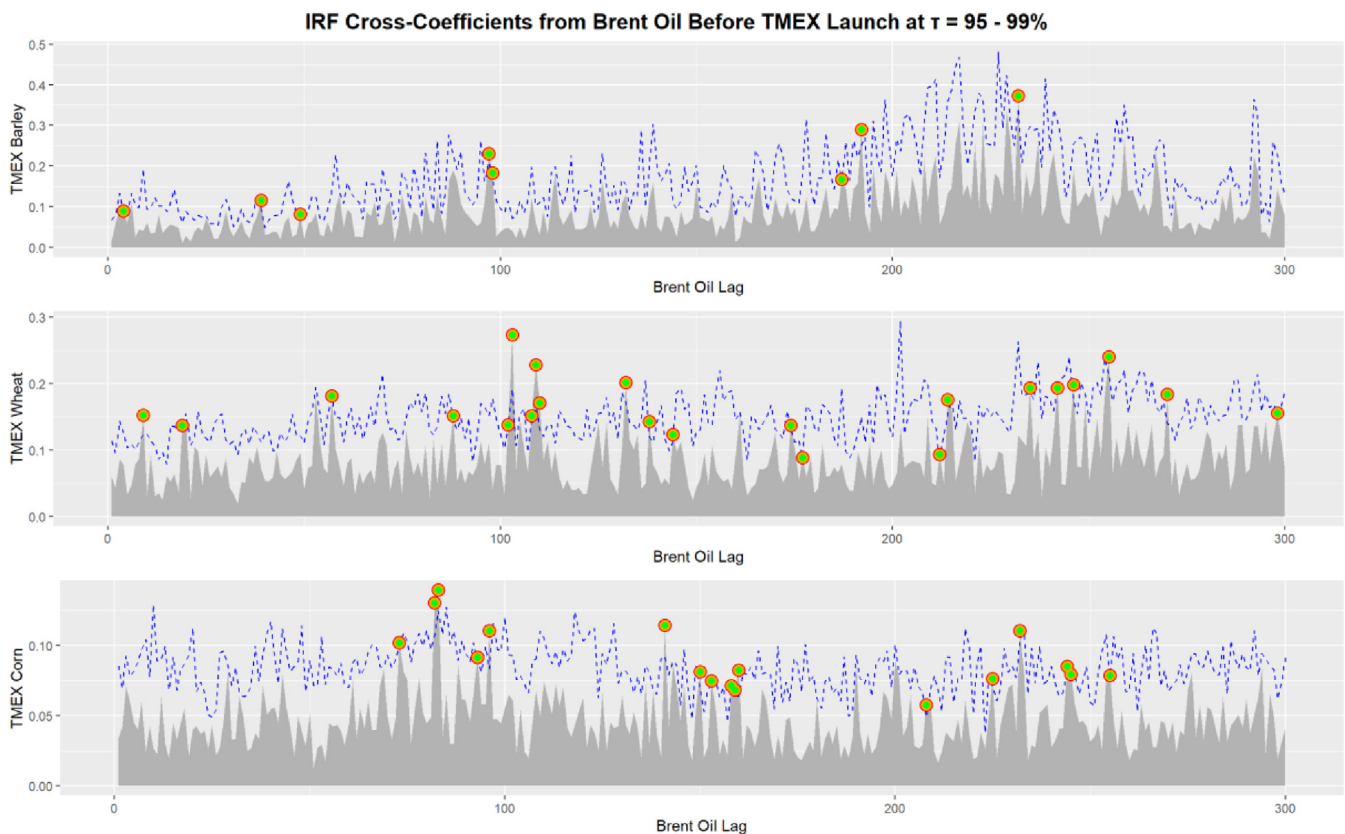


Fig. 7. IRF cross-coefficients from lagged Brent Oil to Turkish agricultural commodities market measured at quantiles 95%–99% (block 95% bootstrap critical values are represented by dashed lines).

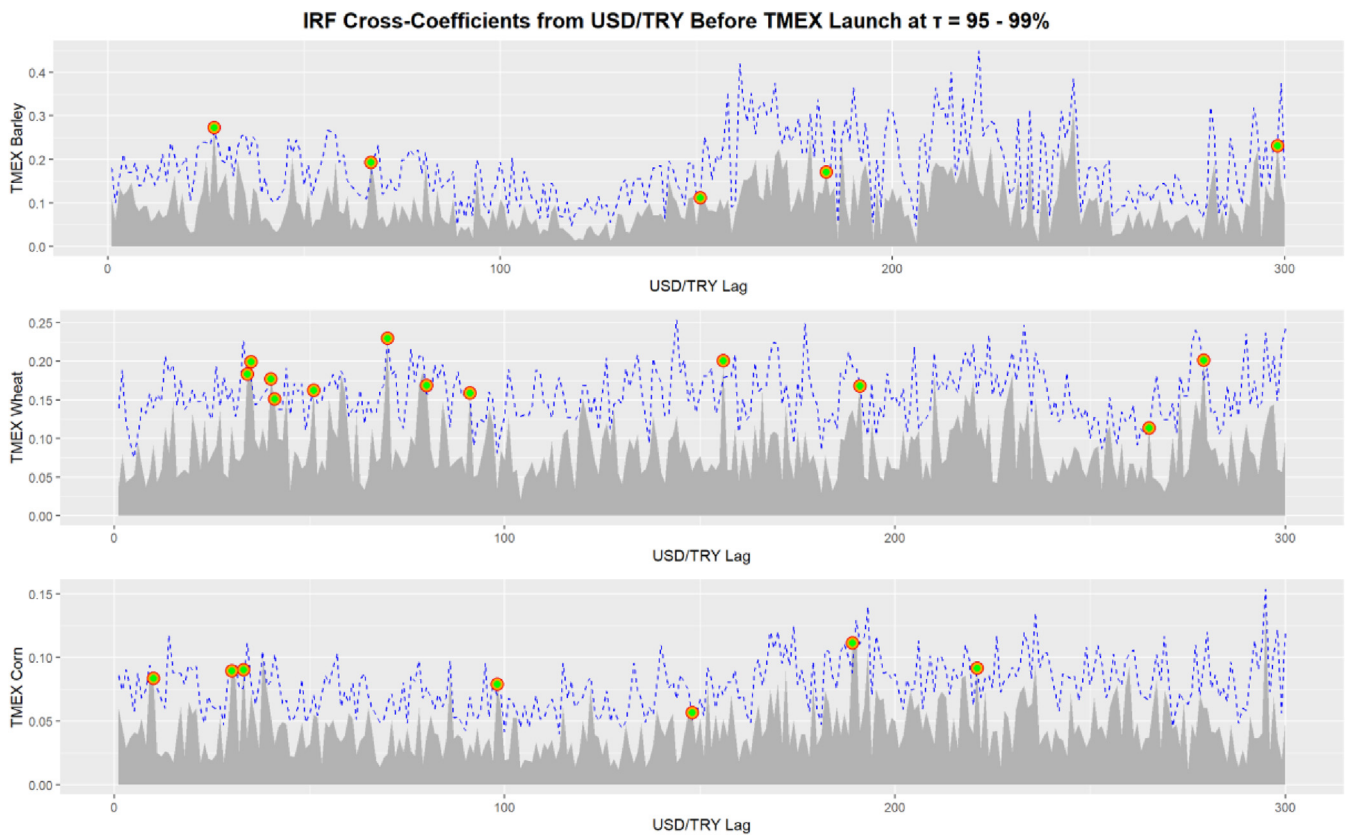


Fig. 8. IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 95%–99% (block 95% bootstrap critical values are represented by dashed lines).

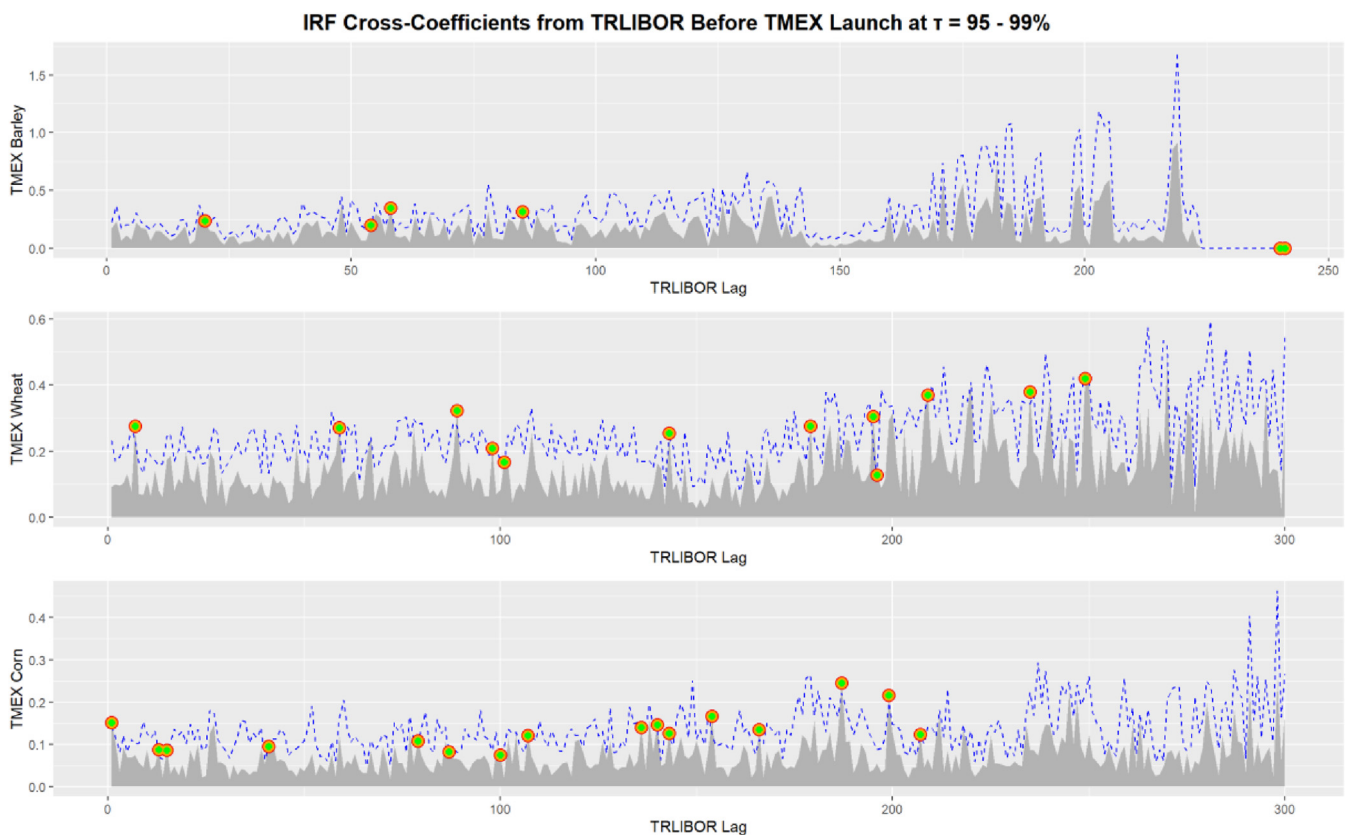
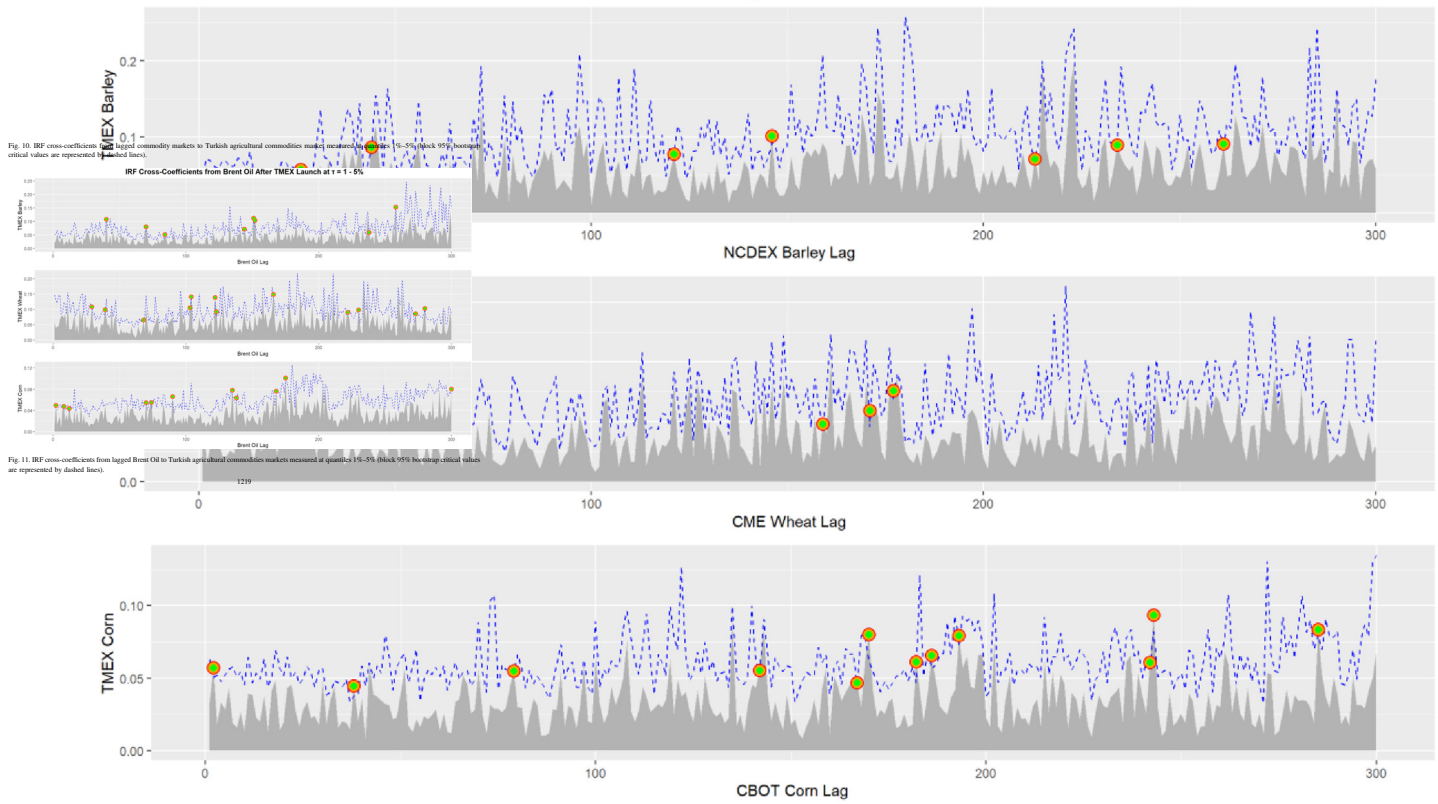


Fig. 9. IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 95%–99% (block 95% bootstrap critical values are represented by dashed lines).

IRF Cross-Coefficients from Commodity Markets After TMEX Launch at $\tau = 1 - 5\%$



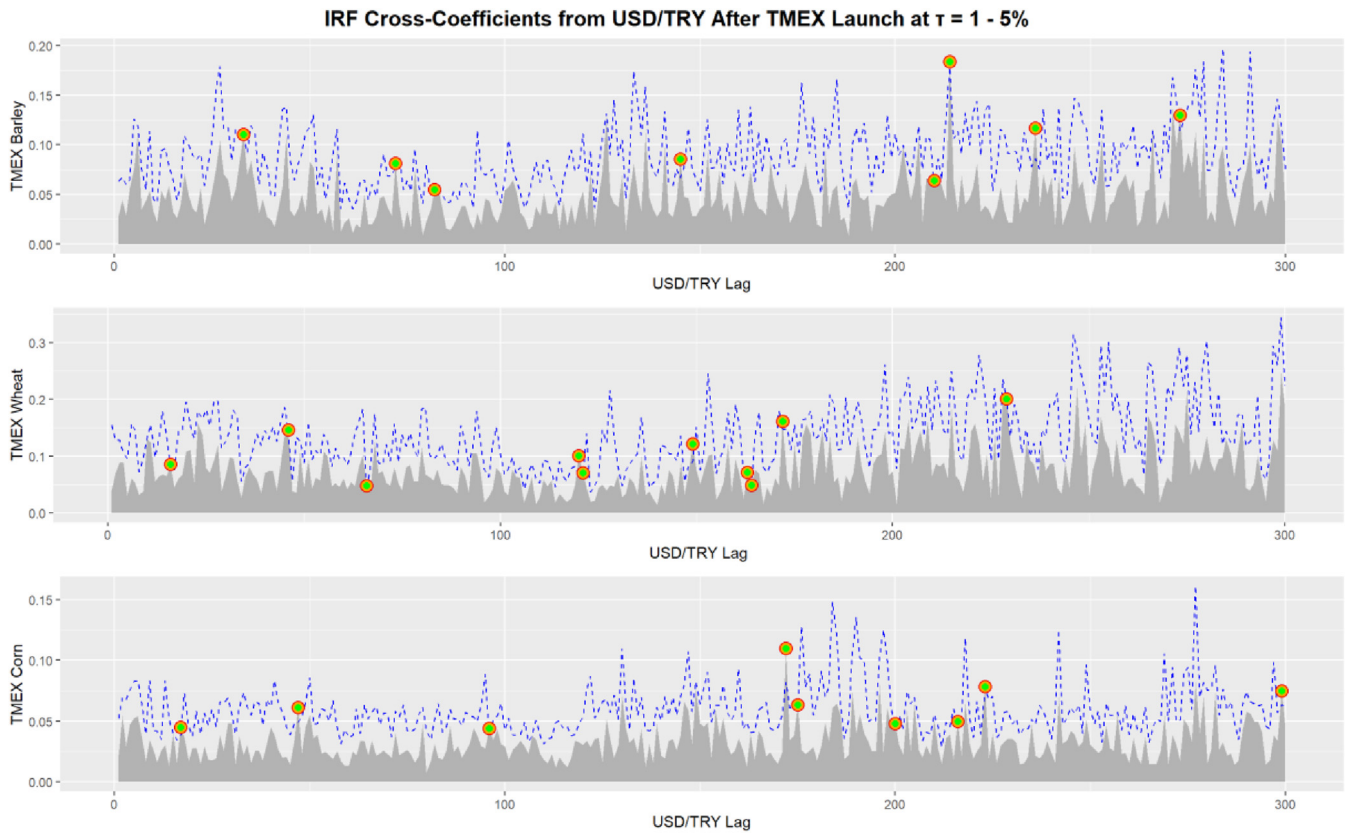


Fig. 12. IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 1%–5% (lock 95% bootstrap critical values are measured by dashed lines).

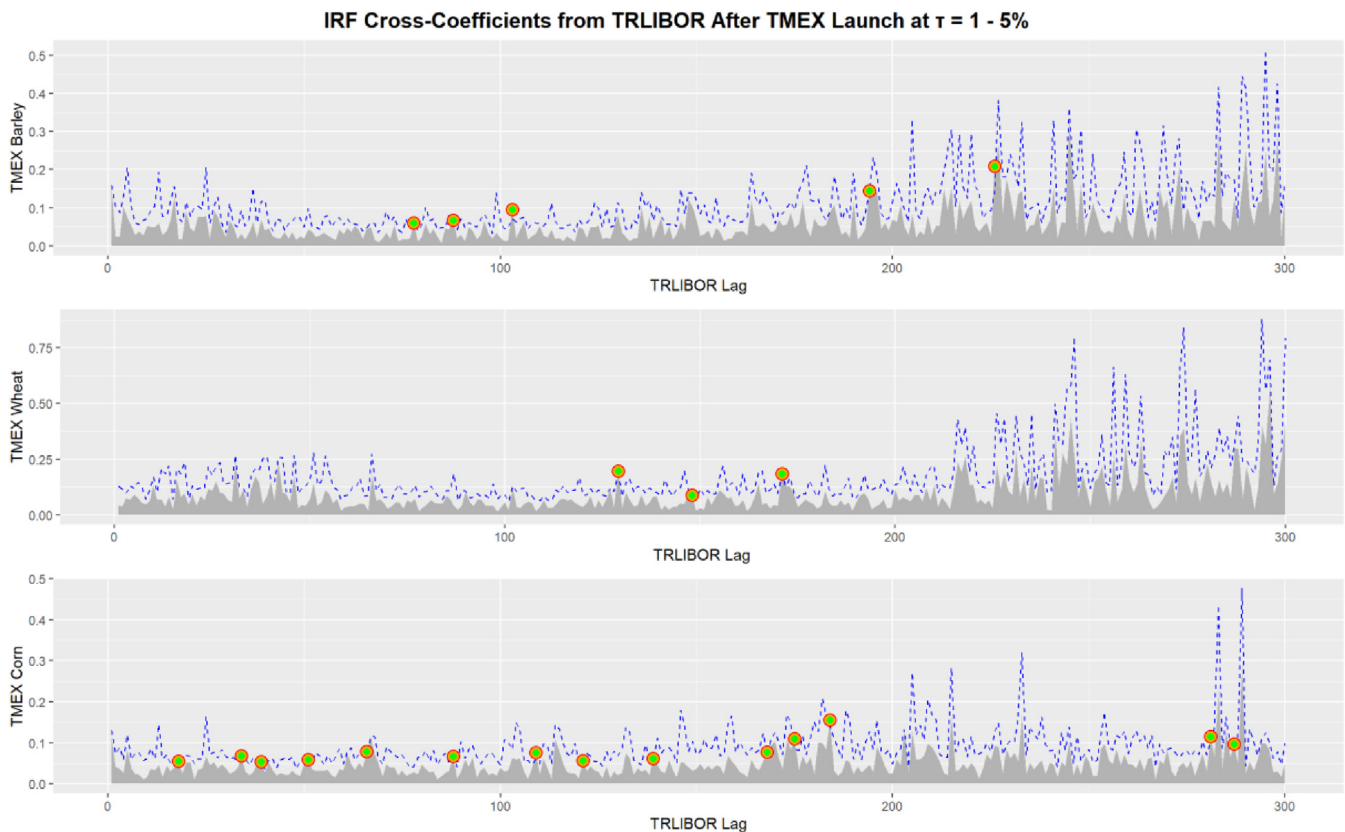


Fig. 13. IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 1%–5% (block 95% bootstrap critical values are represented by dashed lines).

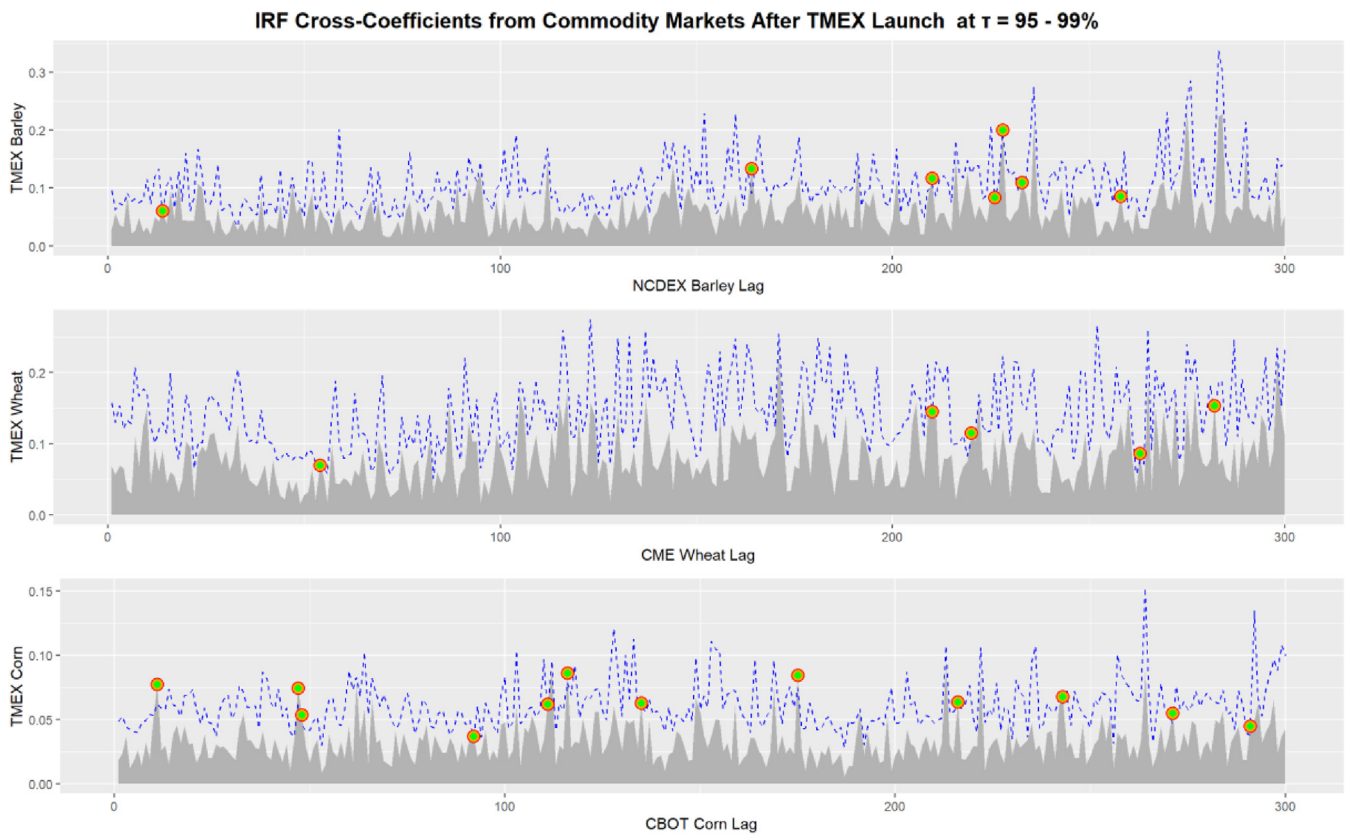


Fig. 14. IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 95%–99% (block 95% bootstrap critical values are represented by dashed lines).

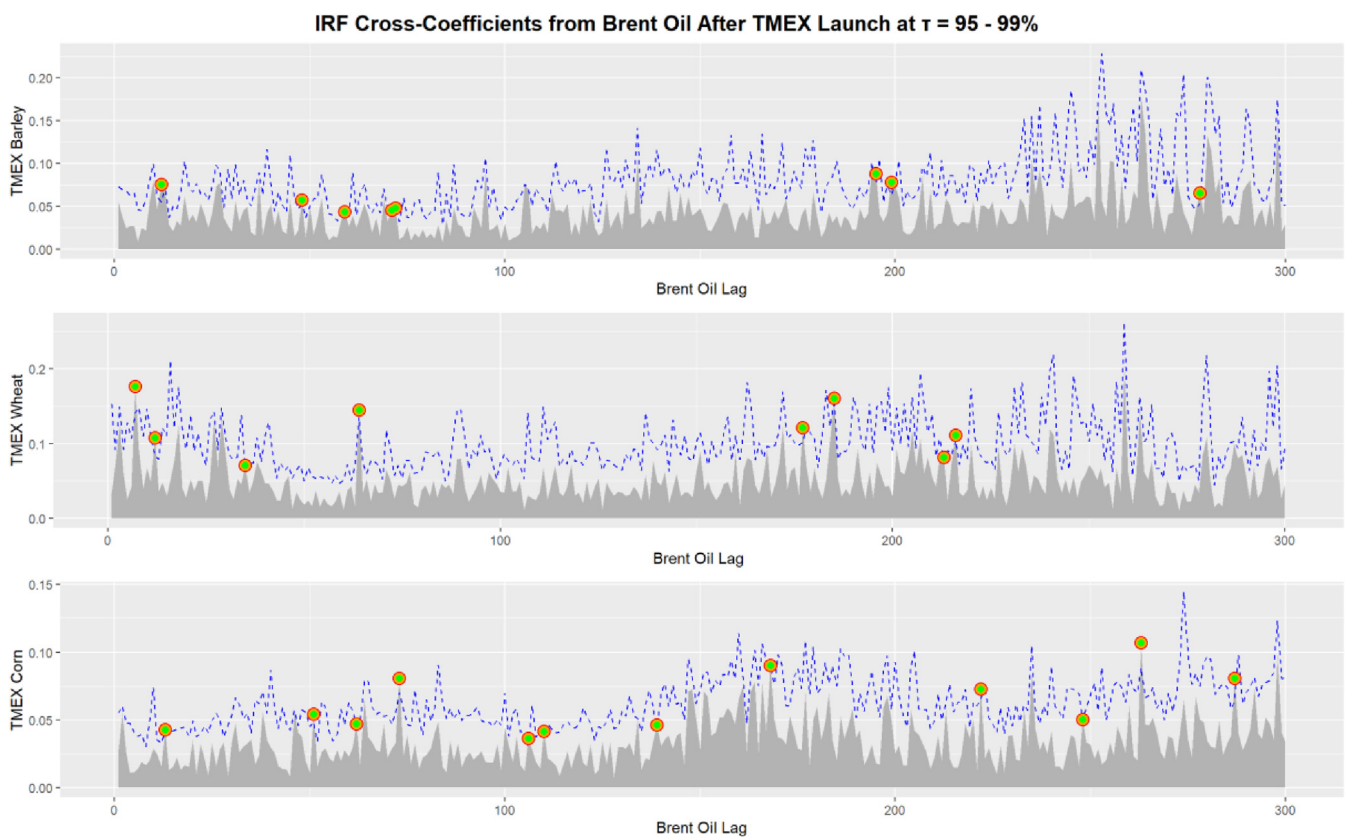


Fig. 15. IRF cross-coefficients from lagged Brent oil to Turkish agricultural commodities market measured at quantiles 95%–99% (block 95% bootstrap critical values are represented by dashed lines).

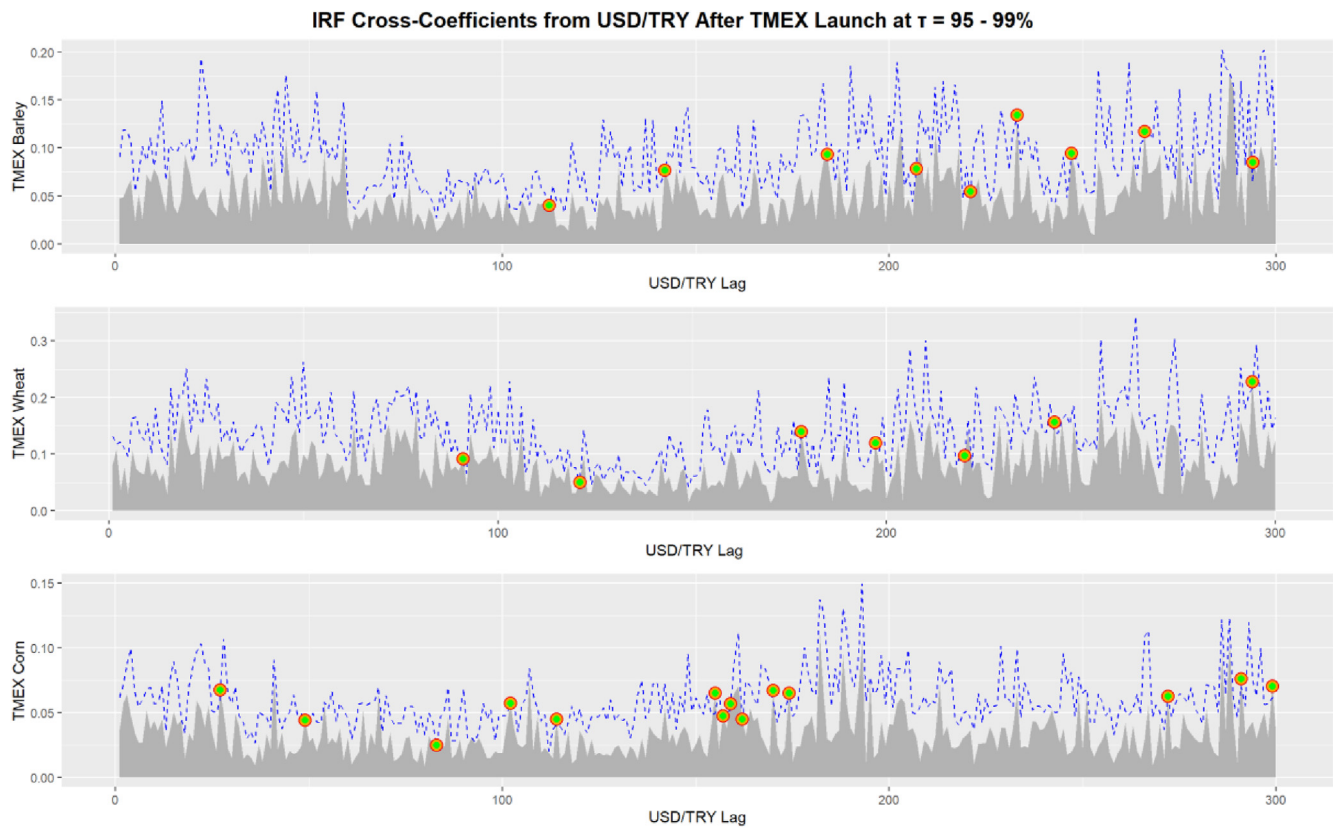


Fig. 16. IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 95%–99% (block 95% bootstrap critical values are represented by dashed lines).

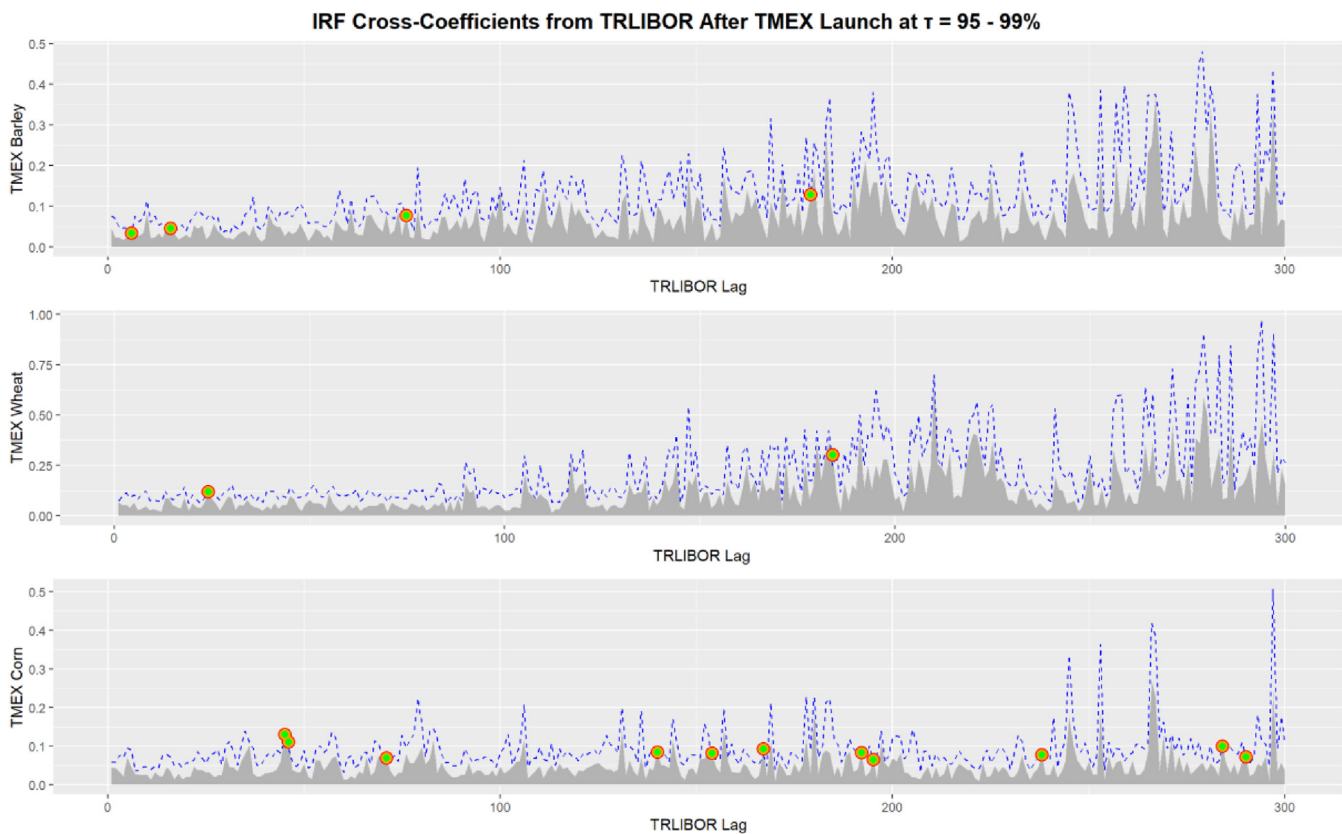


Fig. 17. IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 95%–99% (block 95% bootstrap critical values are represented by dashed lines).

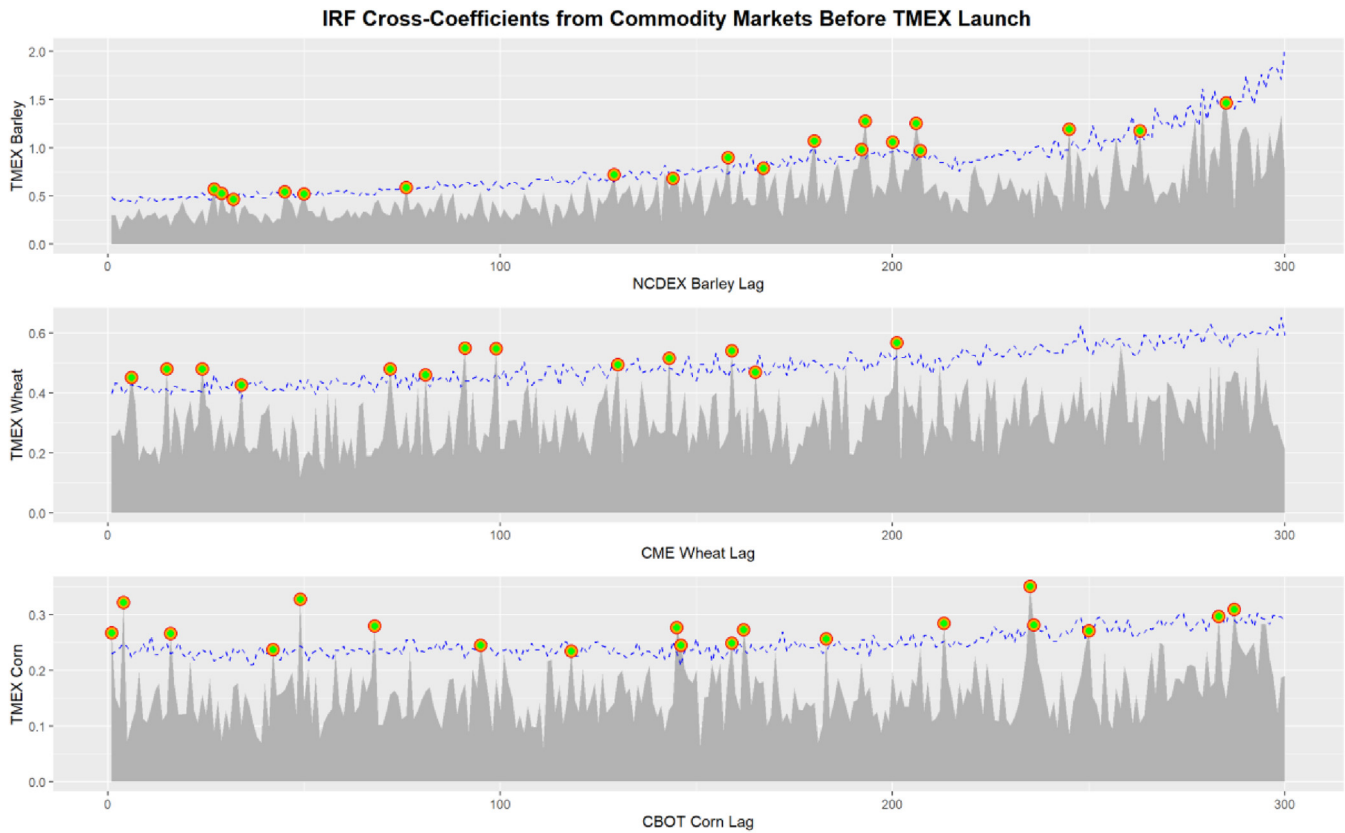


Fig. 18. IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 0–100% (block 95% bootstrap critical values are represented by dashed lines).

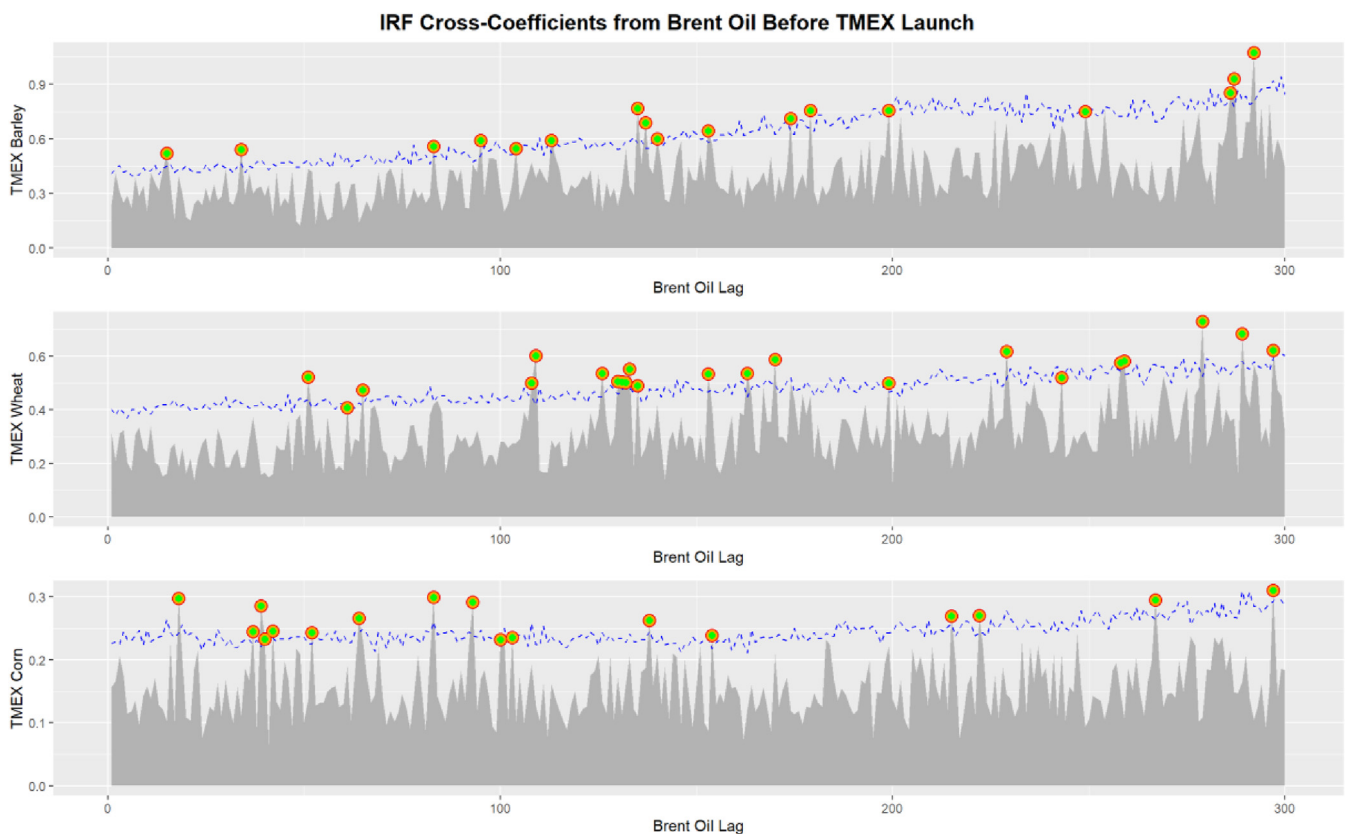


Fig. 19. IRF cross-coefficients from lagged Brent oil to Turkish agricultural commodities market measured at quantiles 0–100% (block 95% bootstrap critical values are represented by dashed lines).

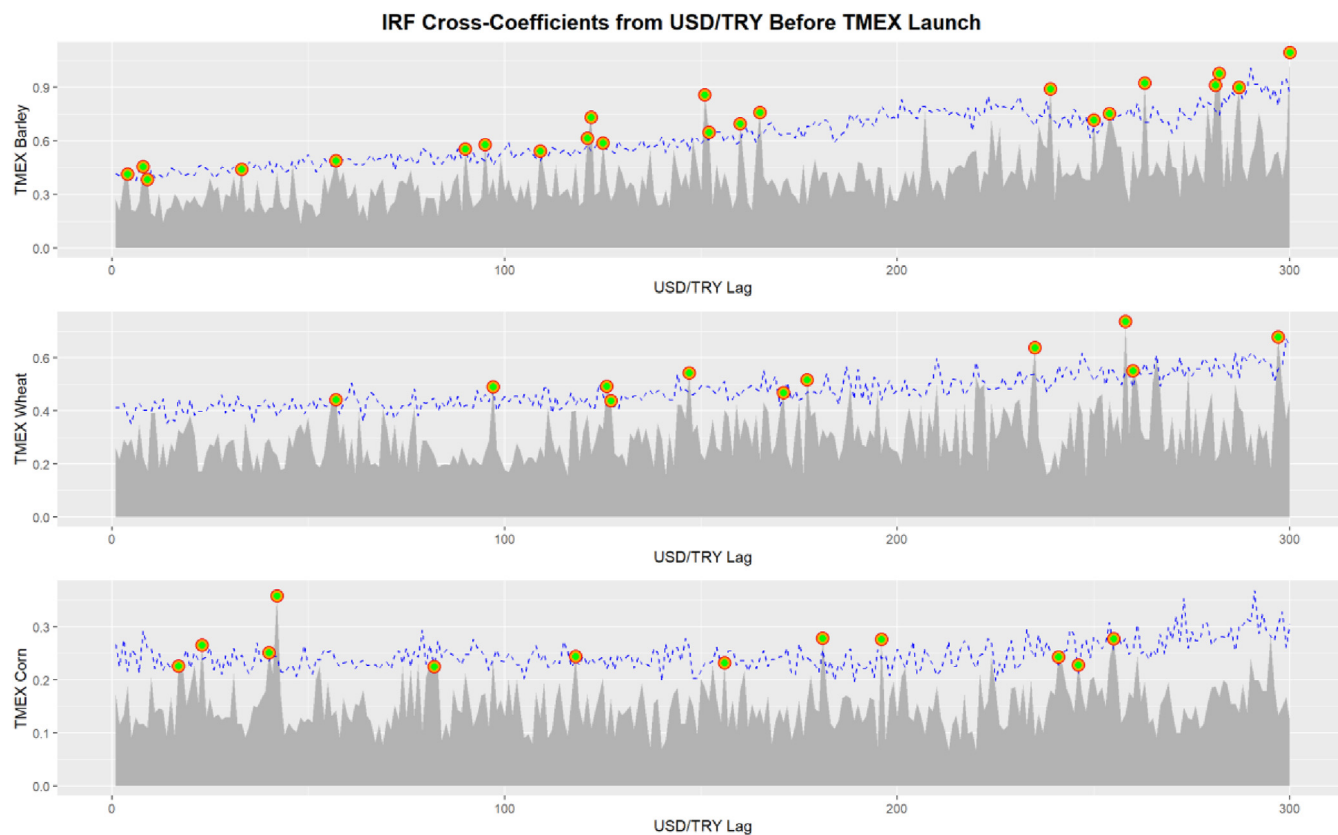


Fig. 20. IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 0–100% (block 95% bootstrap critical values are represented by dashed lines).

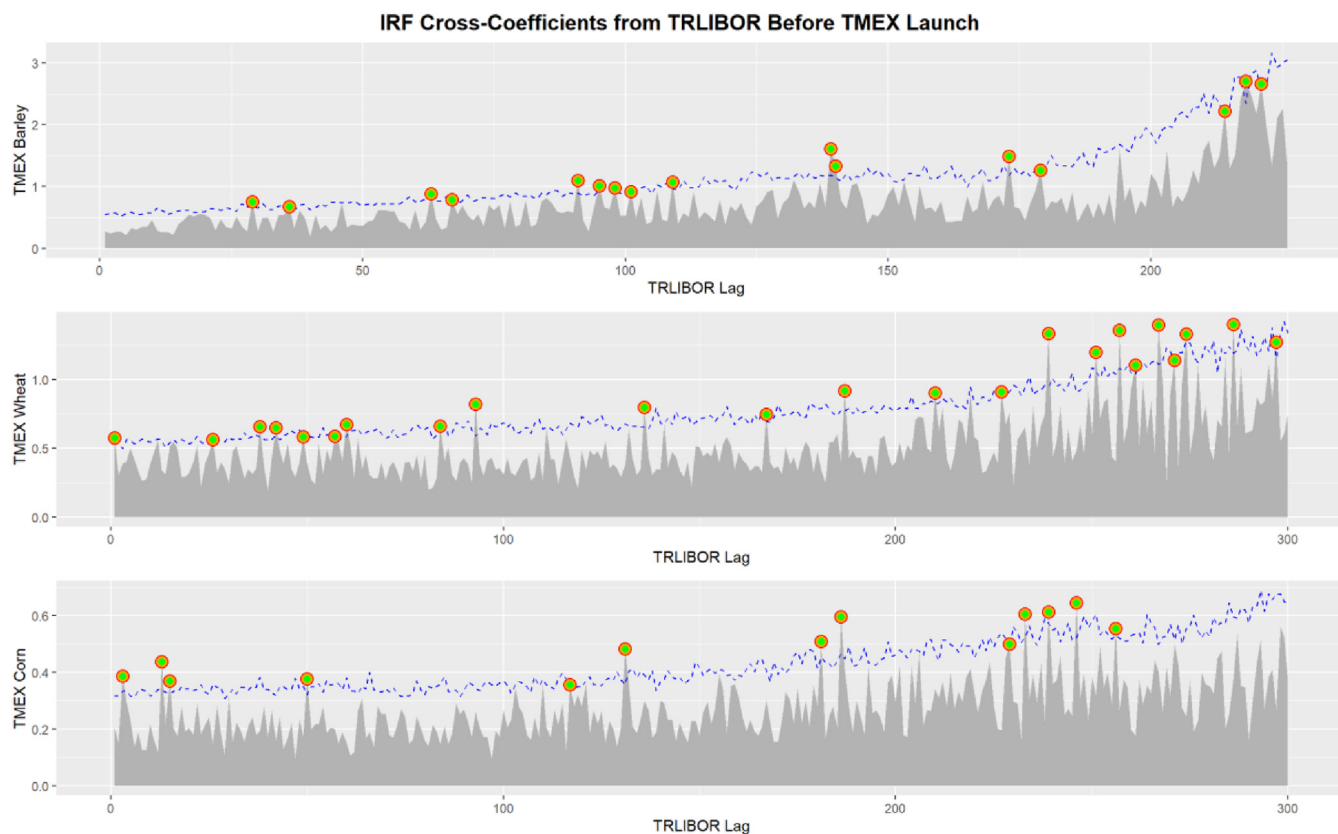


Fig. 21. IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 0–100% (block 95% bootstrap critical values are represented by dashed lines).

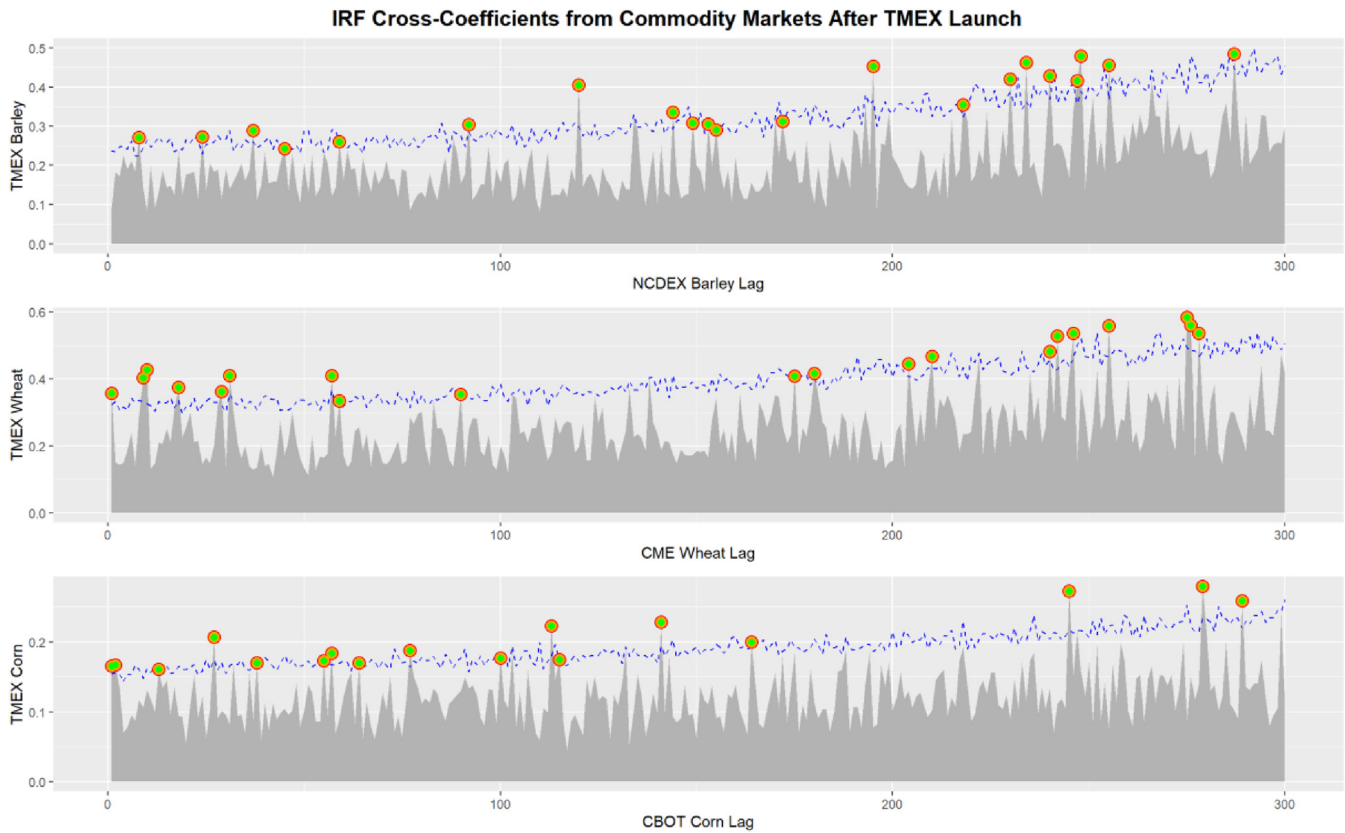


Fig. 22. IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 0–100% (block 95% bootstrap critical values are represented by dashed lines).



Fig. 23. IRF cross-coefficients from lagged Brent oil to Turkish agricultural commodities market measured at quantiles 0–100% (block 95% bootstrap critical values are represented by dashed lines).

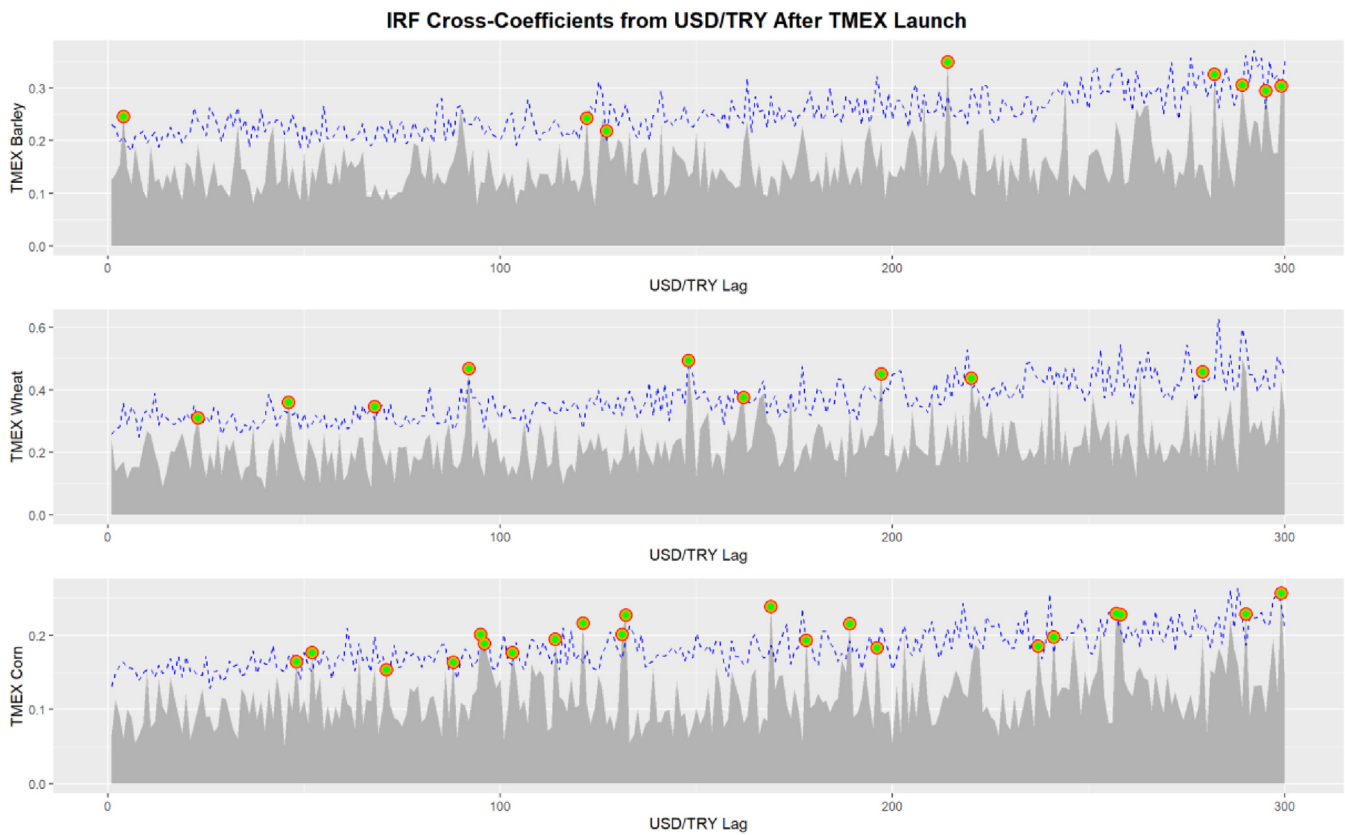


Fig. 24. IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 0–100% (block 95% bootstrap critical values are represented by dashed lines).

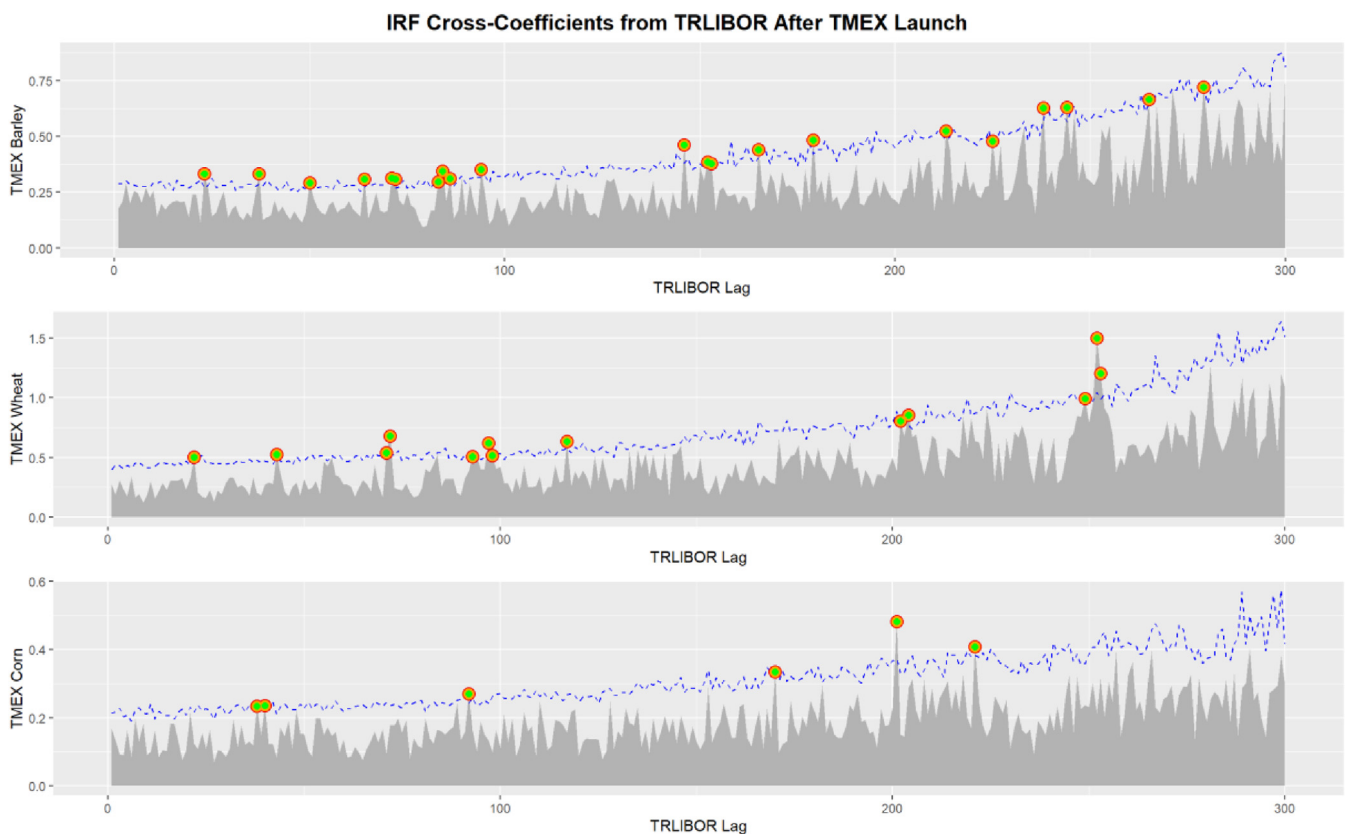


Fig. 25. IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 0–100% (block 95% bootstrap critical values are represented by dashed lines).

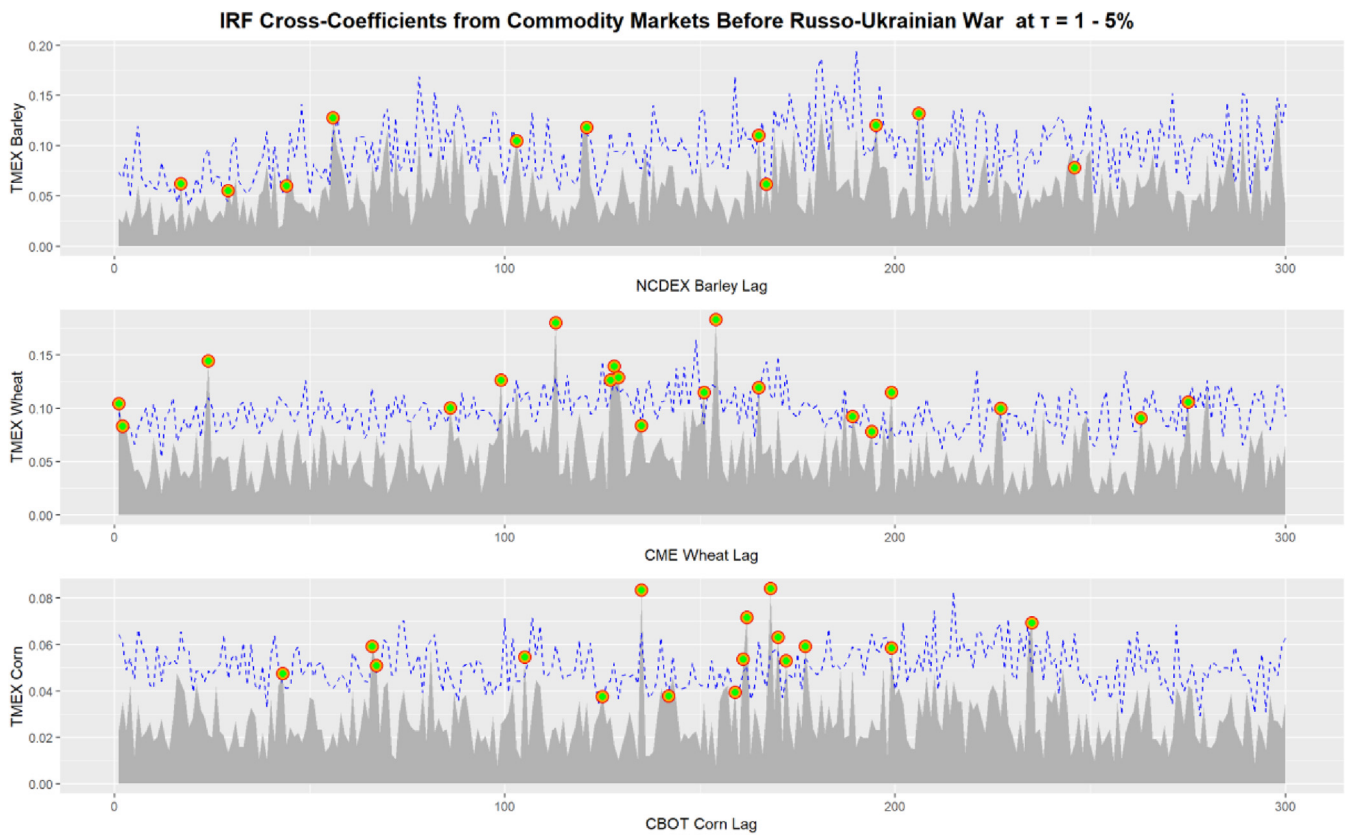


Fig. 26. IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 1–5% (block 95% bootstrap critical values are represented by dashed lines).

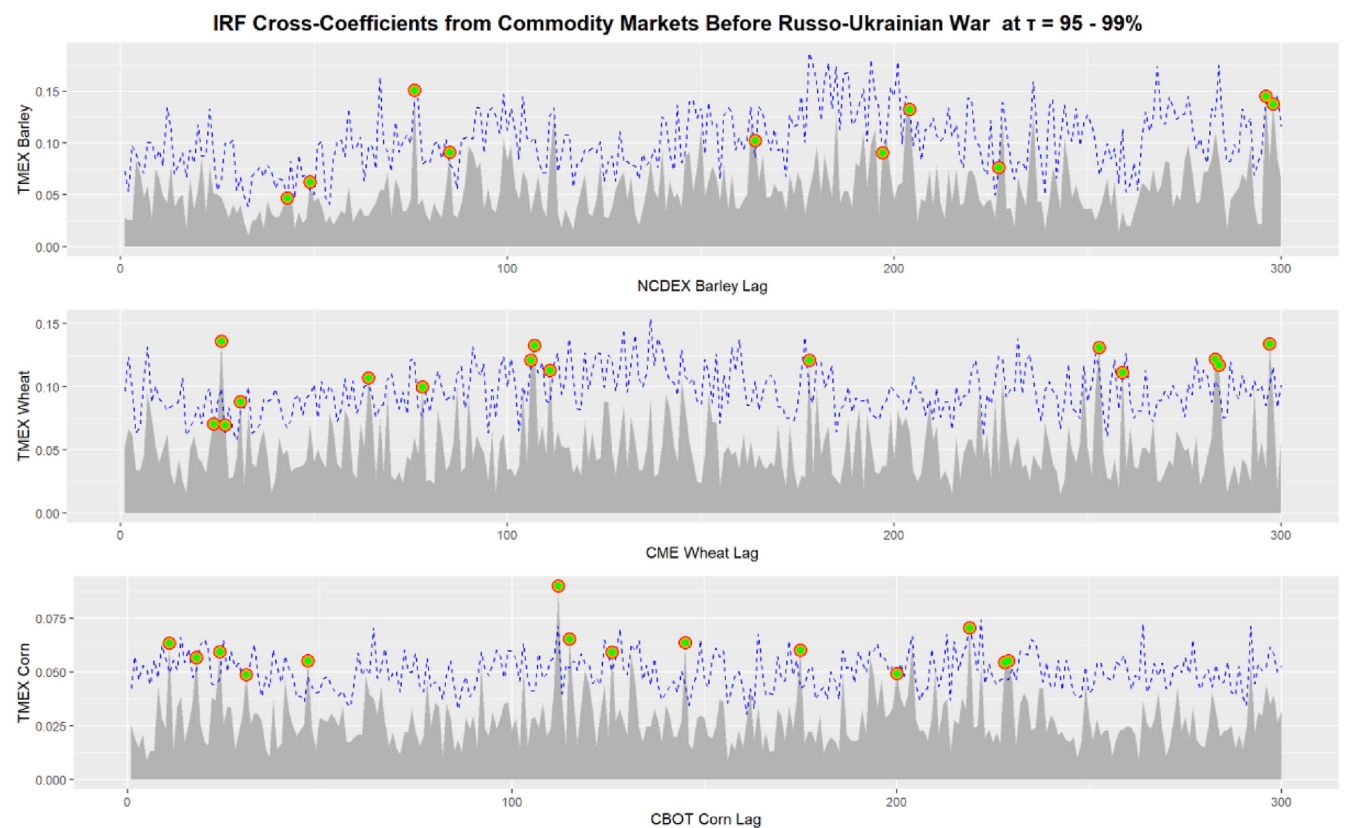


Fig. 27. IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 95–99% (block 95% bootstrap critical values are represented by dashed lines).

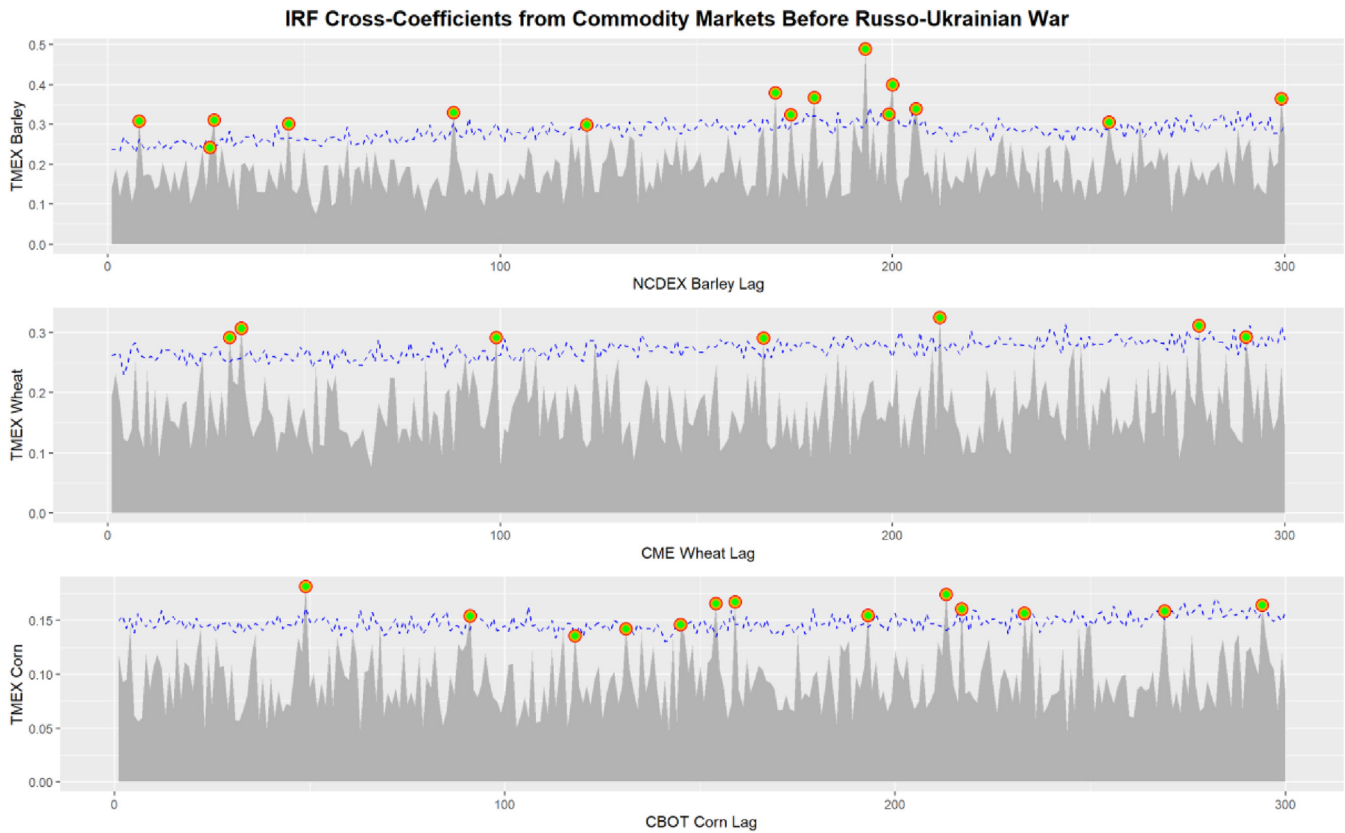


Fig. 28. IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 0–100% (block 95% bootstrap critical values are represented by dashed lines).

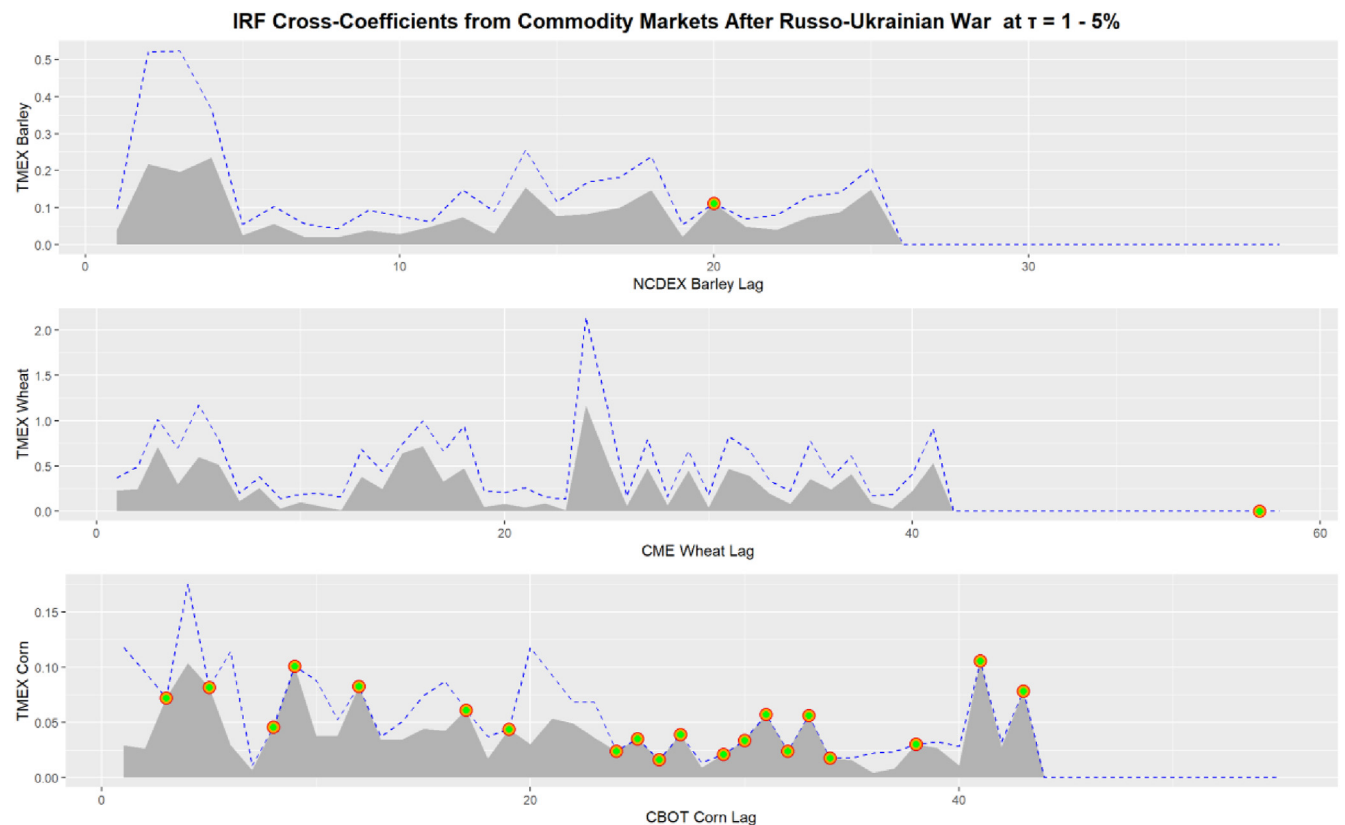


Fig. 29. IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 1–5% (block 95% bootstrap critical values are represented by dashed lines).

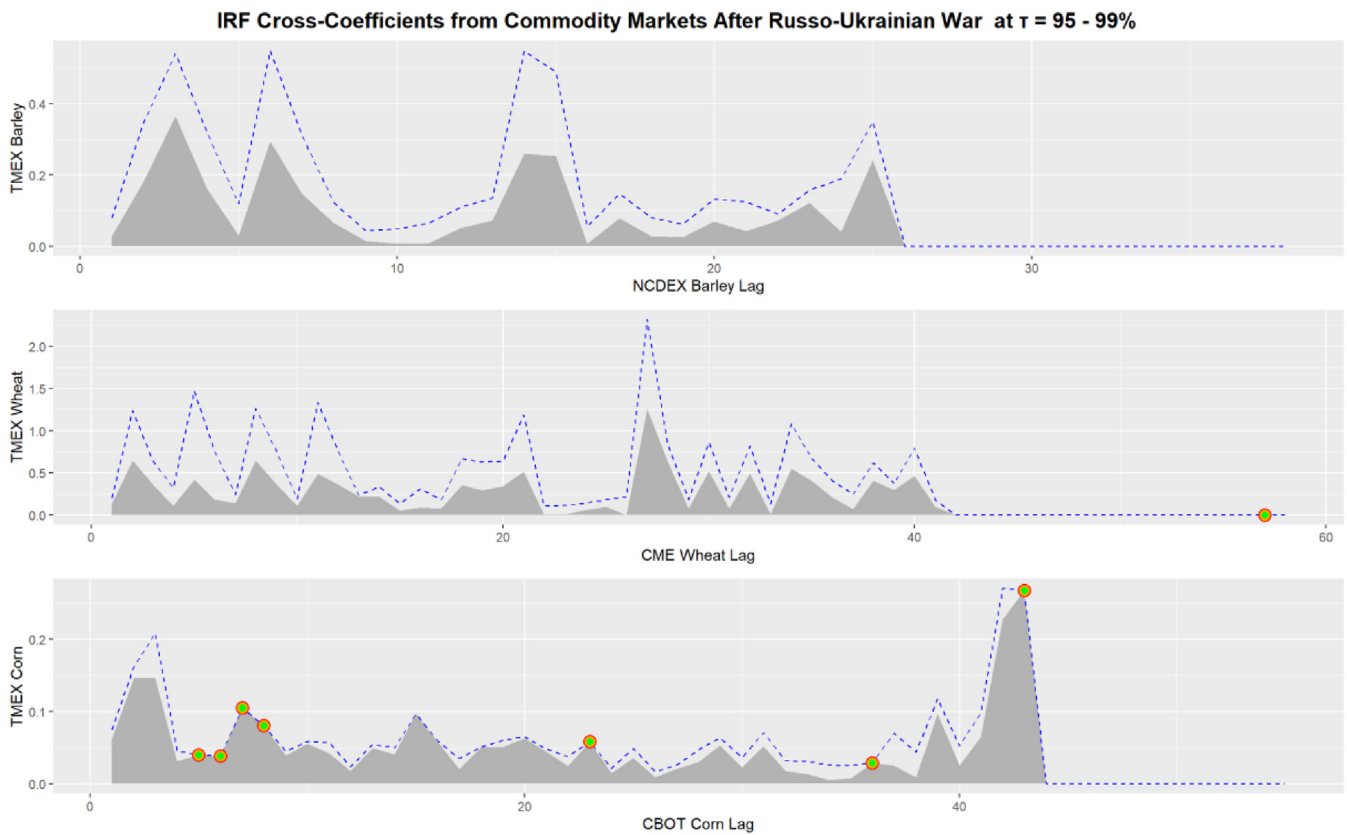


Fig. 30. IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 95–99% (block 95% bootstrap critical values are represented by dashed lines).

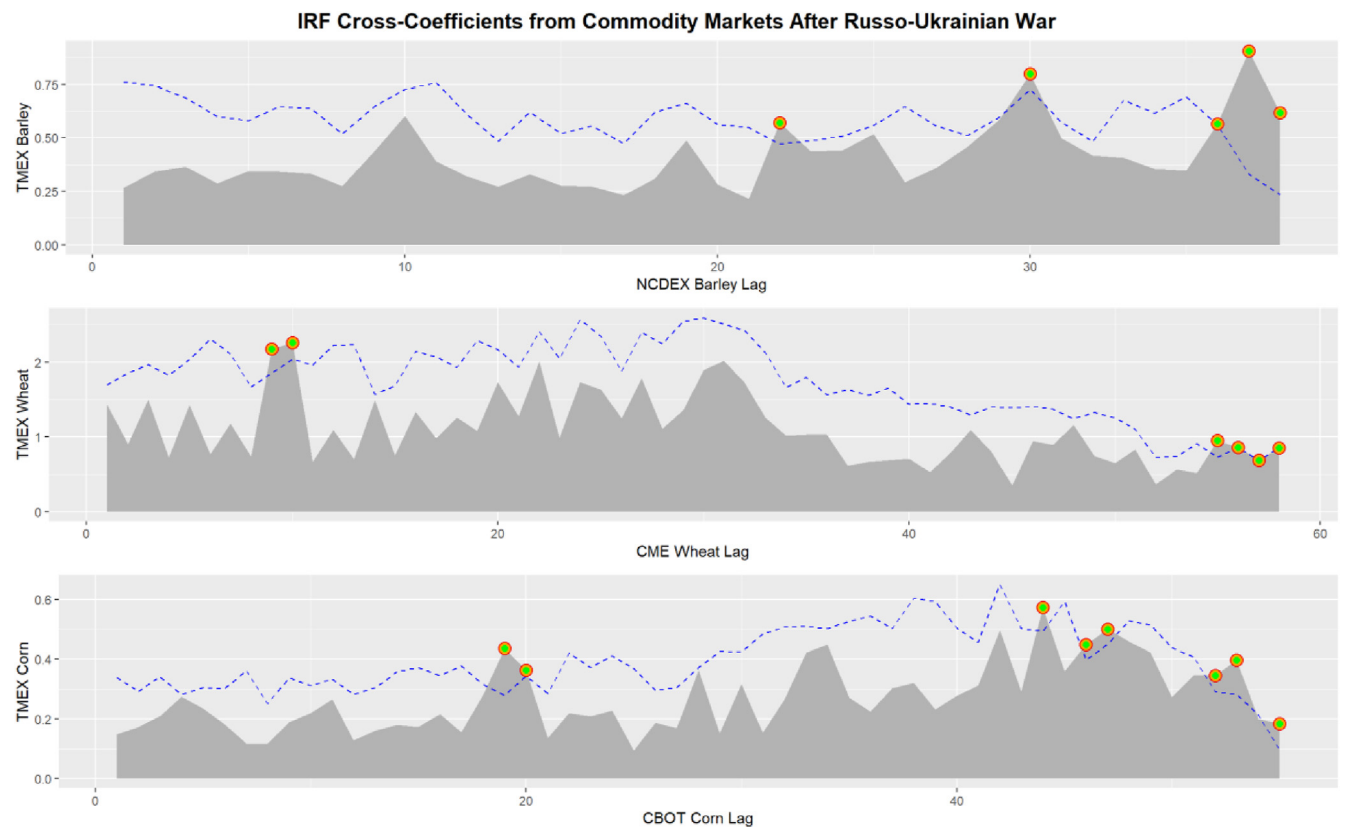


Fig. 31. IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 0–100% (block 95% bootstrap critical values are represented by dashed lines).

4.1. Pre- and Post-TMEX launch

4.1.1. Findings on tail dependence

Figs. 2–9 display the nonlinear correlograms for the period before the TMEX launch, and Figs. 10–17 present results for the period after the TMEX launch. In both periods, the first four graphs (Figs. 2–5 and 10–13) show lower-tail dependence results, while the other four graphs (Figs. 6–9 and 14–17) illustrate higher-tail dependence results.

For the period before the TMEX launch, we find significant and persistent lower- and upper-tail dependence from US commodity markets to Turkish agricultural commodities, indicating comovement in prices, especially for wheat and corn. The number of significant lags on present-day returns of TMEX wheat and corn persists even after 200 days, as illustrated in Figs. 2 and 6. Persistent tail dependence exists from Brent oil to Turkish agricultural commodities for both lower and upper continuums of quantiles (Figs. 3 and 7). When we examine the USD/TRY exchange rate, we observe persistent tail dependence for both quantile continuums for each commodity, as seen in Figs. 4 and 8. The findings also indicate significant and persistent lower- and upper-tail dependence from TRLIBOR to TMEX corn and wheat (Figs. 5 and 9). Although there are only a few significant lags for tail dependence from TRLIBOR to TMEX barley, the effects of extreme events still occur even after 240 days. These results suggest that both low and high values of US Agricultural market, Brent oil, USDTRY, and TRLIBOR drive TMEX commodity prices.

The findings for the period after the TMEX launch demonstrate significant and persistent tail dependence for each pair of agricultural commodities for both continuums of quantiles, as shown in Figs. 10 and 14. For barley, significant lags continue up to the 260th lag, whereas for corn they persist up to almost the 300th lag for the lower tail. The initial lags of wheat and corn are also significant, suggesting that recent prices of US wheat and corn affect the current prices of TMEX wheat and corn. For the upper tail, there are several significant lags after 200 days, and, for wheat and corn, significant lags occur up to almost the 300th lag. The calculated measure of tail dependence yields significant evidence for both lower- and upper-tail dependence from Brent oil prices and USD/TRY exchange rates to the Turkish commodities market, exhibiting persistent characteristics, as the effects prevail for almost 300 days (Figs. 11–12 and 15–16). The findings also suggest strong evidence of tail dependence from TRLIBOR to TMEX corn for both tails, as illustrated in Figs. 13 and 17. However, for tail dependence from TRLIBOR to both TMEX barley and wheat, a few significant lags exhibit significant comovement in the markets.

4.1.2. Findings on mean dependence

Figs. 18–21 display the mean dependence for the period before the TMEX launch, while Figs. 22–25 depict the mean dependence for the period after the TMEX launch. The findings reveal the persistence of mean dependence from US commodities to Turkish commodities in both periods (Figs. 18 and 22). In particular, as seen in Fig. 22, after the TMEX launch,

comovement increases in the barley and wheat pairs. The mean dependence from Brent oil and the USD/TRY exchange rate to Turkish commodities is also highly significant and persistent in both periods (Figs. 19–20 and 23–24). We also find a significant effect of TRLIBOR on the Turkish commodities market, which last for a long time. However, mean dependence is stronger for wheat and corn before the TMEX launch (Fig. 21) than in the period after TMEX was introduced (Fig. 25).

Furthermore, as depicted in most of the figures, the recent lags are significant, providing a good intuition about mean predictability power. For example, to predict future values of TMEX wheat and TMEX corn, the recent lag values of CME wheat and CME corn, and Brent oil for corn price prediction, should be included in their models, as illustrated in Figs. 22 and 23, respectively.

4.2. Before and after the war in Ukraine

The conflict between Russia and Ukraine has had a significant effect on commodity prices, particularly agricultural commodities, due to supply chain disruptions and trade impacts. It caused a global food crisis, with ships stuck in Black Sea ports and a rise in commodity prices. The Food and Agriculture Organization (FAO) Food Price Index rose rapidly, from around 140 (February 2022) before the Russian invasion to 160 (March 2022). However, the signing of the Black Sea Grain Corridor Agreement between Russia and Ukraine on July 22, 2022, played a critical role in resolving the food crisis during the 2022/2023 harvest season. As a result, the FAO Food Price Index declined to a level lower than the value in February 2022. The International Grain Council (IGC) Wheat Index also significantly dropped below its value at the beginning of 2022.

In the TMEX market, the average wheat price initially exceeded TL/ton 5000 (USD 301) compared with the value of around TL/ton 4000 (USD 290) before February 2022. Because of geopolitical risks and concerns about accessing Black Sea region grain, prices remained around TL/ton 6500 (USD 360) during the harvest season in June and July, which was unexpected given the increase in supply. After the Grain Corridor Agreement in July, prices remained steady at around TL/ton 6500–7,000, (USD 360–390) matching the support purchase price of the Turkish Grain Board.

To study this impact, we divided the data into two periods: before and after February 2022. Figs. 26–28 and Figs. 29–31 illustrate nonlinear correlograms for these two periods, respectively. Before February 2022, US commodity price lags had a prolonged impact on the current prices for Turkish commodities for both the left and right tail, as seen in Figs. 26 and 27. In addition, Fig. 28 shows significant and persistent mean dependence between commodity markets.

After February 2022, we find significant and persistent left- and right-tail dependence for corn (Figs. 29 and 30), but not wheat and barley. This might be due to the shortness of the period and, accordingly, the working logic of the methodology. However, the results indicate a significant and persistent mean dependence for each commodity.

4.3. Robustness of dependence

For a robustness check, we employ the nonparametric test for Granger causality in distribution, which is a multivariate extension of the kernel-based Granger-causality test in a tail event developed by [Candelon and Tokpavi \(2016\)](#). This test is quite flexible, as it enables the determination of Granger causality or, in other words, predictability, in certain parts of the distribution of a series, such as the center or tails. Following [Candelon and Tokpavi \(2016\)](#), we use an AR(1)-GARCH(1,1) model to evaluate the time-varying VaR in order to perform the suggested test. We set quantile levels of {1%, 5%, 10%}, {90%, 95%, 99%} and {20%, 30%, ..., 70%, 80%} for the left tail, right tail, and the center of distribution, respectively. For the choice of truncation parameter M , we use the $[1.5T^{0.3}]$ definition where T is the number of observations.

Tables 4 and 5 list the test statistics that suggest the rejection of the null hypothesis of no Granger predictability. The findings show upside and downside risk spillovers or contagion from US agricultural commodities, Brent oil, and macroeconomic variables to Turkish agricultural commodities. Moreover, dynamic interactions are found between commodities on normal days, represented by the center of the distribution that reflects predictability-in-mean.

5. Discussion and policy suggestion

The launching of TMEX on July 26, 2019, was followed by the Covid-19 pandemic beginning in 2020, a global warming-exacerbated drought in 2021, and the Russian invasion of Ukraine in 2022. These phenomena show that the agricultural commodity market is not different from the financial market during periods of stress, and interdependence and possible “contagion” increase volatility and worsen tension in the financial and commodity markets.

The derivatives market provides important hedge instruments for future price discovery and risk management purposes, and, in terms of information transmission between markets, spot and derivatives markets both contribute to spot and forward price discovery. Our findings suggest that the past and most recent prices of US barley, wheat, and corn futures

contract prices affect the current prices of TMEX spot market barley, wheat, and corn prices. In this regard, policy makers would be well advised to launch a local derivative market in order to achieve an efficient local commodity market, as well as for the purpose of risk management-related diversification. The combination of spot and derivatives markets for local market efficiency and their contribution to price discovery analysis offer policy makers and market participants healthier results and valuable insights. These insights can help develop incentives for promoting sustainability and efficiency in the agricultural market. Based on our empirical results, we offer the following comprehensive policy recommendations.

The findings suggest that past and recent US barley, wheat, and corn futures contract prices affect the current TMEX spot market barley, wheat, and corn prices. Therefore, launching a local derivatives market can provide important hedge instruments for future price discovery and risk management purposes in the Turkish agricultural market. This can help market participants manage price risks more effectively and enhance overall market efficiency.

The study highlights that spot and derivatives markets both contribute to spot and forward price discovery. Policy makers should focus on fostering information transmission between these markets to enhance price discovery and efficiency in the agricultural market. This can be achieved through measures such as improving market infrastructure, enhancing market transparency, and promoting market participants' access to both spot and derivatives markets.

The analysis shows significant and persistent tail dependence and mean dependence between various markets, including US agricultural markets, Brent oil, USD/TRY exchange rates, and TRLIBOR, to the Turkish agricultural market. Policy makers should closely monitor these interdependencies and contagion risks during periods of stress, such as during the Covid-19 pandemic, global warming-related drought, and geopolitical tensions. This can help identify potential vulnerabilities and appropriate measures and policies for managing risks, stabilizing the agricultural market, and preventing damage to the system ([Kırcı et al., 2022](#)).

The findings suggest that different commodities exhibit varying degrees of tail dependence and mean dependence with

Table 4
Test statistics of Granger-causality test for agricultural commodity markets.

Predictability direction	Before TMEX Launch	After TMEX Launch	Before Russo- Ukrainian War	After start of Russo-Ukrainian War
CME Wheat ^L → TMEX Wheat ^L	629.9852***	−938.4193***	−1707.8***	−11,253.75***
CME Wheat ^R → TMEX Wheat ^R	425.7031***	31.45265***	−567.7983***	−642.8228***
CME Wheat ^C → TMEX Wheat ^C	−230.5801***	783.9422***	585.0751***	−44.67502***
NCDEX Barley ^L → TMEX Barley ^L	7778.422***	−1002.279***	6550.396***	−8643.66***
NCDEX Barley ^R → TMEX Barley ^R	−152.4719***	2530.297***	−10,169.66***	1062.347***
NCDEX Barley ^C → TMEX Barley ^C	−20.61034***	1782.137***	−74.74514***	612.85***
CBOT Corn ^L → TMEX Corn ^L	335.9358***	−32.01555***	438.3944***	11,782.83***
CBOT Corn ^R → TMEX Corn ^R	817.8813***	−1421.363***	73.57419***	−642.8228***
CBOT Corn ^C → TMEX Corn ^C	952.9896***	302.9512***	−600.5211***	169.1817***

Notes: L, R and C indicate the left tail, the right tail and the center of the distribution respectively. *** indicates statistically significant Granger predictability at the 1% level. For After Russo-Ukrainian War subperiod we set left- and right-tail quantile levels as {0%, 1%, 5%, 10%}, {90%, 95%, 99%, 100%} respectively due to the short observation period.

Table 5
Test statistics of Granger-causality test between energy and macroeconomic variables, and TMEX commodities.

Predictability direction	Before TMEX Launch	After TMEX Launch	Predictability direction	Before TMEX Launch	After TMEX Launch
Brent Oil ^L → TMEX	−391.673***	−1591.672***	USD/TRY ^L → TMEX Wheat ^L	−41.6831***	−69.08312***
Wheat ^L → TMEX	−576.0026***	347.8277***	USD/TRY ^R → TMEX Wheat ^R	−15.51461***	−1504.436***
Wheat ^R → TMEX	−326.6098***	356.3131***	USD/TRY ^C → TMEX Wheat ^C	1353.317***	846.7028***
Brent Oil ^L → TMEX	724.5868***	376.9838***	USD/TRY ^L → TMEX Barley ^L	1364.604***	655.5472***
Wheat ^C → TMEX	−169.6636***	−620.7078***	USD/TRY ^R → TMEX Barley ^R	523.9209***	−620.7078***
Barley ^L → TMEX	234.5062***	934.2144***	USD/TRY ^C → TMEX Barley ^C	2921.266***	2656.313***
Brent Oil ^R → TMEX	594.7447***	−1155.733***	USD/TRY ^L → TMEX Corn ^L	1047.987***	−69.35334***
Wheat ^R → TMEX	−514.6347***	331.0896***	USD/TRY ^R → TMEX Corn ^R	847.5424***	331.0896***
Barley ^C → TMEX	188.2887***	645.7794***	USD/TRY ^C → TMEX Corn ^C	1154.008***	2000.264***

Notes: L, R, and C indicate the left tail, the right tail, and the center of the distribution respectively. *** indicates statistically significant Granger predictability at the 1% level.

other markets. Policy makers and market participants should consider diversifying risk management strategies to account for these differences. This could include using a combination of traditional risk management tools, such as futures contracts and insurance, as well as exploring new risk management techniques, such as weather derivatives or index-based insurance, to effectively manage risks associated with tail and mean dependence between markets. The leading characteristic of futures contracts on spot prices have a predominant feature that can provide investors and portfolio managers with more effective hedging and trading strategies (Cevik et al., 2022).

The launching of TMEX and subsequent events, such as the Covid-19 pandemic, drought, and geopolitical tension, highlight the need for a sustainable and efficient agricultural market. Policy makers should focus on creating incentives and measures to promote sustainability and efficiency in the agricultural market, including supporting agricultural research and development, promoting sustainable farming practices, improving market infrastructure, enhancing market transparency, and providing education and training for market participants.

Given the significant tail dependence observed between variables, particularly in the downside of the market cap size, the book-to-market ratio, and momentum portfolios, policy makers and practitioners should emphasize the importance of effective risk management practices. Information regarding directional connectedness and the role of the markets as transmitters and receivers of risk will help in implementing appropriate policies (Derindere Köseoğlu, 2023). This could include diversification of investments, employing risk mitigation strategies, and using appropriate risk management tools to mitigate potential downside risks.

Considering the significant return and volatility spillovers observed between different markets, policy makers and regulators should enhance their monitoring and surveillance efforts to closely monitor cross-market linkages and potential contagion effects. This could include regular monitoring of market activities, detecting early warning signals of potential risks, and taking timely actions to mitigate them.

6. Conclusion

The tail-dependence methodology is employed to measure both tail and mean dependence from the US agricultural market, Brent oil, USD/TRY currency rate, and overnight interest rates to the Turkish agricultural market. This analysis enables us to evaluate upside and downside asymmetric risk spillovers in terms of tail dependence for the period January 5, 2016–May 31, 2022, which includes the periods before and after the TMEX launch on July 26, 2019, and before and after the Russian invasion of Ukraine on February 24, 2022.

We find significant and persistent lower- and upper-tail dependence from US commodity markets to Turkish agricultural commodities in the period before the TMEX launch. The lower and upper quantiles both show persistent tail dependence from Brent oil to Turkish agricultural commodities. We observe strong and persistent tail dependence for the lower

quantile of each commodity with the USD/TRY exchange rate. The USD/TRY exchange rate significantly affects TMEX wheat and TMEX corn in the upper quantile for a long period. The tail-dependence analyses also reveal significant and persistent lower- and upper-tail dependence from TRLIBOR to TMEX corn and strong upper-tail dependence to TMEX wheat. However, there is relatively little evidence of tail dependence from TRLIBOR to TMEX barley for both tails.

The findings after the TMEX launch demonstrate significant and persistent tail dependence for each pair of agricultural commodities at both the lower and upper quantiles. The initial lags of wheat and corn are also significant, suggesting that recent prices for US wheat and corn affect the current prices for TMEX wheat and corn. There is also significant evidence of both lower- and upper-tail dependence from Brent oil prices and the USD/TRY exchange rate to the Turkish commodities market. Furthermore, the findings suggest strong evidence of tail dependence from TRLIBOR to TMEX corn, particularly for both tails.

The findings on mean dependence before and after the TMEX launch reveal persistent mean dependence from US commodities to Turkish commodities. After the TMEX launch, mean dependence increases, particularly for barley and wheat. Mean dependence from Brent oil and the USD/TRY exchange rate to Turkish commodities is also highly significant and persistent in both periods. We also observe a significant effect of TRLIBOR on the Turkish commodities market that persists for a long time. However, the mean dependence is stronger for wheat and corn before the TMEX launch than afterward.

The IRF findings for the period before the Russian invasion in February 2022 show significant and persistent tail and mean dependence from US commodities to Turkish commodities. After February 2022, we find strong tail dependence for corn in both tails. Mean dependence is also significant for all the agricultural commodity pairs. Furthermore, the nonparametric test of Granger causality in distribution has significant results, which indicate Granger predictability for each commodity and period.

Our findings suggest that past and recent US wheat and corn future contract prices affect the current TMEX spot market wheat and corn prices, which indicates that launching a local derivative market can provide important hedge instruments for price discovery and risk management in the Turkish agricultural market. Policy makers should focus on fostering information transmission between spot and derivatives markets to enhance overall market efficiency. Significant and persistent tail dependence and mean dependence are observed between various markets, and policy makers should closely monitor these interdependencies and contagion risks during periods of stress. Commodities exhibit different degrees of dependence with other markets, and strategies to diversify risk management may be necessary.

Events after the launching of TMEX highlight the need for a sustainable and efficient agricultural market. The empirical results suggest that policy makers should focus on establishing a local derivatives market, fostering information transmission between spot and derivatives markets, monitoring tail and mean dependence between markets as well as diversifying risk management strategies. These actions are essential for

enhancing sustainability and improving overall market efficiency in the Turkish agricultural sector.

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Abbreviations

3-SLS	Three-Stage Least Squares
APARCH	Asymmetric Generalized Auto-Regressive Conditional Heteroskedasticity
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA-GARCH	Auto-Regressive Moving Average Generalized Autoregressive Conditional Heteroskedasticity
BEKK-GARCH	Baba-Engle-Kraft-Kron Generalized Auto-Regressive Conditional Heteroskedasticity
CBOT	Chicago Board of Trade
CBRT	Central Bank of Türkiye
CME	Chicago Mercantile Exchange
CoVaR	Conditional value at risk
DCC	Dynamic Conditional Correlation
FIGARCH	Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity
FAO	Food and Agriculture Organization
GARCH	Generalized Auto-Regressive Conditional Heteroskedasticity
GRG	Gaussian Random Graphs
ICE	Intercontinental Exchange
ICSS	Iterative Cumulative Sums of Squares
IGC	International Grain Council
IRF	Integrated Regression Function
NCDEX	National Commodity and Derivatives Exchange
QQR	Quantile-on-Quantile Regression
QR	Quantile Regression
RICI	Rogers International Commodity Index
TMEX	Turkish Mercantile Exchange
TRLIBOR	Turkish Lira Interbank Offer Rate
USD/TRY	US dollars/Turkish lira
VaR	Value at Risk
WSC	Wavelet Squared Coherence
WTI	West Texas Intermediate

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