

ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

**MACRO STRESS TESTING IN TURKISH BANKING SECTOR AND TAIL
DEPENDENCE IN FINANCIAL, ENERGY AND COMMODITY MARKETS**



PhD. THESIS

Zehra ATİK

Department of Economics

Economics Programme

JANUARY 2024

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

**TÜRK BANKACILIK SEKTÖRÜNDE MAKRO STRES TESTİ VE FİNANSAL,
ENERJİ VE EMTİA PİYASALARINDA KUYRUK BAĞIMLILIĞI**

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To my family,



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TABLE OF CONTENTS

	<u>Page</u>
FOREWORD.....	ix
TABLE OF CONTENTS.....	xi
ABBREVIATIONS	xiii
SYMBOLS	xv
LIST OF TABLES	xvii
LIST OF FIGURES	xix
SUMMARY	xxiii
ÖZET.....	xxv
1. INTRODUCTION.....	1
2. MACRO STRESS TESTING THE CREDIT RISK OF CONVENTIONAL AND PARTICIPATION BANKS IN TURKEY: A NONPARAMETRIC QUANTILE REGRESSION APPROACH	5
2.1. Introduction	5
2.2. Literature Review	9
2.3. Methodology	11
2.4. Data	13
2.5. Empirical Results	16
2.5.1. Nonparametric additive quantile results.....	16
2.5.2. One-step ahead forecast and probability analysis	26
2.5.3. Scenario analysis	34
2.6. Discussion and Policy Suggestion	42
2.7. Conclusion	44
3. LINKS BETWEEN U.S. AND TURKISH AGRICULTURAL COMMODITY MARKETS.....	47
3.1. Introduction	47
3.2. Literature Review	52
3.3. Methodology	55
3.4. Data	58
3.5. Empirical Results	61
3.5.1. Pre-and post-TMEX launch	61
3.5.1.1. Findings on tail dependence.....	61
3.5.1.2. Findings on mean dependence	71
3.5.2. Before and after the war in Ukraine	76
3.6. Robustness Check	80
3.7. Discussion and Policy Suggestion	81
3.8. Conclusion	83
4. NONLINEAR TAIL DEPENDENCE FROM ENERGY TO AGRICULTURAL COMMODITIES	87
4.1. Introduction	87

4.2.	Literature Review	89
4.3.	Methodology	93
4.4.	Data	95
4.5.	Empirical Results	101
4.6.	Robustness Check	104
4.7.	Conclusion and Policy Implications.....	107
REFERENCES.....		111
APPENDIX		125
APPENDIX A: Chapter 4 Apendices.....		125
CURRICULUM VITAE		155



ABBREVIATIONS

3 SLS: Three-Stage Least Squares
APARCH: Asymmetric Generalized Autoregressive Conditional Heteroskedasticity
BEKK-GARCH: Bollerslev-Engle-Kroner-Kroner Generalized Autoregressive Conditional Heteroskedasticity
CBOT: Chicago Board of Trade
CBRT: Central Bank of Turkey
CME: Chicago Mercantile Exchange
DCC-FIGARCH: Dynamic Conditional Correlation Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity
GRG: Gaussian Random Graphs
ICE: Intercontinental Exchange
ICSS: Iterative Cumulative Sums of Squares
IRF: Integrated Regression Function
KS: Kolmogorov-Smirnov
NCDEX: National Commodity and Derivatives Exchange
NPL: Non-Performing Loans
QR: Quantile Regression
QQR: Quantile-on-Quantile Regression
TMEX: Turkish Mercantile Exchange
VaR: Value at Risk
VaR-AGARCH: Value at Risk Asymmetric Generalized Autoregressive Conditional Heteroskedasticity
VAR: Vector Autoregressive
WSC: Wavelet Squared Coherence



SYMBOLS

h_j	: Absolutely continuous derivative
β	: Coefficient of independent variable
φ	: Covariance between two time series
D_t	: Deterministic terms
∞	: Infinity
x_t	: Label for independent variable
y_t	: Label for dependent variable
$\ \cdot\ $	: Magnitude
$\min$	: Minimization
$\Pr$	: Probability
λ	: Smoothing parameter
$\sup$	: Supremum
t	: Time
Y_t	: Time series
X_t	: Time series
τ	: Quantile
Q_{Y_t}	: τ . quantile value of Y_t



LIST OF TABLES

	<u>Page</u>
Table 2.1 : Descriptive Statistics	14
Table 2.2 : Nonparametric additive quantile model estimation results for conventional banks	19
Table 2.3 : Nonparametric additive quantile model estimation results for participation banks	21
Table 2.4 : The tail values of explanatory variables.....	27
Table 2.5 : One-step ahead forecast values of NPL	29
Table 2.6 : Probability analysis results for NPL of conventional banks	32
Table 2.7 : Probability analysis results for NPL of participation banks.....	33
Table 2.8 : Scenario Analysis 1	36
Table 2.9 : 1 st Approach of Scenario Analysis 2	38
Table 2.10 : 2 nd Approach of Scenario Analysis 2	39
Table 3.1 : Data set.....	59
Table 3.2 : Descriptive statistics.....	60
Table 3.3 : Test statistics of Granger-causality test for agricultural commodity markets	80
Table 3.4 : Test statistics of Granger-causality test between energy and macroeconomic variables, and TMEX commodities	81
Table 4.1 : Details for data set.....	96
Table 4.2 : Descriptive statistics.....	97
Table 4.3 : The number of significant lags on current returns	101
Table 4.4 : Test statistics for Granger causality from energy markets to agricultural markets	107



LIST OF FIGURES

	<u>Page</u>
Figure 2.1 : Time series plots of variables	15
Figure 2.2 : Nonparametric quantile effects on NPL for conventional banks.....	20
Figure 2.3 : Nonparametric quantile effects on NPL for participation banks.	23
Figure 2.4 : Nonparametric quantile effects on NPL for public deposit banks.....	25
Figure 2.5 : Nonparametric quantile effects on NPL for private deposit banks.....	26
Figure 3.1 : Time series of commodity prices in terms of US dollars	59
Figure 3.2 : 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)	62
Figure 3.3 : IRF cross-coefficients from lagged Brent Oil to Turkish agricultural commodities market measured at quantiles 1%-5%.....	63
Figure 3.4 : IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 1%-5%	63
Figure 3.5 : IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 1%-5%.....	64
Figure 3.6 : IRF cross-coefficients from lagged Commodity Markets to Turkish agricultural commodities market measured at quantiles 95%-99%	64
Figure 3.7 : IRF cross-coefficients from lagged Brent Oil to Turkish agricultural commodities market measured at quantiles 95%-99%.....	65
Figure 3.8 : IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 95%-99%	65
Figure 3.9 : IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 95%-99%.....	66
Figure 3.10 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 1%-5%	67
Figure 3.11 : IRF cross-coefficients from lagged Brent Oil to Turkish agricultural commodities markets measured at quantiles 1%-5%	67
Figure 3.12 : IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 1%-5%	68
Figure 3.13 : IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 1%-5%.....	68
Figure 3.14 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 95%-99%	69
Figure 3.15 : IRF cross-coefficients from lagged Brent oil to Turkish agricultural commodities market measured at quantiles 95%-99%.....	69

Figure 3.16 : IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 95%-99%.....	70
Figure 3.17 : Figure 3.17. IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 95%-99%	70
Figure 3.18 IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 0-100%.....	72
Figure 3.19 : IRF cross-coefficients from lagged Brent oil to Turkish agricultural commodities market measured at quantiles 0-100%	72
Figure 3.20 : IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 0-100%	73
Figure 3.21 : IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 0-100%	73
Figure 3.22 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 0-100%.....	74
Figure 3.23 : IRF cross-coefficients from lagged Brent oil to Turkish agricultural commodities market measured at quantiles 0-100%	74
Figure 3.24 : IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 0-100%	75
Figure 3.25 : IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 0-100%	75
Figure 3.26 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 1-5%.....	77
Figure 3.27 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 95-99%.....	77
Figure 3.28 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 0-100%.....	78
Figure 3.29 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 1-5%.....	78
Figure 3.30 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 95-99%.....	79
Figure 3.31 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 0-100%.....	79
Figure 4.1 : Time series plots of price series.....	99
Figure 4.2 : Correlation table for the Pre-Covid-19 period.....	99
Figure 4.3 : Correlation table for the Covid-19 period.....	100
Figure 4.4 : Correlation table for the Post-Covid-19 period	100
Figure A.1 : IRF cross-coefficients from lagged Brent Oil to agricultural commodities at quantiles 0-10% with block 95% bootstrap critical values (dashed lines) for Pre-Covid-19 Era.....	127
Figure A.2 : IRF cross-coefficients from lagged Natural Gas to agricultural commodities at quantiles 0-10% for Pre-Covid-19 Era	128
Figure A.3 : IRF cross-coefficients from lagged Gasoline to agricultural commodities market at quantiles 0-10% for Pre-Covid-19 Era	128
Figure A.4 : IRF cross-coefficients from lagged Brent Oil to agricultural commodities at quantiles 90-100% for Pre-Covid-19 Era	129
Figure A.5 : IRF cross-coefficients from lagged Natural Gas to agricultural commodities at quantiles 90-100% for Pre-Covid-19 Era	130

Figure A.6 : IRF cross-coefficients from lagged Gasoline to agricultural commodities market at quantiles 90-100% for Pre-Covid-19 Era	130
Figure A.7 : IRF cross-coefficients from lagged Brent Oil to agricultural commodities at quantiles 0-10% for Covid-19 Era	131
Figure A.8 : IRF cross-coefficients from lagged Natural Gas to agricultural commodities at quantiles 0-10% for Covid-19 Era	131
Figure A.9 : IRF cross-coefficients from lagged Gasoline to agricultural commodities market at quantiles 0-10% for Covid-19 Era	132
Figure A.10 : IRF cross-coefficients from lagged Brent Oil to agricultural commodities at quantiles 90-100% for Covid-19 Era	132
Figure A.11 : IRF cross-coefficients from lagged Natural Gas to agricultural commodities at quantiles 90-100% for Covid-19 Era	133
Figure A.12 : IRF cross-coefficients from lagged Gasoline to agricultural commodities market at quantiles 90-100% for Covid-19 Era	133
Figure A.13 : IRF cross-coefficients from lagged Brent Oil to agricultural commodities at quantiles 0-10% for Post-Covid-19 Era	134
Figure A.14 : IRF cross-coefficients from lagged Natural Gas to agricultural commodities at quantiles 0-10% for Post-Covid-19 Era	134
Figure A.15 : IRF cross-coefficients from lagged Gasoline to agricultural commodities market at quantiles 0-10% for Post-Covid-19 Era	135
Figure A.16 : IRF cross-coefficients from lagged Brent Oil to agricultural commodities at quantiles 90-100% for Post-Covid-19 Era	135
Figure A.17 : IRF cross-coefficients from lagged Natural Gas to agricultural commodities at quantiles 90-100% for Post-Covid-19 Era	136
Figure A.18 : IRF cross-coefficients from lagged Gasoline to agricultural commodities market at quantiles 90-100% for Post-Covid-19 Era	136
Figure A.19 : The cross-quantilogram results for Brent oil at lags 1-100 Pre-Covid-19 Era $\tau=[0-0.10]$	137
Figure A.20 : The cross-quantilogram results for Natural gas at lags 1-100 Pre-Covid-19 Era $\tau=[0-0.10]$	138
Figure A.21 : The cross-quantilogram results for Gasoline at lags 1-100 Pre-Covid-19 Era $\tau=[0-0.10]$	139
Figure A.22 : The cross-quantilogram results for Brent oil at lags 1-100 Pre-Covid-19 Era $\tau=[0.90-1]$	140
Figure A.23 : The cross-quantilogram results for Natural gas at lags 1-100 Pre-Covid-19 Era $\tau=[0.90-1]$	141
Figure A.24 : The cross-quantilogram results for Gasoline at lags 1-100 Pre-Covid-19 Era $\tau=[0.90-1]$	142
Figure A.25 : The cross-quantilogram results for Brent oil at lags 1-100 Covid-19 Era $\tau=[0-0.10]$	143
Figure A.26 : The cross-quantilogram results for Natural gas at lags 1-100 Covid-19 Era $\tau=[0-0.10]$	144
Figure A.27 : The cross-quantilogram results for Gasoline at lags 1-100 Covid-19 Era $\tau=[0-0.10]$	145
Figure A.28 : The cross-quantilogram results for Brent oil at lags 1-100 Covid-19 Era $\tau=[0.90-1]$	146
Figure A.29 : The cross-quantilogram results for Natural gas at lags 1-100 Covid-19 Era $\tau=[0.90-1]$	147
Figure A.30 : The cross-quantilogram results for Gasoline at lags 1-100 Covid-19 Era $\tau=[0.90-1]$	148

Figure A.31 : The cross-quantilogram results for Brent oil at lags 1-100 Post-Covid-19 Era $\tau=[0-0.10]$	149
Figure A.32 : The cross-quantilogram results for Natural gas at lags 1-100 Post-Covid-19 Era $\tau=[0-0.10]$	150
Figure A.33 : The cross-quantilogram results for Gasoline at lags 1-100 Post-Covid-19 Era $\tau=[0-0.10]$	151
Figure A.34 : The cross-quantilogram results for Brent oil at lags 1-100 Post-Covid-19 Era $\tau=[0.90-1]$	152
Figure A.35 : The cross-quantilogram results for Natural gas at lags 1-100 Post-Covid-19 Era $\tau=[0.90-1]$	153
Figure A.36 : The cross-quantilogram results for Gasoline at lags 1-100 Post-Covid-19 Era $\tau=[0.90-1]$	154



MACRO STRESS TESTING IN TURKISH BANKING SECTOR AND TAIL DEPENDENCE IN FINANCIAL, ENERGY AND COMMODITY MARKETS

SUMMARY

This dissertation is a collection of three chapters on the resilience of Turkish banking system, nonlinear tail dependence from U.S. agricultural markets to Turkish agricultural markets, and nonlinear tail dependence from energy commodities to agricultural commodities.

Financial institutions and financial markets exert significant effect on economies due to their critical role. When operating efficiently, they ensure the growth and stability of economies. Nevertheless, inefficiencies or vulnerabilities to shocks in these institutions and markets can result in systemic crises. For instance, deteriorations in the indicators of banks not only affect the banking system but also have repercussions across the entire economy through a feedback mechanism. As emphasized in the literature, higher nonperforming loans impede the real economy by slowing economic activity and credit growth. Financial markets, on the other hand, inherently contain the risk of financial contagion or spillover effects. While offering investment opportunities and facilitating price discovery, which contributing to wealth accumulation and economic advancement, they possess the potential to trigger joint collapses and substantial financial losses in the event of a shock. Thus, examining the vulnerabilities of financial institutions and the interdependence among various financial markets is exceedingly crucial, particularly considering the complexity of this interdependence.

Accordingly, this dissertation evaluates the resilience of the Turkish banking system, the nonlinear dependence from US agricultural markets to Turkish agricultural markets, and the nonlinear dependence from energy commodities to agricultural commodities in separate chapters.

The first chapter focuses on stress testing applied to conventional and participation banks within the Turkish banking sector. It employs the nonperforming loan ratio (NPL) as a pivotal stress variable. To conduct stress testing, the study uses an innovative additive nonparametric quantile regression technique. The objective is to assess how macroeconomic variables—exchange rates, interest rates, unemployment rates, and the public debt to GDP ratio—affect the NPL. The analysis covers monthly observations spanning from January 2005 to February 2020. Additionally, the chapter conducts scenario analyses based on various distributions and examines adverse scenarios concerning extreme tail values of macroeconomic variables. The study reveals the substantial influence of these macroeconomic factors on NPL, emphasizing the importance of stable exchange rates, controlled unemployment rates, and managed public debt. Furthermore, it highlights the necessity for tailored policies concerning different bank types, given observed disparities.

The second chapter examines the relationship between U.S. and Turkish agricultural commodity markets, and also investigates the nonlinear tail dependence from Brent oil, USD/TRY currency rate, and overnight interest rate to Turkish agricultural

commodities. It employs a novel nonlinear measure of tail dependence to explore the connection between these markets. The study analyzes the mean and tail dependence between the markets, considering both lower and upper continuum of quantiles. Additionally, it evaluates significant events such as the Turkish Mercantile Exchange (TMEX) launch and the Ukraine war. The dataset set contains daily returns from January 5, 2016, to May 31, 2022. To ensure robustness, a nonparametric test for Granger causality in distribution is employed. The findings reveal significant and persistent tail and mean dependence from U.S. agricultural futures to Turkish spot markets. This emphasizes the necessity for enhanced information exchange between spot and derivatives markets to strengthen market efficiency. The chapter also addresses the importance of monitoring interconnections and contagion risks among markets, especially during challenging market conditions.

The third chapter investigates the impact of energy commodities—Brent oil, natural gas, and gasoline—on agricultural commodities. It employs a nonlinear measure of tail dependence to analyze the relationship across three distinct periods: pre-Covid-19, during Covid-19, and post-Covid-19. The dataset comprises daily records from June 1, 2017, to June 9, 2023, covering different market periods. Additionally, the chapter utilizes cross-quantilogram analysis and the nonparametric test for Granger causality in distribution for robustness checks. The research reveals significant and persistent lower and upper tail dependence between energy and agricultural commodities across each period. The findings demonstrate nuanced and dynamic tail dependence patterns, indicating asymmetric risk transmissions under varying market conditions. These results have critical implications for effective market strategies, efficient portfolio management in agricultural commodity markets, and the need for resilient regulations during extreme events.

TÜRK BANKACILIK SEKTÖRÜNDE MAKRO STRES TESTİ VE FİNANSAL, ENERJİ VE EMTİA PİYASALARINDA KUYRUK BAĞIMLILIĞI

ÖZET

Bu çalışma, Türk bankacılık sisteminin direnci, ABD tarım piyasalarından Türk tarım piyasalarına doğrusal olmayan kuyruk bağımlılığı ve enerji emtialarından tarım emtialarına doğrusal olmayan kuyruk bağımlılığı üzerine üç bölümden oluşmaktadır.

Finansal kurumlar ve finansal piyasalar kritik konumları nedeniyle ekonomiler üzerinde çok önemli etkilere sahiptirler. Kurum ve piyasalar etkin çalıştıklarında, ekonomilerin büyümesini ve istikrarını korumada büyük katkılar sağlamakla birlikte, bu kurumların ve piyasaların verimsiz çalışmaları veya şoklara karşı dirençsizlikleri sistemik krizlere yol açabilir. Örneğin, bankaların göstergelerindeki kötüleşmeler sadece bankacılık sistemini değil, geri bildirim mekanizması aracılığıyla tüm ekonomiyi etkiler. Literatürde vurgulandığı gibi, takipteki kredilerin yüksek seviyede olması ekonomik faaliyeti ve kredi büyümesini yavaşlatarak reel ekonomiyi etkileyecektir. Finansal piyasaların, yatırım fırsatları ve etkin fiyatlama sağlayarak servet artışı ile ekonomik ilerlemeye katkıda bulunmasının yanı sıra, finansal bulaşma veya yayılma etkisi riskini de içermesi söz konusudur. Bu durum, şoklar karşısında ortak piyasa çöküşlerine ve büyük finansal kayıplara yol açabilir. Bu nedenle, finansal kurumların kırılma noktalarını ve çeşitli finansal piyasalar arasındaki bağımlılığı incelemek son derece önemlidir.

Bu doğrultuda bu tez, Türk bankacılık sisteminin dayanıklılığını, ABD tarım piyasaları ve Türk tarım piyasaları arasındaki doğrusal olmayan bağımlılığı ve enerji emtiaları ile tarımsal emtialar arasındaki doğrusal olmayan bağımlılığı ayrı bölümlerde değerlendirmektedir.

İlk bölümde, Türk bankacılık sektöründeki konvansiyonel ve katılım bankaları için stres testi gerçekleştirilmiştir. Stres değişkeni olarak takipteki kredi oranının (TKO-NPL) kullanıldığı bu çalışmada Koenker (2011) tarafından geliştirilen toplamsal parametrik olmayan kantil regresyon tekniği kullanılmıştır. Çalışmanın amacı, döviz kurları, faiz oranları, işsizlik oranları ve kamu borcunun GSYH'ye oranının TKO'yu nasıl etkilediğini incelemektir. Analizler TKO'nun 0.05, 0.90 ve 0.95 kantil değerleri için yapılmıştır. Veri seti, Ocak 2005'ten Şubat 2020'ye kadar aylık gözlemleri içermektedir.

Ayrıca, bu bölümde, çeşitli dağılımlara dayalı senaryo analizleri yapılmakta ve makroekonomik değişkenlerin aşırı kuyruk değerlerini içeren olumsuz senaryolar incelenmektedir. Senaryo analizi için, hem TKO hem de makroekonomik değişkenler, başlangıçta üç farklı dağılıma (normal, öğrenci t ve lojistik dağılımlar) göre simüle

edilir. Alternatif olumsuz senaryolar, makroekonomik değişkenlerin kuyruk değerlerine (1%, 5%, 95% ve 99%) dayandırılmıştır.

Ek olarak, parametrik olmayan kantil regresyonundan elde edilen sonuçlardan yararlanılarak olasılık analizleri gerçekleştirilmiştir. Bu yaklaşım, stres değişkeninin belirli eşik değerlerine ulaşma olasılığı hakkında fikirler sunmaktadır.

Konvansiyonel ve katılım bankalarının incelenmesi, makroekonomik faktörlere karşı farklı banka tiplerinin farklı hassasiyetlerin olduğunu ortaya çıkarmıştır. Örneğin, olasılık analizlerinden görüleceği üzere, kamu borç oranındaki ve işsizlik oranındaki değişiklikler konvansiyonel bankalar için, TKO'nun yüksek kantil düzeylerinde daha fazla bozucu etkiye sahipken, katılım bankalarında ise TKO'nun düşük kantil düzeylerinde daha fazla artan kırılganlığa yol açmaktadır. Senaryo analizleri ise, katılım bankalarının döviz kurları, işsizlik oranı ve GSMH'ye oranla kamu borcu gibi aşırı senaryolara daha duyarlı olduğunu ortaya koymaktadır.

Analizler, ele alınan makroekonomik faktörlerin TKO üzerindeki önemli etkisini ortaya koymakta ve istikrarlı döviz kurları, kontrol altında tutulan işsizlik oranları ve iyi yönetilen kamu borcunun önemini vurgulamaktadır. Sonuçlar TKO ile makroekonomik değişkenler arasındaki doğrusal olmayan ilişkilerin ve makroekonomik değişkenlerin stres değişkeninin farklı kantilleri üzerinde farklılaşan etkilerinin göz önünde bulundurularak, ekonomik durgunluklar veya istikrarsızlık dönemlerinde daha hedef odaklı ve etkili politika önlemleri geliştirilmesi gerektiğini ortaya koymaktadır. Ek olarak bulgular farklı banka tiplerine yönelik özelleştirilmiş politikaların gerekliliğini de vurgulamaktadır.

İkinci bölümde, ABD ve Türk tarım emtia piyasaları arasındaki ilişki ile Brent petrol, USD/TRY döviz kuru ve gecelik faiz oranının Türk tarım emtialarına olan etkisi Escanciano ve Hualde (2021) tarafından geliştirilen doğrusal olmayan kuyruk bağımlılığı ölçüsü kullanarak incelenmiştir. Çalışma, piyasalar arasındaki ortalamada bağımlılık ve kuyruk bağımlılığını, hem alt hem de üst kuyruk için tek bir kantil değeri yerine kantil aralıklarını ele alarak analiz etmektedir. Buna göre alt kuyruk için %1 ile %5 arasındaki kantilleri içeren kantil aralığı kullanılırken, üst kuyruk için %95 ile %99 arasındaki kantilleri içeren kantil aralığı ele alınmıştır. Ortalamada bağımlılık için tüm dağılımın tamamı (0-100%) kullanılmıştır. Analizler 300 adet hareketli blok bootstrap kullanılarak gerçekleştirilmiş olup %95 kritik değer kullanılmıştır. Gecikme sayısı olarak da 300 gün ele alınmıştır.

Ayrıca, analizler Türkiye Ürün ve İhtisas Borsası (TÜRİB) kuruluşu ve Ukrayna savaşı gibi önemli olayları ele alarak bu olaylardan öncesi ve sonrası için gerçekleştirilmiştir. Veri seti, 5 Ocak 2016'dan 31 Mayıs 2022'ye kadar olan günlük fiyatları içermektedir.

Çalışmada ayrıca, Candelon ve Tokpavi (2016) tarafından geliştirilen dağılımda parametrik olmayan Granger nedensellik testi de ana bulguları doğrulamak amaçlı kullanılmıştır. Test yapılırken, alt kuyruk, üst kuyruk ve dağılımın merkezi dikkate alınmıştır. Bu doğrultuda alt kuyruk, üst kuyruk ve dağılımın merkezi için sırasıyla {1%, 5%, 10%}, {90%, 95%, 99%} ve {20%, 30%, ..., 70%, 80%} kantil seviyeleri belirlenmiştir.

Bulgular, ABD buğday, mısır ve arpa gelecek sözleşme fiyatlarından TÜRİB buğday, mısır ve arpa spot fiyatlarına anlamlı ve kalıcı ortalamada bağımlılık ve kuyruk bağımlılığı olduğunu ortaya koymaktadır. Ayrıca Brent petrol fiyatının, döviz kurunun ve faiz oranının Türk tarımsal piyasalar üzerinde anlamlı etkisi olduğunu da göstermektedir. Dağılımda parametrik olmayan Granger nedensellik testi de ABD

tarım emtialarından, Brent petrolü, döviz kuru ve faiz oranından Türk tarım emtialarına nedensellik olduğunu ortaya koymuştur.

Bu çalışma, piyasa verimliliğini güçlendirmek için politika yapıcılarının spot ve türev piyasalar arasındaki bilgi alışverişine öncelik vermesinin gerekliliğini göstermektedir. Anlamlı ve kalıcı ortalama bağımlılık ve kuyruk bağımlılığı, özellikle zorlu piyasa koşullarında, piyasalar arası etkileşim ve finansal bulaşma risklerinin dikkatli bir şekilde izlenmesinin gerekliliğini vurgulamaktadır. Piyasa bağımlılıklarındaki farklı seviyeler göz önüne alındığında, çeşitli risk yönetimi stratejileri geliştirme hayati öneme sahiptir. TÜRİB kuruluşu sonrası olaylar, sürdürülebilir ve verimli bir tarımsal pazarın acil ve etkili bir şekilde gerekliliğini vurgulamaktadır. Bu sonuçlar ışığında, politika yapıcılar, yerel türev piyasalar oluşturma, bilgi akışını teşvik etme, piyasa bağımlılığını izleme ve risk yönetimi stratejilerini çeşitlendirme konularına odaklanmalıdırlar.

Üçüncü bölümde, enerji emtialarının—Brent petrol, doğal gaz ve benzin—tarım emtialarına (buğday, soya fasulyesi, mısır, pamuk, şeker, pirinç, yulaf, kahve ve kakao) olan etkisini incelenmektedir. Analizler Escanciano ve Hualde (2021) tarafından geliştirilen yeni bir doğrusal olmayan kuyruk bağımlılığı ölçüsü kullanarak hem alt kuyruk hem de üst kuyruk için yapılmış olup, tek bir kantil değeri yerine birden fazla kantilleri içeren aralıklar kullanılmıştır. Buna göre alt kuyruk için %0 ile %10 arasındaki kantilleri içeren kantil aralığı kullanılırken, üst kuyruk için %90 ile %100 arasındaki kantilleri içeren kantil aralığı ele alınmıştır. Analizler 300 adet hareketli blok bootstrap kullanılarak gerçekleştirilmiş olup %95 kritik değer kullanılmıştır. Gecikme sayısı olarak da 300 gün ele alınmıştır. Böylelikle kuyruk olaylarına ilişkin çok daha kapsayıcı sonuçlar elde edilmiştir. Aynı zamanda analizler Covid-19 öncesi, Covid-19 süreci ve Covid-19 sonrası dönemler için ayrı ayrı yapılmış olup farklı piyasa koşullarının kuyruk bağımlılığında ne derece değişiklik yarattığı analiz edilmiştir. Covid-19 öncesi dönem için 01.06.2017 - 06.01.2020, Covid-19 dönemi için 07.01.2020 - 26.01.2022 ve Covid-19 sonrası dönem için 27.01.2022 - 09.06.2023 tarihleri arasındaki günlük veriler kullanılmıştır.

Ek olarak ana analizlerden elde edilen sonuçları doğrulamak amacıyla, Han ve arkadaşlarının (2016) çapraz kuantilogram tekniği ve Candelon ve Tokpavi'nin (2016) dağılım içi Granger nedensellik parametrik olmayan testi de uygulanmıştır. Çapraz kuantilogram tekniğinde, alt kuyruk kantil aralığı $[0, 0.10]$, üst kuyruk kantil aralığı ise $[0.90, 1.0]$ olarak belirlenmiştir. Gecikme sayısı her dönem için 100 olarak ayarlanmıştır. Anlamlılığı belirlemek için analiz, 1000 bootstrap tekrardan elde edilen %95 güven aralıklarına dayanmaktadır. Candelon ve Tokpavi'nin (2016) dağılım içi Granger nedensellik parametrik olmayan testinde ise Alt kuyruk, üst kuyruk ve dağılımın merkezi için sırasıyla $\{1\%, 5\%, 10\%\}$, $\{90\%, 95\%, 99\%\}$ ve $\{20\%, 30\%, \dots, 70\%, 80\%\}$ kantil seviyeleri belirlenmiştir.

Sonuçlar, her dönem için tüm enerji emtialarından tüm tarım emtialarına anlamlı ve kalıcı alt ve üst kuyruk bağımlılığını göstermektedir. Sonuçlar, farklı piyasa dönemlerinde enerji ve tarımsal emtialar arasında kendine özgü ve dinamik kuyruk bağımlılığı göstermektedir. Bu çalışma, farklı piyasa koşulları altında farklılaşan derecelerde kuyruk bağımlılığını ortaya koymaktadır. Ayrıca, bulgular, çapraz kuantilogram ve doğrusal olmayan Granger nedensellik testinin sonuçları tarafından da desteklenmektedir.

Analiz sonuçları, tarım emtia piyasalarında etkili pazar stratejileri ve verimli portföy yönetimi için önemli uygulamalar ve politika ipuçları sağlamaktadır. Öncelikle, aşırı

olaylar sırasında enerji ve tarımsal piyasalar arasındaki kalıcı bağımlılığı kabul etmek, politika yapıcılarının daha etkili düzenlemeler oluşturmalarına olanak tanır. Bu araştırma sonuçları bu nedenle, yüksek risk iletim dönemlerinde piyasaları stabilize etme stratejileri oluşturmak için bir temel olarak kabul edilebilir. Enerji piyasasındaki düzenlemeler tarım emtialarını önemli ölçüde etkilediği için, düzenlemeler yapılırken enerjiden tarım emtialarına risk yayılımı dikkate alınması gereken bir faktördür. İkinci olarak, bu çalışma, tarımsal piyasaların enerji piyasası şoklarına karşı hassasiyetini vurgulamakta olup, tarımsal emtiaların enerji emtiaları için portföy çeşitlendirmesi açısından ideal bir alternatif olmadığını öne sürmektedir. Yatırımcılar ve portföy yöneticileri, bu sonuçları baz alarak yatırım kararlarını ve risk yönetimi stratejilerini geliştirebilirler. Ayrıca, farklı piyasa koşulları altındaki kuyruk olaylarının yayılma etkilerinin farklılıklarını ve farklı emtia çiftleri arasındaki etkileşimlerin özgünlüğünü göz önüne alarak, piyasa katılımcıları portföyleri dinamik olarak uyarlayarak, piyasa koşullarıyla uyumlu hale getirebilirler.



1. INTRODUCTION

This dissertation comprises three chapters that explore the resilience of the Turkish banking system, investigate nonlinear tail dependence extending from U.S. agricultural markets to Turkish agricultural markets, and examine nonlinear tail dependence from energy commodities to agricultural commodities.

The first chapter conducts a stress testing for conventional banks and participation banks by employing their nonperforming loan ratio (NPL) as the stress variable. In order to implement stress testing, the additive nonparametric quantile regression technique developed by Koenker (2011) is utilized. The analyses are conducted for 0.05, 0.90, and 0.95 quantile values of NPL. The examined macroeconomic variables include the exchange rate, interest rate, unemployment rate, and public debt to GDP ratio. The dataset covers monthly observations from January 2005 to February 2020.

For scenario analysis, both the stress variable representing the banking system and the macroeconomic variables are initially simulated according to three different distributions (normal, student t, and logistic distributions). Alternative adverse scenarios are based on the tail values (1%, 5%, 95%, and 99%) of the macroeconomic variables.

In addition, the probability analysis is also conducted, leveraging the outcomes derived from nonparametric quantile regression. This analytical approach offers insights into the likelihood of the stress variable reaching specific thresholds.

The research reveals the substantial impact of analyzed macroeconomic variables on NPL, emphasizing the importance of maintaining a stable exchange rate, controlling unemployment, and managing public debt. Tailoring policies considering bank types is crucial, given the disparities observed.

Examining conventional and participation banks uncovers distinct vulnerabilities to macroeconomic fluctuations. Variations in the public debt ratio and unemployment rate have a more damaging effect on higher quantile levels of NPL for conventional banks,

while lower quantile levels of NPL for participation banks demonstrate increased fragility, as illustrated by the probability analysis. Scenario analyses reveal that participation banks are more susceptible to extreme scenarios related to exchange rates, unemployment rate, and public debt to GDP ratio.

The implications drawn from first chapter analyses hold substantial importance for policymakers, financial institutions, and economists. Understanding these nonlinear relationships between NPL and macroeconomic indicators across different quantiles is vital in devising more targeted and effective policy measures during economic downturns or periods of instability. This insight aids in developing more nuanced risk management strategies for financial institutions, particularly during times of economic volatility.

The second chapter delves into the connections between U.S. and Turkish agricultural commodity markets, employing a novel nonlinear measure of tail dependence developed by Escanciano and Hualde (2021). The study examines the mean and tail dependence between these markets, considering both lower continuum of quantiles and upper continuum of quantiles, and also pivotal events such as the Turkish Mercantile Exchange (TMEX) launch and the Ukraine war. The dataset comprises daily agricultural commodity returns of wheat, barley and corn covering the period from January 5, 2016, to May 31, 2022. In addition, the nonlinear tail dependence from Brent oil, USD/TRY currency rate, and overnight interest rate to Turkish agricultural commodities is also investigated.

The nonparametric test for Granger causality in distribution, an extension of the kernel-based Granger-causality test developed by Candelon and Tokpavi (2016), is also employed for robustness check.

The findings show significant and persistent tail and mean dependence from US wheat, corn and barley returns based on future contract prices to current TMEX spot market wheat, corn and barley returns, and also Brent oil, currency rate and interest rate have significant impact on Turkish agricultural markets. Additionally, the outcomes the robustness check yield significant test statistics, leading to the rejection of the null hypothesis of no Granger predictability. It is imperative for policymakers to prioritize enhancing information exchange between spot and derivatives markets to bolster market efficiency. The identified persistent tail and mean dependence among various markets

emphasize the need for vigilant monitoring of interconnections and contagion risks, especially during challenging market conditions. Given the differing levels of market interdependence, devising diverse risk management strategies becomes crucial. Post-TMEX introduction events emphasise the urgency of a sustainable and efficient agricultural market. Policymakers should focus on creating a local derivatives market, fostering information flow, monitoring market interdependence, and diversifying risk management strategies to enhance the sustainability and efficiency of the Turkish agricultural sector.

The third chapter investigates the tail dependence from energy commodities (Brent oil, natural gas and gasoline) to agricultural commodities (wheat, soybean, corn, cotton, sugar, rice, oat, coffee and cocoa) by employing Escanciano and Hualde's (2021) nonlinear measure of tail dependence. In this chapter the analyses are conducted also for both lower and upper continuum of quantiles for three distinct periods: pre-Covid-19, during Covid-19, and post-Covid-19. The sample data cover daily records for seven days a week, ranging from 01.06.2017 to 06.01.2020 for the pre-Covid-19 period, from 07.01.2020 to 26.01.2022 for the Covid-19 period, and from 27.01.2022 to 09.06.2023 for the post-Covid-19 period. Additionally, two analytical approaches, Han et al.'s (2016) cross-quantilogram analysis and Candelon and Tokpavi's (2016) nonparametric test for Granger causality in distribution, are employed for robustness check.

The findings reveal a significant and persistent lower and upper tail dependence for all commodity pairs in each period. The results show nuanced and dynamic tail dependence patterns between energy and agricultural commodities during distinct market periods. The analysis highlights varying degrees of tail dependence, indicating asymmetric risk transmissions under different market conditions. Furthermore, the findings are validated by the outcomes of cross-quantilogram and the nonparametric test for Granger causality in distribution.

The research findings carry vital implications for policy and practical applications, providing essential insights for effective market strategies and efficient portfolio management in agricultural commodity markets. Firstly, acknowledging the persistent interdependence between energy and agricultural markets during extreme events allows

policymakers to create more resilient regulations. These research outcomes serve as a foundation for devising strategies to stabilize markets during periods of high-risk transmission. Given the risk transmission from energy to agricultural commodities, regulatory actions in the energy market significantly impact agricultural commodities. Secondly, this study highlights the susceptibility of agricultural markets to energy market shocks, suggesting that agricultural commodities may not serve as ideal substitutes for energy commodities in portfolio diversification. Investors and portfolio managers can utilize these insights to enhance investment decisions and risk management strategies. Furthermore, considering the differences in tail spillover effects under diverse market conditions and the specificity of interactions between different commodity pairs, market participants can adapt portfolios dynamically, aligning them with evolving market conditions.

2. MACRO STRESS TESTING THE CREDIT RISK OF CONVENTIONAL AND PARTICIPATION BANKS IN TURKEY: A NONPARAMETRIC QUANTILE REGRESSION APPROACH

2.1. Introduction

Stress testing serves as a pivotal measure evaluating the risk exposure of financial institutions and systems, assessing their vulnerability to ‘exceptional but plausible’ adverse scenarios. Initially utilized by financial entities to assess portfolio risks, the adoption of stress tests by policymakers and regulatory agencies aims to identify systemic vulnerabilities within the financial system, preempting potential crises (Acharya et al., 2018; Kok et al., 2022).

After the unexpected global financial crisis of 2008, the significance of stress tests heightened, prompting the exploration of innovative methodologies in response to perceived shortcomings in existing techniques. As a result, meticulous analyses scrutinizing the resilience of banks and financial sectors to financial shocks superseded reliance solely on historical precedents or expert opinions. The 2008 crisis starkly showcased the severe repercussions of financial system shocks on macroeconomic activities, emphasizing the imperative for robust capital structures, liquidity reserves, and high asset quality in fortifying institutions against unexpected, severe shocks. Thus, the focal has shifted towards crisis prediction and prevention by adopting proactive measures ensued.

Evident from historical occurrences, financial sector crises are triggered not only by internal dynamics but also by macroeconomic and financial sector changes and shocks, which often yield more severe repercussions. Consequently, for effective policy implementation, identifying extant risks and potential threats in the finance sector and economy remains fundamental. Discerning the pivotal macroeconomic or financial factors

impacting the financial system is crucial to strategize proactive measures. Particularly, comprehending the idiosyncratic conditions and risk sources within different banking models—such as Islamic banking, recognized as participation banking in Turkey—is pivotal. Participation banks, adhering to Islamic Law, function on an interest-free, asset-based financial system, distinguishing themselves from conventional banks reliant on debt-based financing. Since the main concept of participation banking is risk sharing, the depositors are the shareholders and investment accounts holders (IAH) who share the profits, losses, and risks of their investments in the bank (Hasan and Dridi, 2011). Thus, understanding and regulating these distinctions are vital for effective risk management.

The intricate link between bank-specific and macroeconomic variables necessitates an accurate comprehension to avert errors in risk identification and policy formulation. Therefore, this study delves into dissecting the dynamics of conventional and participation banking separately, elucidating their varying sensitivities to risks and their corresponding responses.

The central queries of this research revolve around the Turkish Banking Sector's sensitivity to risks and the differential impact of these risks on conventional and participation banks.

The Turkish banking sector, boasting a 150-year history, holds a significant position within the financial system. Over the past decade, it has undergone rapid evolution, now comprising 91% of the overall financial sector. Notably, the sector's assets to GDP ratio surged from 80% in 2010 to 120% in 2020, aligning closely with the average of emerging countries and representing approximately one-third of that in developed nations (BSTDB, 2022; TBB, 2020). Standing at 71% of GDP, outstanding loans in Turkey rank highest in the Black Sea Trade and Development Bank (BSTDB) Region (BSTDB, 2022), while the capital adequacy ratio (CAR) of the Turkish banking sector by the end of 2020 closely mirrored that of emerging markets (CBRT, 2021). Following structural reforms post the 2000-2001 crises, the sector underwent a critical transformation, fortifying its resilience against economic downturns. Its ability to withstand adverse global conditions post the 2008 crisis further attests to this robustness. However, recent turbulence in the Turkish economy has raised concerns about the fragility of the sector, evidenced by significant

declines in the stock values of major banks. Banks worldwide face with various financial risks including credit, liquidity, interest, and exchange rate risks. The uncertainties stemming from the Covid-19 pandemic, escalations in US-China tensions, the Russia-Ukraine conflict, global energy and food crises, surges in inflation, rapid currency depreciation, and geopolitical risks collectively exacerbate the financial risks faced by Turkish banks, dampening future prospects.

Meanwhile, the participation banking system has garnered increasing attention from financial practitioners and academia as an alternative to conventional banking, particularly in the wake of the 2008 crisis. Notably, the Islamic Financial Services Industry: Stability Report (2020, 2023) highlights the remarkable growth of the participation banking system, which surged from a global share of 920 billion US dollars in 2015 to a substantial volume of 2.4 trillion US dollars in 2019, and further increased to 3.25 trillion US dollars in 2022.

This study utilizes an additive nonparametric quantile regression technique developed by Koenker (2011) to analyze the impact of various macroeconomic variables on the stress variable. Traditionally, parametric quantile regression models have dominated stress testing literature due to their utility in modelling rare events within the banking system. Initially pioneered by Koenker and Bassett (1978), parametric quantile regression has been extensively used in various economic areas such as growth analysis, risk management, hedging, financial contagion, and spillovers (Aït-Sahalia and Lo, 2000; Cai and Xu, 2008). While offering advantages over conditional mean regression by providing insights into the entire distribution rather than solely the conditional mean, parametric quantile regression is limited by its imposition of a linear functional form on the relationship between the dependent and independent variables. Consequently, it struggles to capture nonlinearities within the model. Especially in stress testing, an integral aspect of risk management, there exists weak theoretical and empirical support for a linear model when analyzing the relationship between the stress variable and macroeconomic variables (Kanas and Molyneux, 2018). Additionally, parametric approaches assume normality and stationarity in data, assumptions that are often unmet in practical scenarios. Cai and Xu (2008) suggest that parametric quantile regression might lack the flexibility to account for non-linearities and interactions among regressors. Nonparametric techniques, as

highlighted by Moretti et al. (2008), hold particular advantages in stress testing, particularly when long-term time series data on macroeconomic variables are unavailable. Furthermore, the high heterogeneity in explanatory variables within the banking sector may result in multimodal and thick tail distributions, making the use of standard quantile regression prone to biased outcomes (Kanas and Molyneux, 2018; Sheftin, 2008; Schechtman and Gaglianone, 2012).

Due to these reasons, this research utilizes an additive nonparametric quantile regression method, as introduced by Koenker et al. (2011), for conducting stress testing analysis. Moreover, the probability and scenario analyses are conducted, leveraging the outcomes derived from nonparametric quantile regression. This analytical approach offers insights into the likelihood of the stress variable reaching specific thresholds, contingent upon diverse macroeconomic variable values across various scenarios. Consequently, this method enables one to derive more resilient and robust conclusions (Kanas and Molyneux, 2018).

For scenario analysis, both the stress variable representing the banking system and the macroeconomic variables are initially simulated according to three different distributions (normal, student t, and logistic distributions). Alternative adverse scenarios are based on the tail values (1%, 5%, 95%, and 99%) of the macroeconomic variables.

The evaluation aims to cover the longest continuous period available within the dataset. Consequently, all analyses are conducted within the pre-pandemic period spanning from January 2005 to February 2020, comprising a total of 182 monthly observations. Deliberately excluding the Covid-19 period is essential since data from this phase might potentially distort parameter estimates due to disparities from non-pandemic observations (Lenza and Primiceri, 2022). To facilitate parameter estimation, the deliberate exclusion of observations linked to the pandemic period aligns with recommendations (Schorfheide and Song, 2021). The analysis utilizes aggregated data pertaining to Turkish deposit-taking banks.

This research presents several contributions to empirical literature. Primarily, it introduces a novel stress testing methodology for the Turkish Banking System, a methodology previously utilized solely by Kanas and Molyneux (2018) for stress testing in the U.S.

banking sector. In contrast to prior stress testing studies in Turkey, which predominantly relied on the Credit Portfolio view and VAR model (Küçüközmen and Yüksel, 2007; Altıntaş, 2012; Başarır, 2016; Beşe, 2007; İskender, 2014; Sakarya and Akkuş, 2017; Karaaslan and Sayılır, 2019), this study adopts an additive nonparametric quantile regression approach. This methodology allows one to utilize quantile regression, avoiding potential limitations inherent in linear parametric models. Specifically, the refraining from imposing constraints on the relationship between the stress variable and risk variables allows for inferences to be drawn concerning the entire distribution of the stress variable. Secondly, this stress testing analysis facilitates differentiation in the impact of macroeconomic variables on the stress variable between conventional and participation banks. Hence, it allows for a comparative analysis of risk sensitivities within the Turkish banking sector. This distinction is crucial in discerning the varying effects across banking types. Thirdly, by examining both lower and higher quantiles, this study provides comprehensive insights into the stress variable's sensitivity to macroeconomic variables across different levels. This analysis adds depth by considering various thresholds. Lastly, the stress tests are reinforced by probability and scenario analyses, further substantiating the findings of the study.

2.2. Literature Review

Bankruptcy risk has received substantial attention in financial studies due to the pivotal role banks play in economic functions, their failure posing a systemic threat to the economy. Extensive research has employed various modeling approaches to predict bank failures and default rates, considering their potential to propagate systemic risks. Stress testing typically involves micro and macro approaches. Micro stress testing evaluates the resilience of individual financial institutions, focusing on internal risk management, while macro stress testing assesses the resilience of the entire financial system, emphasizing vulnerabilities leading to systemic risk (Adrian et al., 2020).

In micro stress testing, prevailing methodologies include simple and multivariate discriminant analysis (e.g. Altman, 1968; Cox and Wang, 2014), probit and logit regressions (e.g. Martin, 1977; Ohlson, 1980; Cole and Gunther, 1998), rating transition

systems (rating migrations) (e.g. Belkin et al., 1998; Miu and Özdemir, 2009), survival analysis and Cox proportional hazards models (e.g. Lane et al., 1986; Shumway, 2001), and machine learning-based methodologies (e.g. Ravi and Pramodh, 2008; Iturriaga and Sanz, 2015; Gogas et al., 2018).

Macro stress testing and studies on the relationship between macroeconomic variables and credit risk have also been extensively conducted. The origin of macro stress testing and macroeconomic credit risk modeling can be traced back to pioneering studies by Wilson (1997a, b), in which he explores the sources of systematic variation in default rates using macroeconomic and financial factors. Wilson models the default rate as a function of macroeconomic and financial variables and measures the sensitivity and default probability by subjecting these factors to shocks. The literature follows a sequence: constructing empirical models to unveil macroeconomic variable-stress variable relationships, and subsequently creating adverse stress scenarios to gauge stress variable impacts and major risk factors (among others Sorge and Virolainen, 2006; Elsinger et al., 2006; Otani et al., 2009; Schechtman and Gaglianone, 2012; Kanas and Molyneux, 2018; Grundke et al., 2019; Méndez-Marcano, 2021).

Standard linear regression models (e.g., Kalirai and Scheicher, 2002; Podlich et al., 2010; Grundke et al., 2019) and Vector Autoregressive (VAR) models (e.g., Boss, 2002; Virolainen, 2004; Rongjie and Yang, 2011; Vazquez, 2012; Chavleishvili and Manganelli, 2019; Méndez-Marcano, 2021) are commonly employed in macro stress testing studies, with stress variables being modeled as functions of macroeconomic variables. However, prevalent macro stress testing techniques possess limitations. Assuming a linear relationship between macroeconomic variables and stress variables without prior knowledge is unrealistic. Furthermore, interrelationships among explanatory variables can pose model specification problems, which can be addressed using nonparametric regression models (Cai and Xu, 2008). The presence of heterogeneity in explanatory variables can lead to multimodal and thick-tailed distributions, necessitating the consideration of nonlinearity in the parameters (Sheftin, 2008; Schechtman and Gaglianone, 2012). Nonparametric models are more effective in financial risk management than parametric models and have significant implications for tail

probabilities (Aït-Sahalia and Lo, 2000). Moreover, nonparametric models are better suited for modeling uncertainty when macroeconomic time series data is relatively short (Moretti et al., 2008). Hence, nonparametric approaches are preferred. For example, Schechtman and Gaglianone (2012) conducted macro-stress testing on credit risk, focusing on the tails. They employed both Wilson's model (1997a, b) and the quantile regression (QR) method (Koenker and Xiao, 2002). Using QR, they assessed the tails of credit risk distributions under negative macroeconomic scenarios. Kanas and Molyneux (2018) found that the standard quantile regression technique fails to capture the significant relationship between macroeconomic variables and banking risk measured by quantiles of the dependent variable. They argued that the additive semiparametric quantile regression technique (Koenker, 2010, 2011) is superior and utilized it for macro stress testing in the US banking system.

Despite the breadth of research on stress testing in conventional banking, studies on participation banks are limited. Sensitivity scenarios, solvency stress testing, and VaR techniques have been employed in exploring the resilience of participation banks (Elsiefy, 2012; Chattha, 2016; Kurniadi et al., 2018). In the context of the Turkish banking sector, existing stress testing studies predominantly rely on parametric techniques (Sakarya and Akkuş, 2017; Hassan et al., 2016).

The contribution of this chapter to the literature lies in applying a novel stress testing methodology to the Turkish Banking System, previously employed only in the US banking sector by Kanas and Molyneux (2018). Unlike prior studies for the Turkish banking system, this approach sidesteps the restrictions posed by linear parametric models, harnessing the advantages offered by quantile regression method. Additionally, this study extends stress testing to both conventional and participation banks, exploring macroeconomic factor effects across various stress variable quantiles.

2.3. Methodology

In this study, the additive nonparametric quantile regression technique developed by Koenker et al. (2011) is employed to accurately capture the relationship between NPL (Non-Performing Loans) and key macroeconomic variables, namely the exchange rate,

interest rate, unemployment rate, and public debt ratio. This analysis aims to uncover vulnerabilities within the Turkish banking system. Obtaining the true dynamics between these variables is crucial for ensuring the accuracy of the subsequent analyses. As emphasized by Aït-Sahalia and Lo (2000), utilizing a nonparametric approach is more suitable within the context of risk analysis.

Additive econometric models, originally introduced by Breiman and Friedman (1985), Hastie (1986), and Hastie (1990), have garnered significant attention from researchers due to their practical approach to non-parametric regressions. Specifically, additive models treat the nonparametric components of the model as if they consist of additive pieces of low dimension. This characteristic allows for valuable dimension reduction and helps to circumvent the well-known “curse of dimensionality” problem.

The generic form of an additive nonparametric quantile regression is expressed as follows:

$$Q_{y_t|D_t, x_t}(\tau|D_t, x_t) = D_t' \beta_0 + \sum_{j=1}^J h_j(x_{tj}) \quad (2.1)$$

with $\tau \in (0,1)$

In the equation above involves D_t signifies the deterministic terms (in this instance, the intercept), which is the only parametric component within the model. Additionally, x_{ij} corresponds to covariates or regressors. The continuous functions h_j , which can take the form of univariate $\mathcal{R} \rightarrow \mathcal{R}$ or bivariate $\mathcal{R}^2 \rightarrow \mathcal{R}$ functions, constitute the nonparametric components. The vector $h = (h_1, \dots, h_J)$ possesses absolutely continuous derivatives, denoted by h' .

Equation 2.1 serves as a valuable tool for stress testing as it enables the modeling of tail risks, specifically addressing the probability of incurring a loss due to an extreme event. In practical applications, the most common tails of interest are often at percentiles such as 0.01, 0.05, 0.90, 0.95, and 0.99. The aforementioned additive nonparametric quantile regression offers potential in modeling the impact of rare events on the stress variable.

For estimating Equation 2.1, various techniques can be employed, including kernel smoothing estimator, local polynomial regression, or spline-based regression with total smoothing penalties (Hazelton, 2015). In line with the approach introduced by Koenker et al. (2011), the quantile smoothing splines method developed by Koenker et al. (1994)

is adopted. This method allows one to solve the following equation, aiding in the estimation of the parameter β_0 and determining the effects of regressors on different quantiles of the dependent variable:

$$\min_{(\beta_0, h)} \sum \rho_\tau(y_t - D_t' \beta_0 - \sum h_j(x_{tj})) + \lambda_0 \|\beta_0\|_1 + \sum_{j=1}^J \lambda_j V(\nabla h_j) \quad (2.2)$$

where

$\rho_\tau(u) = u(\tau - I(u < 0))$, $\beta_0 \in \mathcal{R}^{\rho_0}$, $\|\beta_0\|_1 = \sum_{k=1}^K |\beta_k|$, K representing total number of elements in vector D_t . As the model is fully nonparametric, D_t includes only a constant term. In equation 2.2, λ 's are the smoothness parameters and $V(\nabla h_j)$ represents total variation of $h': \mathcal{R} \rightarrow \mathcal{R}$ as

$$V(h'(x)) = \int |h''(x)| dx$$

$$V(\Delta h) = \int \|\nabla^2 h(x)\| dx$$

Where $\nabla^2 h(x)$ is the Hessian of h and $\|\cdot\|$ stands for the Hilbert-Schmidt.

Once equation 2.1 is solved, the confidence bands for nonparametric components can be obtained as explained in Koenker et al. (2011).

It should be noted that the smoothness parameters λ 's can be chosen using SIC information criterion which might be expressed as follows:

$$SIC(\lambda) = T \ln \hat{\sigma} \lambda + 0.5 p(\lambda) \ln(n) \quad (2.3)$$

where $\hat{\sigma}(\lambda) = T^{-1} \sum_{t=1}^T \rho_\tau(y_t - \hat{h}(D, x))$, T is the sample size, $p(\lambda)$ is the effective dimension of the estimated model : $\hat{h}(D, x) = D' \hat{\beta}_0 + \sum_{j=1}^J \hat{h}_j(x)$

2.4. Data

The dataset comprises monthly observations spanning from January 2005 to February 2020, retrieved from the databases of the Turkish Banking Regulation and Supervision Agency (BRSA) and the Central Bank of the Republic of Turkey (EVDS). For this study, the focus is solely on deposit-taking banks, excluding development and investment banks

from the analysis. Throughout the analytical period, the Turkish banking sector consisted of 32 deposit banks (comprising 3 state-owned and 29 privately-owned) alongside 6 participation banks as of February 2020 (BRSA, 2020). Notably, the asset size of the Turkish Banking Sector witnessed a growth from 6,108 billion TL in December 2020 to 9,213 billion TL by the end of 2021, resulting in a 1.28 asset size to GDP ratio (BRSA, 2022).

The selection of macroeconomic variables is based on existing literature (Boss, 2002; Quagliariello, 2009; Demirgüç-Kunt and Huizinga, 2011; Louzis et al., 2012; Beck et al., 2013; Kanas and Molyneux, 2018) and their effectiveness in terms of policy decisions. The macroeconomic variables—exchange rate (USD/TRY), policy interest rate, unemployment rate, and public debt to GDP ratio—are regarded as significant barometers for assessing the economy and guiding policy implications. Due to the unavailability of historical default rates for the Turkish banking system, the precedent set in literature (Schechtman and Gaglianone, 2012; Messai and Jouini, 2013; Kanas and Molyneux, 2018; Patra and Pathi, 2020; Askari et al., 2021) is followed and Non-Performing Loan (NPL) is utilized as the stress variable for the econometric modeling of credit risk. Furthermore, while acknowledging that banks confront various risks such as liquidity, foreign exchange, and market risks, our rationale for employing NPL as a banking stability indicator rests on credit risk being the most prominent cause of financial instability in developing and emerging economies (Buncic and Melecky, 2013; Feyen and Mare, 2021).

Table 2.1 : Descriptive Statistics

Series	Mean	Median	Std. Dev.	Min	Max	Skew	Kurt	JB	BDS
NPL of Conventional Banks (%)	3.72	3.31	0.94	2.70	6.19	0.942	-0.346	6.525**	35.687***
NPL of Participation Banks (%)	4.20	3.95	0.95	2.96	7.09	0.835	0.011	6.547**	34.352***
NPL of Public Banks (%)	3.60	2.90	1.59	2.01	9.59	1.899	3.206	6.585**	18.456***
NPL of Private Banks (%)	3.49	3.24	1.01	2.24	6.54	1.074	0.615	6.283**	30.674***
The Exchange Rate	2.43	1.80	1.39	1.17	6.35	1.397	0.839	6.242**	26.108***
The Interest Rate (%)	11.09	8.00	5.49	4.50	24.00	0.786	-0.530	6.210**	51.146***
The Unemployment Rate (%)	10.36	10.00	1.55	8.00	14.00	0.847	-0.252	5.982*	33.647***
The Public Debt Ratio (%)	20.29	17.66	11.10	5.97	46.17	0.437	-0.935	5.995**	64.923***

Notes: This table displays the mean, median, standard deviation (Std. dev), minimum and maximum values, skewness (Skew), kurtosis (Kurt), as well as the test statistics of the Jarque-Bera (JB) normality test and the BDS test of nonlinearity. Additionally, ABP represents the p-value of the Data Driven Box Pierce test of Escanciano and Lobato (2009) for serial correlation with the null hypothesis of no serial correlation. Significance levels are denoted by *, **, and ***, representing significance at 10%, 5%, and 1%, respectively.

Table 2.1 presents descriptive statistics for the NPL ratios of banks along with explanatory variables. As expected, both the NPL ratios and explanatory variables exhibit right skewness. Consequently, the arithmetic means of the series exceed their median values. The NPL ratio is observed to be higher for participation banks compared to conventional banks, while the NPL ratio for public banks slightly surpasses that of private banks. The Jarque-Bera normality test highlights the non-normality of all variables. Furthermore, the BDS test (Brock-Dechert-Scheinkman,1987) rejects the linearity of variables, supporting the use of nonparametric analysis. Figure 2.1 depicts time series plots of these series.

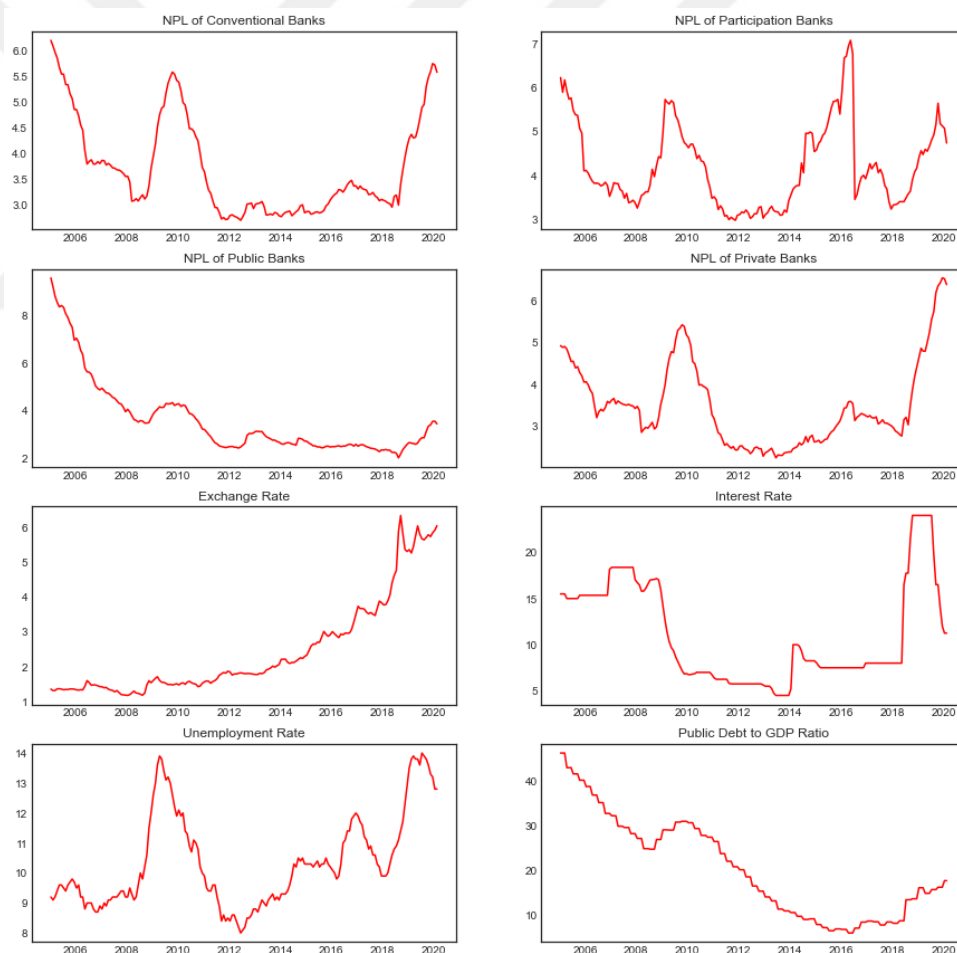


Figure 2.1 : Time series plots of variables

2.5. Empirical Results

2.5.1. Nonparametric additive quantile results

In line with stress testing practices in the literature, Equation 2.1 is estimated for quantiles 0.05, 0.90, and 0.95. The selection of smoothing parameters (λ) is determined using the SIC information criterion outlined in Equation 2.3. Table 2.2 presents the outcomes for conventional banks. Observing the F statistics and quantile fidelity values, aligned with the Gaussian likelihood, all variables exhibit statistical significance across all quantiles. Figure 2.2 portrays the nonparametric effect of macroeconomic variables on the stress variable for conventional banks. The graphs, derived from additive nonparametric quantile regression, distinctly display the course of estimated effects and the direction of the relationship between independent and dependent variables, alongside their 95% pointwise confidence intervals. Notably, the effects of macroeconomic variables on stress variables prove statistically significant across all quantiles of interest. However, the relationship between NPL and certain macroeconomic variables varies among quantiles. For instance, at the 5th percentile, there is a near-constant effect of the exchange rate on NPL for conventional banks. However, at the 90th and 95th percentiles, this impact becomes less stable. This behavior demonstrates significant nonparametric tendencies at higher quantiles, initially displaying a relatively negative relation that later reverses once the depreciation of the exchange rate crosses a certain threshold. Especially, in April 2018, the dollar-to-Turkish lira exchange rate hit 4 TL per USD for the first time in the research period and continued to rise thereafter. Consequently, an increased effect of the exchange rate hike on NPL is observed after this period.

To prevent an increase in the NPL, maintaining stability in the exchange rate holds significant importance. When borrowers cannot hedge against foreign exchange risks, they tend to postpone their loan repayments, leading to a rise in the NPL (Beck et al., 2015).

In studies within the stress testing literature, the direction of the currency rate effect on default rates differs (Messai and Jouini, 2013; Atanasijević and Božović, 2016; Kanas and Molyneux, 2018; Patra and Pathi, 2020; Küçüközmen and Yüksel, 2006; Askari et al., 2021).

As illustrated in Figure 2.2, there is a negative relationship between the interest rate and the NPL of conventional banks at the 0.90 and 0.95 quantiles, indicating that higher interest rates correspond to lower NPL. Conversely, at the lower quantile (0.05), an increase in interest rates initially demonstrates a diminishing effect up to 15%, followed by an incline. The initial decline in effect up to 15% of the interest rate might be attributed to the economic growth impact of increasing interest rates, as it encourages capital inflows. When NPL levels are low and do not signify an imminent need for intervention, an increase in NPL with rising interest rates is expected. However, at the 0.90 and 0.95 quantile levels, the overall decreasing effect cannot solely be explained by economic growth but rather by banks taking precautions due to higher NPL leading to increased credit risk. Moreover, the loan cost escalates with rising interest rates, causing a decrease in loan demand. Consequently, borrowers willing to accept this higher cost may carry higher potential risks. The credit rationing mechanism proposed by Stiglitz and Weiss (1981) could play a substantial role in this context. Banks might employ credit rationing strategies, becoming more selective and providing fewer but higher-quality loans under such circumstances, potentially reducing NPL.

It is important to highlight that increases in interest rates impact debt solvency, potentially leading to higher NPL or default rates (Louzis et al., 2010). Conversely, as mentioned earlier, interest rate hikes can stimulate economic growth by encouraging capital inflows, thereby influencing NPL.

Several studies indicate an increasing relationship between the interest rate and credit risk (Virolainen, 2004; Schechtman and Gaglianone, 2012; Kanas and Molyneux, 2018; Patra and Pathi, 2020). However, some research demonstrates an inverse relationship between credit risk and the interest rate (Boss, 2002; Kalirai and Scheicher, 2002).

Across all quantiles, a higher unemployment rate displays a clear and relatively linear relation with increased NPL. Numerous studies have also identified a positive correlation between the unemployment rate and NPL (Kalirai and Scheicher, 2002; Küçüközmen and Yüksel, 2007; Schechtman and Gaglianone, 2012; Messai and Jouini, 2013; Karaaslan and Sayılır, 2019; Askari et al., 2021). As the unemployment rate climbs, individuals may encounter difficulties in loan repayment, consequently leading to a rise in NPL.

Additionally, at peak levels of unemployment, individuals may lose their jobs, further impacting their ability to repay loans and consequently contributing to an increase in NPL.



Table 2.2 : Nonparametric additive quantile model estimation results for conventional banks

Panel A				
τ: 0.05				
Parametric coefficients				
	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	3.322	0.918	3.619	0.000404***
Significance of non-parametric coefficients				
	EDF	Lambda	F-value	Pr(>F)
Exchange Rate	3	0.5	5.168	0.00199**
Unemployment Rate	13	0.05	5.485	4.37E-08***
Interest Rate	4	1	5.853	0.000209***
Public Debt to GDP	7	1	60.431	<2E-16***
Quantile Fidelity at tau = 0.05 is 1.87328				
Panel B				
τ: 0.90				
Parametric coefficients				
	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	3.8045	0.9732	3.909	1.45E-04***
Significance of non-parametric coefficients				
	EDF	Lambda	F-value	Pr(>F)
Exchange Rate	32	0.02	6.399	5.11E-15***
Unemployment Rate	1	0.8	30.236	1.83E-07***
Interest Rate	5	0.9	10.173	2.70E-08***
Public Debt to GDP	3	6	76.077	<2E-16***
Quantile Fidelity at tau = 0.90 is 2.68686				
Panel C				
τ: 0.95				
Parametric coefficients				
	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	3.5327	0.9945	3.55E+00	0.000523***
Significance of non-parametric coefficients				
	EDF	Lambda	F-value	Pr(>F)
Exchange Rate	29	0.01	8.17E+00	<2E-16***
Unemployment Rate	4	0.2	6.91E+00	4.25E-05***
Interest Rate	4	0.7	1.22E+01	1.53E-08***
Public Debt to GDP	2	4	77.797	<2E-16***
Quantile Fidelity at tau = 0.95 is 1.41907				
Notes: EDF is the effective degrees of freedom.				
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1				

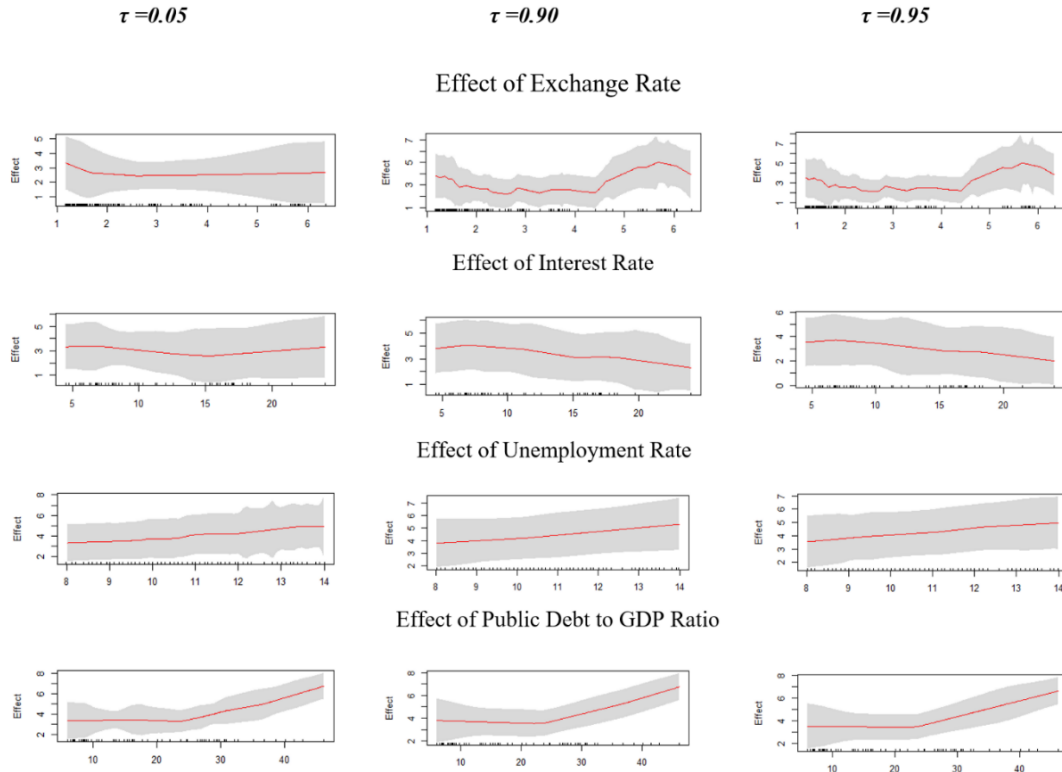


Figure 2.2 : Nonparametric quantile effects on NPL for conventional banks.

Finally, public debt exhibits an increasing impact on NPL. As depicted in Figure 2.2, this effect becomes more prominent once the public debt reaches a share of 25% in GDP. Below this threshold, the influence of public debt remains relatively stable. However, at higher quantiles, particularly after the public debt-to-GDP ratio surpasses 25%, it becomes a critical determinant of NPL, showing a direct correlation where higher public debt aligns with increased NPL. Public debt signifies economic vulnerability and places a burden on taxpayers, thereby exerting an adverse influence on NPL. The positive relationship between higher public debt and increased NPL may also be explained by the limitation it imposes on the government's fiscal capacity. During financial stress, high debt restricts the government's ability to counteract the adverse impacts of financial crises (Acharya et al., 2018; Ari et al., 2019). Additionally, Messai and Jouini (2013) and Askari et al. (2021) support the idea of an increasing effect of federal debt on NPL. Similarly, employing the same additive nonparametric quantile analysis, Kanas and Molyneux (2018) investigate the effect of federal debt on NPL within the US banking system. Their findings indicate a

generally non-linear and increasing relationship between federal debt and NPL for both $\tau=0.90$ and $\tau=0.95$.

Table 2.3 : Nonparametric additive quantile model estimation results for participation banks

Panel A				
τ: 0.05				
Parametric coefficients				
	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	2.6809	0.7715	3.475	0.00066***
Significance of non-parametric coefficients				
	EDF	Lambda	F-value	Pr(>F)
Exchange Rate	11	0.06	12.114	2.22E-16***
Unemployment Rate	4	0.5	3.12E+01	<2E-16***
Interest Rate	3	0.9	5.00E+00	0.00244**
Public Debt to GDP	2	9	6.219	0.00252**
Quantile Fidelity at tau = 0.05 is 4.06587				
Panel B				
τ: 0.90				
Parametric coefficients				
	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	5.316	2.024	2.627	0.00955***
Significance of non-parametric coefficients				
	EDF	Lambda	F-value	Pr(>F)
Exchange Rate	5	0.2	1.27E+01	2.89E-10***
Unemployment Rate	9	0.2	3.8	0.000248***
Interest Rate	6	0.4	2.179	0.048182***
Public Debt to GDP	11	1	25.899	<2E-16***
Quantile Fidelity at tau = 0.90 is 5.96503				
Panel C				
τ: 0.95				
Parametric coefficients				
	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	2.3676	0.9009	2.628	0.00947***
Significance of non-parametric coefficients				
	EDF	Lambda	F-value	Pr(>F)
Exchange Rate	9	0.1	3.01E+01	<2E-16***
Unemployment Rate	12	0.1	5.528	8.79E-08***
Interest Rate	3	0.7	5.882	0.000798***
Public Debt to GDP	9	0.1	3.01E+01	<2E-16***
Quantile Fidelity at tau = 0.95 is 4.06755				
Notes: EDF is the effective degrees of freedom.				
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1				

Table 2.3 indicates strong statistical significance for all macroeconomic variables concerning participation banks.

In contrast to conventional banks, the nonparametric impacts of the exchange rate for participation banks display relatively sharp fluctuations. However, the estimated effects of the exchange rate become more moderate post-April 2018, particularly after reaching 4 TL. This could be partly attributed to the effective utilization of various financial instruments by participation banks, such as Murabaha, for managing exchange rate risks (Mansour and Doğukanlı, 2019).

The relationship between the interest rate and NPL shows a piecewise linear pattern. Interest rate hikes exhibit a positive correlation with NPL until reaching a rate of 13%; after this threshold, the impact of the interest rate begins to decline. This trend is relatively consistent compared to conventional banks, potentially attributable to the interest-free financing model adopted by participation banks, which might diminish the variation in the effect of the interest rate on NPL compared to conventional banks.

Regarding the unemployment rate, participation banks demonstrate a similar increasing effect on NPL as seen in conventional banks. However, in the case of the public debt ratio, the impact on NPL is less pronounced for participation banks compared to conventional banks, with NPL rising notably at higher levels of public debt. This observation suggests that participation banks might be more tolerant of greater levels of public debt compared to their conventional counterparts.

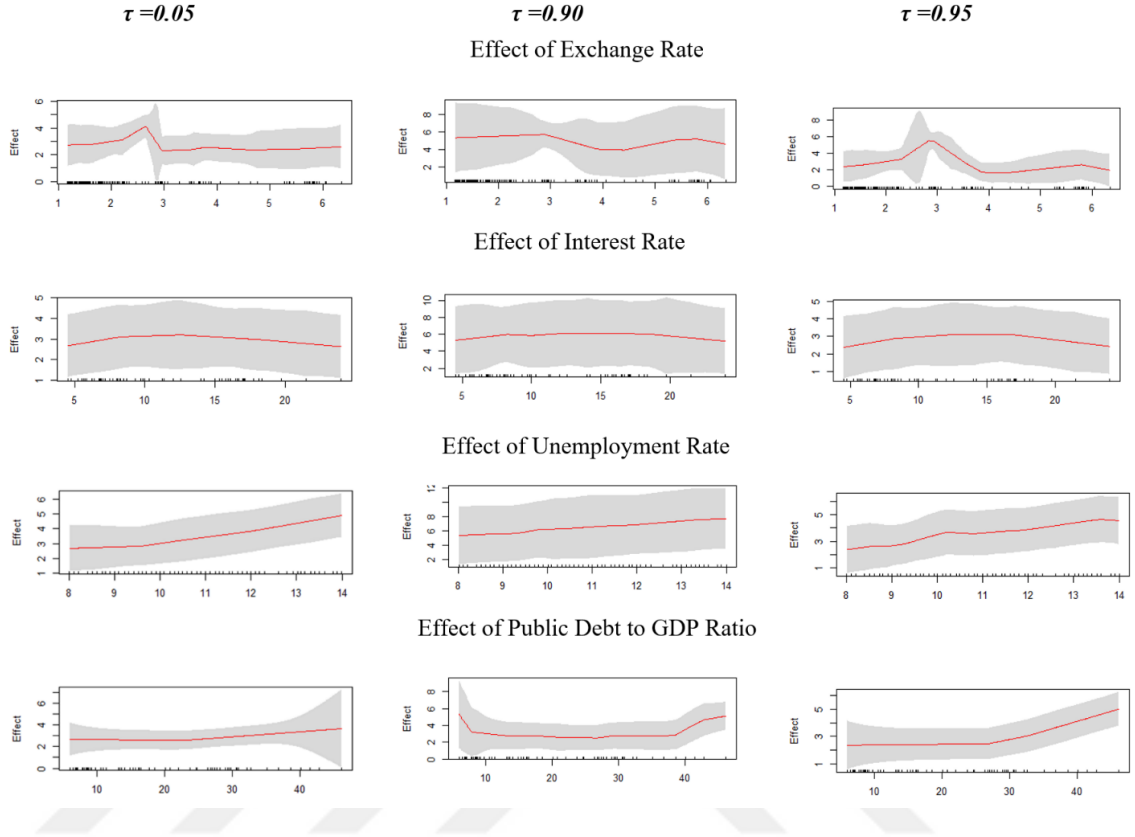


Figure 2.3 : Nonparametric quantile effects on NPL for participation banks.

As the analyses are based on aggregated banking data that does not differentiate between public and private deposit banks, a separate analysis is conducted for public deposit and private deposit banks to comprehensively discern the precise impact of macroeconomic variables with a more detailed assessment. Over time, the share of asset size belonging to public deposit banks within the total sector has shown an increasing trend since 2012, climbing to 41 percent in 2020—a growth of 12.05 percent, despite experiencing a decreasing trend from 1959. Interestingly, among the top three banks ranked by asset size, all are public banks. In contrast, the proportion of total asset size attributed to private deposit banks declined from 59.7% in 2005 to 30.6% in 2020 (TBB, 2022). Specifically, as of 2020, the total asset sizes for public deposit banks and private deposit banks stand at 3.3 billion TL and 2.7 billion TL, respectively.

Figures 2.4 and 2.5 illustrate that both the exchange rate and the unemployment rate significantly impact NPL in private deposit banks, indicating a higher vulnerability of these banks to shocks in the exchange rate and unemployment rate.

Regarding the impact of interest rates, a notable distinction is observed between public and private deposit banks, particularly at the 0.90 and 0.95 quantile levels. This disparity suggests that the decreasing relationship between NPL and the interest rate in private deposit banks might be attributed to the credit rationing mechanism (Stiglitz and Weitz, 1981). When borrowing costs rise, demand for loans decreases in both bank types. Although the adverse effect emerges after a 20% interest rate, the decreased demand might have mitigated the harmful impact of an interest rate increase for public deposit banks. Nevertheless, higher interest rates also lead to a reduction in bank lending, apparent in the behavior of private deposit banks, as borrowers willing to accept higher costs pose a higher risk of default. Consequently, both total loans and non-performing loans decline.

As illustrated in the figures, it is evident that public debt significantly affects both public and private deposit banks, yet its impact appears more pronounced on public deposit banks. This finding holds importance in understanding the role of public deposit banks, particularly during crises when stabilization is crucial. Economies burdened with high levels of debt, potentially encountering elevated external borrowing costs, might struggle to provide support to public deposit banks and may even rely on these banks for their own funding (Ture, 2021). The implications are substantial—excessive indebtedness not only hampers the ability of public deposit banks to stabilize the economy but also, as indicated by our findings, elevates the NPL ratio, further diminishing their capacity to contribute to economic support.

For robustness check, model estimations are carried out using the weighted average lending rate of the CBRT instead of the policy rate, yielding similar outcomes. Furthermore, estimations are performed with different lags of macroeconomic variables via, affirming the consistency of findings across various lags. Therefore, the results demonstrate robustness concerning the temporal influence of exogenous variables.

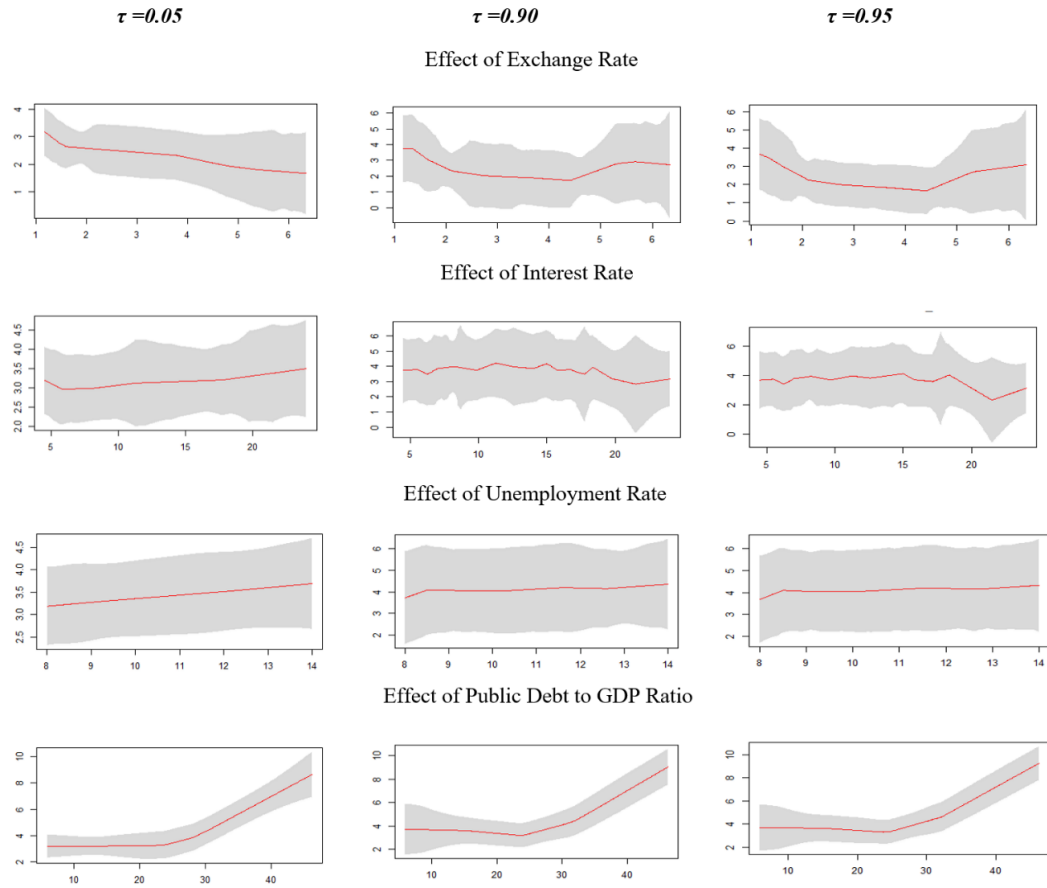


Figure 2.4 : Nonparametric quantile effects on NPL for public deposit banks.

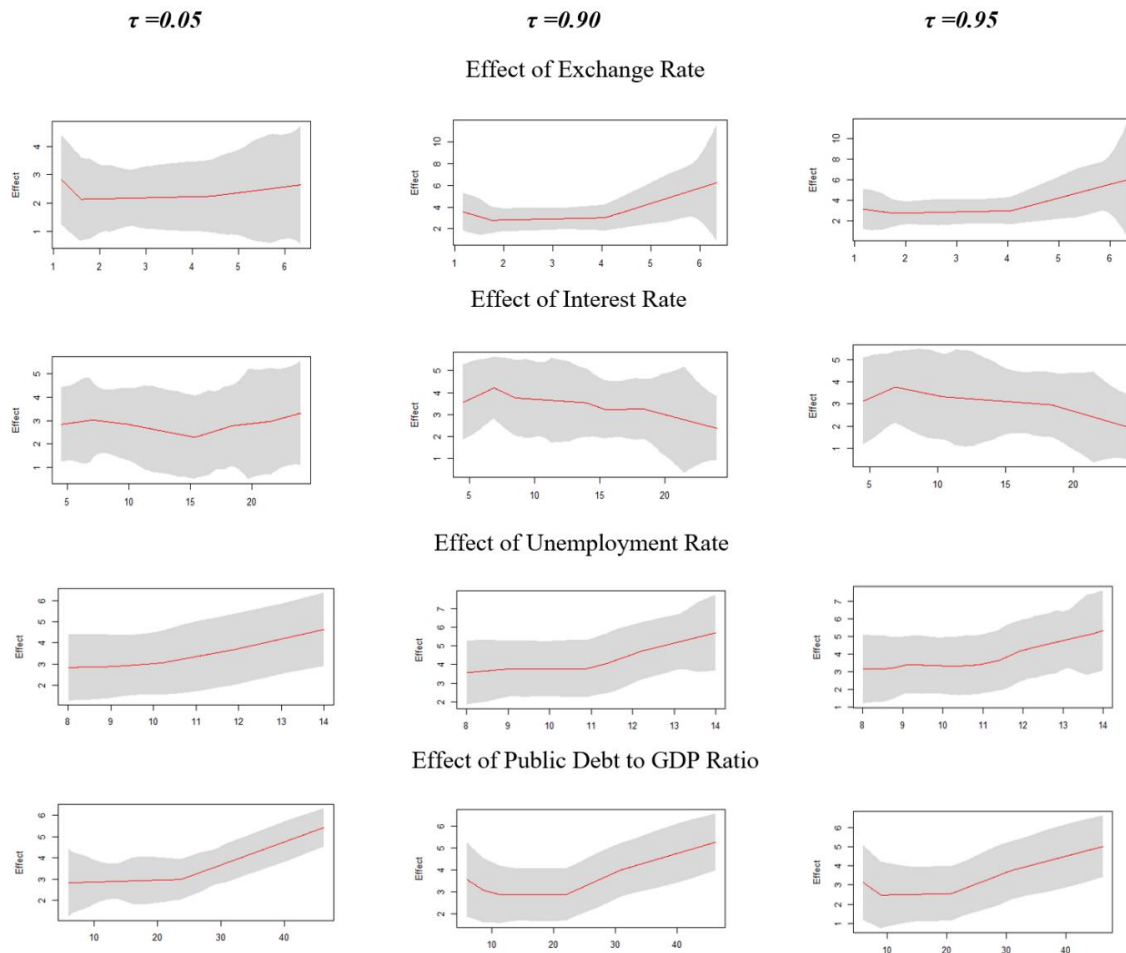


Figure 2.5 : Nonparametric quantile effects on NPL for private deposit banks.

2.5.2. One-step ahead forecast and probability analysis

In the context of one-step ahead forecasts aiming to predict the next period value of the dependent variable, two methodologies are employed. First, the focus is directed towards one individual macroeconomic variable at a time, utilizing the extreme tail value of that variable along with the latest observed values for the other variables, and the nonparametric additive quantile models identified in Section 2.5.1 are estimated. Then, forecasts for NPL are made (Table 2.5-Panel A). Second, these models are estimated by using extreme tail values of more than one macroeconomic variable at a time and NPL is forecasted for the subsequent period (Table 2.5-Panel B). Table 2.5 displays predicted values for different quantiles of the NPL corresponding different tail values of macroeconomic variables. The extreme tail values considered are the 1st, 5th, 95th, and 99th

percentiles for each macroeconomic variable, while the other macroeconomic variables are set to their most recent observations during this process.

Table 2.4 : The tail values of explanatory variables

	1%	5%	95%	99%
Exchange Rate	1.176	1.239	5.769	6.052
Unemployment Rate	8.132	8.50	13.68	13.90
Interest Rate	4.50	5.237	24.00	24.00
Public Debt to GDP Ratio	5.969	6.837	40.667	46.166

For conventional banks, results indicate that at the 95th percentile value of the exchange rate, the predicted NPL reaches its peak values of 5.82% and 5.88% for the 0.90 and 0.95 quantiles of NPL, respectively.

Higher extreme values of the unemployment rate lead to a corresponding increase in the forecasted NPL. When utilizing the 1st and 99th percentiles of the unemployment rate, the predicted NPL rises from 2.32% to 3.91% for tau 0.05, from 4.43% to 5.89% for tau 0.90, and from 4.39% to 5.77% for tau 0.95.

One step-ahead prediction results for the interest rate align with those derived from the nonparametric quantile regression, as depicted in Figure 2.2. For tau 0.90 and 0.95, the forecasted NPL values show an increase, ranging between 5.63-4.15% and 5.79-4.26%, respectively. As noted earlier, a rise in interest rates can boost economic growth but may also prompt banks to implement credit rationing, potentially leading to reduced NPL.

However, the most striking finding emerges concerning the public debt to GDP ratio. Even at tau 0.05, the predicted NPL stands at 5.90% for the 95th percentile and 6.93% for the 99th percentile value of the public debt to GDP ratio. Furthermore, the projected NPL values for tau 0.90 and 0.95 range from 5.76% to 8.70% and 5.64% to 8.72%, respectively.

For participation banks, the interest rate exerts the least influence on the NPL compared to all other variables, with the NPL exhibiting minimal increases, ranging from 4.1% to 4.4% overall. Conversely, the unemployment rate displays a consistent increasing impact across all NPL quantiles. Utilizing the 95th and 99th percentile values of the unemployment rate, a significant surge from approximately 3% to 5% is observed across all NPL

quantiles. This discovery highlights that even at lower levels of NPL, an upsurge in the unemployment rate poses a risk to bank stability.

The exchange rate also exerts a significant impact on participation banks, potentially causing the NPL to exceed 5%.

Similar to conventional banks, participation banks demonstrate susceptibility to the public debt ratio. Even at the 0.05 quantile level of NPL, an increase in public debt propels the NPL beyond 5%, reaching 5.6% at the 99th percentile of the debt ratio. As the public debt escalates, the predicted NPL increases for the 0.90 and 0.95 quantile levels, and when the public debt reaches its 99th percentile value, NPL increase to 7.33% and 7.5%, respectively. This suggests that excessive public debt severely impacts the health of these banks.

In Panel B of Table 2.5, the alternative combination results using the 99th percentile values of macroeconomic variables are presented. The NPL increases when multiple macroeconomic variables deteriorate, as expected. Even at the 0.05 quantile level of NPL, combining the public debt to GDP ratio with other macroeconomic variables drives the NPL to 7% and beyond for conventional banks and exceeds 5% for participation banks. Specifically, the simultaneous worsening of the unemployment rate and the public debt ratio leads to a higher NPL. At higher quantile levels, this combination results in the NPL rising to 9% for conventional banks and approximately 8% for participation banks.

Table 2.5 : One-step ahead forecast values of NPL

		Conventional Banks			Participation Banks		
	τ	0.05	0.90	0.95	0.05	0.90	0.95
Panel A							
Exchange Rate	0.01	4.270	4.710	4.455	4.685	5.353	5.000
	0.05	4.180	4.612	4.324	4.738	5.367	5.036
	0.95	3.576	5.852	5.880	4.483	5.204	5.218
	0.99	3.597	5.572	5.572	4.541	4.941	4.918
Unemployment Rate	0.01	2.317	4.433	4.385	2.972	3.059	3.076
	0.05	2.380	4.501	4.492	3.007	3.172	3.249
	0.95	3.900	5.828	5.724	5.008	5.298	5.269
	0.99	3.910	5.892	5.761	5.125	5.338	5.214
Interest Rate	0.01	4.013	5.634	5.790	4.044	4.237	4.252
	0.05	4.029	5.717	5.845	4.129	4.362	4.352
	0.95	3.993	4.145	4.261	4.000	4.132	4.307
	0.99	3.993	4.145	4.261	4.000	4.132	4.307
Public Debt to GDP Ratio	0.01	3.528	5.760	5.646	4.620	7.536	4.860
	0.05	3.530	5.746	5.640	4.614	6.570	4.864
	0.95	5.902	7.833	7.957	5.344	5.975	6.704
	0.99	6.928	8.701	8.718	5.600	7.333	7.504
Panel B							
Exchange Rate and Public Debt to GDP	0.99	6.928	8.703	8.720	5.600	7.335	7.507
Exchange Rate and Unemployment Rate	0.99	3.910	5.894	5.764	5.125	5.340	5.217
Exchange Rate and Interest Rate	0.99	3.993	4.147	4.263	4.000	4.134	4.310
Unemployment Rate and Public Debt to GDP	0.99	7.241	9.020	8.907	6.184	7.730	7.801
Unemployment Rate and Interest Rate	0.99	4.307	4.465	4.450	4.584	4.530	4.604
Interest Rate and Public Debt to GDP	0.99	7.324	7.274	7.407	5.059	6.524	6.894
Exchange Rate, Unemployment Rate and Public Debt to GDP	0.99	7.241	9.022	8.910	6.184	7.732	7.803
Exchange Rate, Interest Rate and Public Debt to GDP	0.99	7.324	7.276	7.409	5.059	6.526	6.896
Unemployment Rate, Interest Rate and Public Debt to GDP	0.99	7.638	7.593	7.596	5.643	6.921	7.190
Exchange Rate, Interest Rate, Unemployment Rate and Public Debt to GDP	0.99	7.637	7.595	7.598	5.643	6.923	7.193

The probability analysis, on the other hand, aims determining the likelihood of a stress variable being either lower or higher than specific threshold values. This approach enables an understanding of how fluctuations in macroeconomic variables could impact the stress variable. Utilizing distributions that encompass the characteristics of financial variables, rather than relying solely on autoregressive models assuming a normal distribution, is preferred. Considering this perspective, Student t and Logistic distributions are more

fitting for modeling situations with thicker tails in financial data. Meanwhile, the Extreme Value distribution proves useful for modeling extreme situations such as financial crises. Therefore, Normal, Logistic, Extreme Value, and Student t distributions are applied to compute the probabilities.

The probability analysis relies on forecasted NPL values derived from the nonparametric additive quantile model. To generate these forecasts, new values for macroeconomic variables are introduced. Each variable undergoes an individual prediction process using its updated values, while the remaining independent variables retain their most recent observed values. For generating new values within defined ranges for each macroeconomic variable, the uniform distribution is employed.

To establish the range, the method involves considering the maximum and minimum values of each macroeconomic variable. The lower threshold is established by subtracting half of the minimum value from the minimum value of the independent variable, while the upper threshold is determined by adding half of the maximum value to the maximum value of the independent variable. This process sets the lower and upper threshold values for the exchange rate, interest rate, unemployment rate, and public debt ratio at 0.6 TL and 9.5 TL per USD, 2.25% and 36%, 4% and 21%, and 3% and 69.25%, respectively.

Each new value derived specifically for each macroeconomic variable is assigned as the new observation value for the relevant independent variable. Simultaneously, the other independent variables are held constant at their latest observed values. This process provides the predicted NPL values corresponding to each new value of the macroeconomic variables.

To retrieve probabilities, 35,000 forecasted NPL values are utilized to mimic the population distribution and characteristics. The lower and upper thresholds for NPL are set at 5.35% (post-2008 crisis (2009)) and 13.13% (following the 2001 crisis (2002)).

Tables 2.6 and 2.7 outline the outcomes of the probability analysis for conventional banks and participation banks. The results indicate that, overall, the probabilities of NPL being below 5.35% outweigh the probabilities of NPL falling within the range of 5.35% to 13.13%, and exceeding 13.13% for both types of banks across all NPL quantile levels. However, at higher quantiles indicating higher risk levels, there is a decrease in the

probability of NPL being below 5.35%, coupled with increases in the probability of NPL falling within the range of 5.35% to 13.13%, and surpassing 13.13%.

For conventional banks, especially fluctuations in the public debt ratio, unemployment rate, and interest rate contribute to a considerable decline in the probability of NPL being below 5.35%. Additionally, fluctuations in the public debt ratio elevate the likelihood of NPL exceeding 13.13% to 17.1% at $\tau=0.90$ and 18.3% at $\tau=0.95$. On the other hand, for participation banks, variations in the unemployment rate specially increase the likelihood of NPL surpassing 13.13%, reaching 15.4% at $\tau=0.90$ and 14.3% at $\tau=0.95$. Variability in factors other than the interest rate also leads to a significant reduction in the probability of NPL being less than 5.35%.

Table 2.6 : Probability analysis results for NPL of conventional banks

	Public Debt to GDP Ratio			Exchange Rate			Unemployment Rate			Interest Rate		
Distributions	The probabilities for $\tau=0.05$											
	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13
Normal	0.824	0.111	0.065	0.948	0.052	0.000	0.820	0.132	0.048	0.819	0.179	0.003
Logistic	0.673	0.177	0.151	0.958	0.042	0.000	0.709	0.189	0.103	0.784	0.205	0.011
Extreme Value	0.856	0.113	0.031	1.000	0.000	0.000	0.851	0.131	0.018	0.862	0.138	0.000
Student t	0.824	0.111	0.065	0.954	0.040	0.006	0.820	0.132	0.048	0.819	0.179	0.003
	The probabilities for $\tau=0.90$											
	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13
Normal	0.643	0.251	0.106	0.857	0.097	0.046	0.590	0.365	0.045	0.596	0.340	0.064
Logistic	0.511	0.318	0.171	0.732	0.155	0.113	0.511	0.417	0.072	0.505	0.397	0.098
Extreme Value	0.676	0.258	0.065	0.888	0.094	0.017	0.629	0.358	0.014	0.636	0.338	0.026
Student t	0.643	0.251	0.106	0.857	0.097	0.046	0.590	0.365	0.045	0.596	0.340	0.064
	The probabilities for $\tau=0.95$											
	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13
Normal	0.646	0.242	0.111	0.861	0.093	0.046	0.584	0.377	0.039	0.584	0.354	0.062
Logistic	0.510	0.307	0.183	0.734	0.152	0.114	0.509	0.427	0.064	0.495	0.410	0.095
Extreme Value	0.676	0.251	0.073	0.893	0.090	0.017	0.624	0.366	0.010	0.624	0.351	0.025
Student t	0.646	0.242	0.111	0.861	0.093	0.046	0.584	0.377	0.039	0.584	0.354	0.062

Table 2.7 : Probability analysis results for NPL of participation banks

	Public Debt to GDP Ratio			Exchange Rate			Unemployment Rate			Interest Rate		
Distributions	The probabilities for $\tau=0.05$											
	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13
Normal	0.680	0.310	0.010	0.729	0.256	0.015	0.769	0.160	0.072	0.785	0.215	0.000
Logistic	0.631	0.347	0.023	0.680	0.296	0.025	0.637	0.222	0.141	0.769	0.230	0.001
Extreme Value	0.721	0.279	0.000	0.859	0.141	0.000	0.796	0.167	0.037	0.830	0.170	0.000
Student t	0.680	0.310	0.010	0.725	0.243	0.032	0.769	0.160	0.072	0.785	0.215	0.000
	The probabilities for $\tau=0.90$											
	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13
Normal	0.702	0.238	0.061	0.779	0.192	0.030	0.746	0.173	0.081	0.664	0.332	0.004
Logistic	0.599	0.311	0.090	0.704	0.239	0.057	0.610	0.237	0.154	0.624	0.364	0.012
Extreme Value	0.919	0.081	0.000	0.817	0.177	0.006	0.775	0.181	0.045	0.708	0.292	0.000
Student t	0.627	0.292	0.081	0.779	0.192	0.030	0.746	0.173	0.081	0.664	0.332	0.004
	The probabilities for $\tau=0.95$											
	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13	NPL<5.35	5.35<NPL<13.13	NPL>13.13
Normal	0.698	0.228	0.073	0.786	0.151	0.063	0.737	0.185	0.078	0.693	0.306	0.001
Logistic	0.584	0.295	0.121	0.661	0.217	0.122	0.607	0.250	0.143	0.664	0.331	0.005
Extreme Value	0.735	0.231	0.034	0.829	0.146	0.025	0.768	0.191	0.040	0.736	0.264	0.000
Student t	0.698	0.228	0.073	0.786	0.151	0.063	0.736	0.185	0.078	0.693	0.306	0.001

2.5.3. Scenario analysis

Scenario analysis is carried out by utilizing three distributions—normal, student t, and logistic—considering the characteristics of financial variables. This approach diverges this study from the methodology employed by Kanas and Molyneux (2018), where autoregressive models are built on arbitrarily defined coefficients.

In the first scenario analysis, random simulations are conducted for the stress variable. Employing observed values of the NPL and the maximum likelihood technique, the mean and variance are estimated individually for the normal, logistic, and student t distributions. Utilizing these estimated mean and variance values, a simulated series comprising 182 observations is derived through Monte Carlo simulation. This Monte Carlo simulation process is iterated 5000 times, generating a sample distribution based on the three different distributions for the NPL. Subsequently, one of the simulated series is randomly selected, and a nonparametric additive quantile model is estimated using observed macroeconomic variables, achieved through grid search for the smoothing parameter (λ). To determine the smoothing parameters for each macroeconomic variable in a nonparametric additive quantile model, more than 10,000 combinations of smoothing parameters are constructed for grid search. Instead of opting for a single model with one specific smoothing parameter combination, we consider all combinations that meet the condition of statistical significance for each independent variable. Nonparametric additive quantile models are then established using these lambda combinations. Subsequently, these models are estimated and utilized for one-step ahead predictions of the NPL. This prediction method involves employing the 99th percentile value of one macroeconomic variable at a time while keeping other variables at their latest observed values. Through this process, the intervals within which the stress variable fluctuates under exceptional conditions are determined.

In the second scenario analysis, two approaches are employed. The first approach involves simulating each macro variable through random simulations based on three distributions. These simulations incorporate the observed stress variable and the simulated independent variables to estimate a nonparametric additive quantile model. This estimation includes employing grid search once more to determine smoothing parameters that yield

statistically significant independent variables. Subsequently, the obtained smoothing parameter combinations are applied to build nonparametric additive quantile models. One-step ahead forecasts for the stress variable are then made for each of these models by using the 99th percentile value of the explanatory variables along with the latest observed values for the other variables. In the second approach, each macro variable is simulated 182 times using the three distributions separately to match the length of the series, which consists of 182 observations. From each simulated series, the 99th percentile value is drawn for each macroeconomic variable. Afterward, series are constructed for each macro variable, comprising the 99% harmful tail values of the simulated series. These series, along with the observed NPL, undergo grid search for smoothing parameters to estimate nonparametric additive quantile models. Fitted values of NPL are obtained considering multiple smoothing parameter combinations that provide statistically significant results, and the mean and maximum values of the fitted NPL are found.

Table 2.8 displays the forecasted values of NPL derived from the first scenario analysis. The left side of the table presents Normal, Logit, and Student t distributions, denoting the distribution utilized for simulating the NPL. The variables—exchange rate, unemployment rate, interest rate, and public debt to GDP ratio—denote the variables where the 99% tail value is used. As prediction values for the NPL are acquired for all combinations of smoothing parameters, both the mean and maximum values of the predicted NPL are documented in the table.

Table 2.8 : Scenario Analysis 1

	Conventional Banks				Participation Banks			
	<i>tau=0.90</i>		<i>tau=0.95</i>		<i>tau=0.90</i>		<i>tau=0.95</i>	
	Mean	Max	Mean	Max	Mean	Max	Mean	Max
Exchange Rate								
<i>Normal</i>	3.94	4.63	3.79	3.91	6.31	7.22	6.51	6.51
<i>Logit</i>	4.15	4.41	4.60	4.90	4.67	5.26	5.00	5.61
<i>Student t</i>	4.17	5.30	4.22	5.99	4.12	4.13	4.05	4.36
Unemployment Rate								
<i>Normal</i>	3.91	4.23	3.56	3.65	6.32	7.25	6.53	6.53
<i>Logit</i>	4.18	4.65	4.37	4.77	4.86	5.83	5.17	6.15
<i>Student t</i>	3.86	5.24	4.11	5.59	4.35	4.37	5.01	5.46
Interest Rate								
<i>Normal</i>	2.99	4.28	4.07	4.22	4.86	5.17	4.18	4.18
<i>Logit</i>	4.66	5.47	5.27	5.78	4.60	5.53	5.40	5.96
<i>Student t</i>	4.84	6.05	4.51	5.39	4.71	4.73	3.60	4.12
Public debt to GDP Ratio								
<i>Normal</i>	6.96	7.55	5.24	5.35	6.78	7.50	6.74	6.74
<i>Logit</i>	4.29	4.78	4.58	5.90	4.05	5.34	5.10	6.21
<i>Student t</i>	2.21	3.16	2.46	3.75	4.12	4.19	3.32	4.08

Tables 2.9 and 2.10 show the findings of the second scenario analysis. On the left side of both tables, the distributions (Normal, Logit, and Student t) used for simulating the macroeconomic variables are presented in bold. In Table 2.9, the macroeconomic variables utilizing their 99% tail values are indicated in italic.

For conventional banks, the first scenario analysis illustrates that responses to adverse exchange rate tails fall within the average range of 3.94-4.17% at tau 0.90 and 3.79-4.60% at tau 0.95, with peak values of 5.30% and 5.99%, respectively. Notably, mean NPL predictions are higher in the first approach of the second scenario analysis, ranging from 5.57-5.73% for $\tau=0.90$ and 5.60-5.67% for $\tau=0.95$. In contrast, the second approach of the second scenario analysis suggests a mean of approximately 4% for fitted NPL values, while maximum values indicate potential threats, reaching up to 6.86% and 7.08% for tau 0.90 and 0.95, respectively. These findings align somewhat with previous studies employing Credit Portfolio View and VAR models (Küçüközmen and Yüksel, 2007; Altıntaş, 2012). Participation banks appear more vulnerable to exchange rate shocks, as

indicated in the tables. The first scenario analysis particularly displays a wide fluctuation range in the average predicted NPL, spanning between 4.12-6.31% for τ 0.90 and 4.05-6.51% for τ 0.95. Tables 2.8 and 2.10 also highlight the possibility of NPL reaching 7% and beyond.

The mean predicted NPL for conventional banks ranges from 3.86-4.18% at τ =0.90 and 3.56-4.37% at τ =0.95 in response to the rise in the unemployment rate, as revealed in the first scenario analysis. The first approach of the second scenario analysis indicates higher mean predicted NPL, averaging between 5.62-5.91%, with maximum values reaching up to 5.87% at τ =0.90 and 6.02% at τ =0.95. Furthermore, the analysis indicates that when the unemployment rate comprises the 99% tail value of the simulated series, maximum values increase remarkably. As given in Table 2.10, the NPL may escalate to 6.60% and 6.42% for τ 0.90 and 0.95, respectively. This finding is significant, considering a study (Önder et al., 2016) where NPL reached 7% due to deterioration in not only the unemployment rate but also other macroeconomic indicators. However, this analysis shows that even a deterioration in the unemployment rate alone can drive NPL up to 7 percent. Participation banks, on the other hand, exhibit higher mean and maximum NPL values compared to conventional banks. For τ =0.90, the mean predicted NPL ranges between 4.35-6.32%, 5.18-6.41%, and 4.58-4.80%; and for τ =0.95, the ranges are 5.01-6.53%, 4.99-6.53%, and 4.72-4.85% according to the scenario analyses, respectively. However, the findings also suggest the potential for NPL to reach 7.25 percent at τ =0.90 and 7.59 percent at τ =0.95.

Table 2.9 : 1st Approach of Scenario Analysis 2

	Conventional Banks				Participation Banks			
	<i>tau=0.90</i>		<i>tau=0.95</i>		<i>tau=0.90</i>		<i>tau=0.95</i>	
	Mean	Max	Mean	Max	Mean	Max	Mean	Max
Exchange Rate								
<i>Normal</i>								
Exchange Rate	5.57	5.57	5.67	5.70	5.26	5.39	5.30	5.61
Unemployment Rate	5.79	5.79	6.07	6.36	5.79	5.90	5.78	6.12
Interest Rate	4.67	4.67	4.56	5.05	4.32	4.40	4.33	4.58
Public debt to GDP Ratio	8.39	8.39	8.53	8.81	7.80	7.94	7.72	8.17
<i>Logit</i>								
Exchange Rate	5.73	5.73	5.62	5.72	5.24	5.58	5.23	5.65
Unemployment Rate	5.58	5.59	5.90	6.27	5.70	5.98	5.71	6.09
Interest Rate	4.94	4.95	4.64	5.33	4.28	4.52	4.33	4.80
Public debt to GDP Ratio	8.34	8.37	8.38	8.63	7.88	8.29	7.80	8.39
<i>Student t</i>								
Exchange Rate	5.58	5.80	5.60	5.81	5.11	5.40	5.26	5.89
Unemployment Rate	6.20	6.53	6.22	6.55	5.76	6.00	5.85	6.37
Interest Rate	4.34	5.04	4.39	4.91	4.02	4.24	4.10	4.42
Public debt to GDP Ratio	8.58	9.03	8.49	9.03	7.73	8.02	7.66	8.23
Unemployment Rate								
<i>Normal</i>								
Exchange Rate	5.65	5.65	5.90	6.01	5.18	5.49	6.19	6.34
Unemployment Rate	5.65	5.65	5.91	6.02	5.18	5.49	6.19	6.34
Interest Rate	4.34	4.34	4.66	4.71	4.47	4.73	4.33	4.34
Public debt to GDP Ratio	9.58	9.58	9.44	9.61	8.62	9.35	8.76	8.80
<i>Logit</i>								
Exchange Rate	5.86	5.87	5.85	5.99	5.28	5.28	4.99	5.36
Unemployment Rate	5.86	5.87	5.85	5.99	5.28	5.28	4.99	5.36
Interest Rate	5.06	5.09	5.00	5.17	4.49	4.49	4.34	4.43
Public debt to GDP Ratio	9.48	9.61	9.56	10.14	8.32	8.32	7.42	8.22
<i>Student t</i>								
Exchange Rate	5.64	5.84	5.63	5.70	6.36	6.81	6.43	6.77
Unemployment Rate	5.62	5.83	5.62	5.69	6.41	6.84	6.53	6.88
Interest Rate	4.40	4.52	4.48	4.57	4.44	4.59	4.59	4.76
Public debt to GDP Ratio	9.35	9.70	9.19	9.27	9.00	9.49	8.96	9.53
Interest Rate								
<i>Normal</i>								
Exchange Rate	5.57	5.57	5.60	5.89	5.54	5.61	4.77	4.77
Unemployment Rate	5.65	5.65	5.34	6.15	5.20	5.29	5.17	5.17
Interest Rate	5.57	5.57	5.60	5.89	5.46	5.52	4.78	4.78
Public debt to GDP Ratio	8.69	8.70	8.60	8.85	8.22	8.40	7.48	7.48
<i>Logit</i>								
Exchange Rate	5.71	6.03	5.60	5.75	5.08	5.18	4.99	5.07
Unemployment Rate	5.70	6.09	5.01	5.20	4.93	5.10	5.52	5.62
Interest Rate	5.38	5.86	5.60	5.74	4.97	5.10	4.94	5.02
Public debt to GDP Ratio	8.56	8.96	8.68	8.89	8.05	8.16	8.27	8.33
<i>Student t</i>								
Exchange Rate	5.91	6.04	5.68	5.86	4.90	5.01	4.99	5.40
Unemployment Rate	5.73	5.86	5.20	5.39	5.41	5.51	5.59	6.10
Interest Rate	5.80	5.93	5.64	5.80	4.82	4.93	4.93	5.17
Public debt to GDP Ratio	8.80	8.92	8.68	8.85	7.79	7.99	7.97	8.59
Public debt to GDP Ratio								
<i>Normal</i>								
Exchange Rate	5.57	5.57	5.58	5.65	4.86	4.86	4.92	4.92
Unemployment Rate	6.02	6.04	5.97	6.09	5.49	5.49	5.34	5.34
Interest Rate	4.09	4.13	4.11	4.24	3.90	3.90	4.18	4.19
Public debt to GDP Ratio	5.57	5.57	5.58	5.65	4.86	4.86	4.92	4.92
<i>Logit</i>								
Exchange Rate	5.77	5.82	5.78	5.84	5.08	5.08	5.11	5.11
Unemployment Rate	6.10	6.29	6.12	6.36	5.58	5.58	6.07	6.07
Interest Rate	4.64	4.84	4.53	4.88	4.38	4.39	4.31	4.31
Public debt to GDP Ratio	5.79	5.84	5.80	5.88	5.13	5.13	5.11	5.11
<i>Student t</i>								
Exchange Rate	5.71	5.85	5.62	5.77	5.12	5.62	5.21	5.63
Unemployment Rate	6.06	6.20	5.96	6.12	5.52	5.97	5.60	5.99
Interest Rate	4.12	4.19	4.12	4.17	4.13	4.20	4.12	4.49
Public debt to GDP Ratio	5.72	5.87	5.64	5.78	5.18	5.69	5.30	5.71

Table 2.10 : 2nd Approach of Scenario Analysis 2

	Conventional Banks				Participation Banks			
	<i>tau=0.90</i>		<i>tau=0.95</i>		<i>tau=0.90</i>		<i>tau=0.95</i>	
	Mean	Max	Mean	Max	Mean	Max	Mean	Max
Exchange Rate								
<i>Normal</i>	3.95	6.25	4.03	6.74	4.68	7.14	4.80	7.67
<i>Logit</i>	3.93	6.19	4.05	6.76	4.65	7.43	4.73	7.38
<i>Student t</i>	3.88	6.86	3.93	7.08	4.52	7.20	4.60	7.54
Unemployment Rate								
<i>Normal</i>	4.08	6.60	4.06	6.23	4.80	7.09	4.82	7.12
<i>Logit</i>	3.93	6.55	4.02	6.42	4.70	7.10	4.85	7.59
<i>Student t</i>	3.95	6.54	4.02	6.21	4.58	7.16	4.72	7.12
Interest Rate								
<i>Normal</i>	3.94	6.30	3.98	6.31	4.41	7.96	4.67	7.52
<i>Logit</i>	3.88	6.19	3.99	6.20	4.63	7.16	4.64	7.47
<i>Student t</i>	4.08	6.19	4.02	6.32	4.57	7.46	4.67	7.57
Public debt to GDP Ratio								
<i>Normal</i>	3.88	6.35	4.28	7.24	4.40	7.48	5.06	7.42
<i>Logit</i>	4.18	7.91	4.16	7.11	4.77	7.03	5.37	7.62
<i>Student t</i>	4.06	6.19	4.12	6.30	4.67	7.52	4.71	7.55

The mean predicted NPL for conventional banks due to the interest rate shock ranges from 2.99-4.84% at $\tau=0.90$ and 4.07-4.51% at $\tau=0.95$ in the first scenario. In the first approach of the second scenario, the interest rate shock results in NPL values between 5% -6%, with both mean and maximum values falling within this range. However, the second approach suggests a potential for NPL to reach 6.30%. As for participation banks, both the first scenario and the first approach of the second scenario reveal relatively tolerable values, with mean estimated NPL ranging between 4-5.5% for both quantiles and a maximum value of 5.53% for $\tau=0.90$ and 5.96% for $\tau=0.95$. Conversely, the second approach, utilizing the 99% tail values of the simulated interest rate, indicates the possibility of NPL reaching as high as 7.96% and 7.57% for $\tau=0.90$ and $\tau=0.95$, respectively. These findings align with prior studies in the literature, reporting NPL within the range of 3.5% to 8% (Küçüközmen and Yüksel, 2007; İskender, 2014; Başarır, 2016; Altıntaş, 2012).

The impact of the public debt to GDP ratio on the NPL of conventional banks appears harmful, with estimated means spanning from 2.21% to 6.96% for $\tau=0.90$ and 2.46% to 5.24% for $\tau=0.95$, as outlined in Table 2.8. Additionally, the maximum predicted NPL values reach 7.55% and 5.90% for 0.90 and 0.95 quantiles, respectively. In the first approach of the second scenario analysis, mean predicted NPL values range from 5.57% to 5.80%, while the maximum value stands around 5.88% for both quantiles. Moreover, the second approach of the second scenario analysis indicates higher maximum values, specifically 7.91% for $\tau=0.90$ and 7.24% for $\tau=0.95$. Regarding participation banks, the public debt to GDP ratio also significantly impacts the NPL. The mean predicted NPL generally ranges from 4.05% to 7.50% for $\tau=0.90$ and 3.32% to 6.74% for $\tau=0.95$. Table 2.10 shows that the estimated NPL might reach 7.52% for $\tau=0.90$ and 7.62% for $\tau=0.95$, presenting potential risks for these banks.

The results of the scenario analysis align with the findings from the probability analysis. Generally, the probability of the NPL falling below 5.35% is higher than the likelihood of surpassing 13.13%, and it is also higher than the probability of the NPL being between 5.35% and 13.13%. However, for higher quantiles of the NPL, the probability of it falling within the range of 5.35% to 13.13% notably increases, exceeding the likelihood of exceeding 13.13%. Scenario analysis reveals that the NPL may exceed 5.35%, consistent with the probability analysis, but no situation exceeding 13.13% has been encountered.

Both conventional and participation banks demonstrate significant sensitivity to four macroeconomic variables. However, when examining the impact across simulated variables and distributions for participation banks, it becomes evident that the interest rate has the least influence on the NPL. Specifically, an adverse shock to the public debt to GDP ratio significantly disrupts the stability of the NPL. Additionally, both the unemployment rate and the exchange rate have the potential to substantially increase the NPL.

In comparison to conventional banks, participation banks appear to be more vulnerable to adverse scenarios, displaying higher mean and maximum values overall. These outcomes, considering the structural disparities and operational dynamics between these bank types, are not unexpected and imply differing capacities to manage crises. While some studies

have previously suggested that participation banks exhibited greater resilience during the global financial crisis of 2008 and maintained higher survival rates (Beck et al., 2013; Mollah et al., 2017; Pappas et al., 2017), the recent impact of the Covid-19 outbreak has revealed higher insolvency and asset risk for participation banks, resulting in lower survival rates (Elnahass et al., 2021), aligning with the findings of this research.

The Covid-19 pandemic has vividly emphasized the critical significance of stress testing in the banking sector. Unforeseen external shocks can lead to severe consequences, as witnessed globally, where banks experienced notable instability and diminished financial performance during the pandemic. Considering the uncertain nature of future crises, it becomes essential to identify key risk factors and accurately assess their impact on the banking system. Mitigating pre-crisis vulnerabilities and addressing non-performing loans (NPLs) are crucial steps toward recovery during severe financial turmoil (Ari et al., 2020). The destabilization of NPLs not only impacts the banking system but also reverberates across the entire economy through a feedback mechanism. As indicated in the literature, higher NPLs impede the real economy by slowing economic activity and credit growth (Nkusu, 2011; De Bock and Demyanets, 2012; Huljak et al., 2020). Higher NPLs reduce bank profitability, necessitate higher capital requirements due to greater risk weights, and subsequently result in a decline in credit supply. Furthermore, the increase in NPLs reduces bank lending, widens credit spreads, and contributes to a decrease in GDP growth. Therefore, reducing NPLs has a positive effect on both macroeconomic and financial conditions (Huljak et al., 2020).

Comparing the Covid-19 crisis to the global financial crisis of 2008, notable differences emerge: banks are currently better capitalized but less profitable, and government debt ratios are higher (Bertay and Huizinga, 2021). Governments worldwide have implemented measures to mitigate the adverse effects of the Covid-19 outbreak and support the economy, which has placed a burden on government budgets, consequently increasing public debt. While these interventions are essential, careful monitoring is crucial due to the detrimental impact of public debt on NPLs and the resulting feedback loop. Without effective government policies, a hypothetical scenario of a double-hit Covid-19 predicts a 2.8% higher NPL for the Euro area and North America, and a 3.4% higher NPL for

emerging market economies compared to the NPLs in 2019. However, with government intervention, projected increases in NPLs are significantly lower—0.11%, 0.14%, and 0.14% for the Euro area, North America, and emerging market economies, respectively (OECD, 2021).

2.6. Discussion and Policy Suggestion

The findings of this chapter indicate that both conventional and participation banks exhibit resilience to fluctuations in the interest rates. Concerning NPL, although there are occasional values hovering between 5-6% in the scenario analysis, they generally range between 4-5%.

Figures 2.2-2.4 and Table 2.5 show that, rather than increases in interest rates, escalation in the exchange rate and the public debt ratio serve as the factors driving NPL. Furthermore, the scenario analysis outcomes highlight that NPL reaches its maximum values mainly due to surges in the exchange rate and public debt ratio. Hence, policymakers need to scrutinize every aspect meticulously and devise prudent policies accordingly.

The current scenario is rife with challenges including global energy crises, mounting inflation, and currency rate hikes, all posing threats to the economy. Amidst these conditions, certain actions in the banking sector because of pandemic—such as keeping credit channels open, offering more lenient collateral terms, extending credit limits, reducing credit risk weights, enhancing loan value ratios, and issuing more loans—played a role rendering the banking sector more susceptible to potential adverse shocks.

Difficulties within the real sector are anticipated to hinder both companies and households in meeting their loan obligations, subsequently pressuring banks into facing capital and liquidity issues. The prospect of non-bank lenders encountering losses also raises concerns for overall financial stability. The rise in exchange rates and inflation rates poses significant risks to both businesses and households, potentially impacting loan repayment abilities.

Despite government support in loans, the economic deceleration both in Turkey and globally due to the pandemic, coupled with the high expenses associated with the epidemic containment measures, have rendered the economy delicate. With substantial resource consumption by the government and financial institutions, any adverse shock impacting either the real or financial sectors holds the potential to trigger a crisis with a cascading effect, given the interconnectedness prevalent in credit markets.

It is important to highlight that public debt, alongside private-sector debt, has surged to unprecedented levels. The tightening of monetary policies in developed nations has consequential effects on emerging countries, leading to local currency depreciation due to the interconnected nature of economic policies (World Bank, 2022). Moreover, Turkey faces increased exchange rates, geopolitical risks, escalating inflation rates, and diminished capital and foreign exchange liquidity, thereby exposing its banking sector to risks associated with macroeconomic and financial instability (Fitch, 2022).

Implementing an expansionary monetary policy by reducing policy rates could be important to bolster the economy and facilitate increased access to loans amid the pandemic. However, persistently low interest rates posed challenges for banks, shrinking their net interest margin and gross returns, prompting financial institutions to take on more risks.

Continuously low interest rates further strained bank profitability in subsequent periods. Banks that struggle to generate profits exceeding their cost of equity have become less willing to extend loans and other financial services to households and businesses, limiting the flow of credit crucial for the economy. Moreover, risks assumed to compensate for reduced profits could escalate problems. Therefore, policymakers must strike a balance that upholds financial stability and the soundness of financial institutions while bolstering economic activity. They should consider various strategies to safeguard and fortify capital, such as curtailing dividend payments and sharing buybacks (IMF, 2020). Additionally, low interest rates hampered foreign capital inflow. Thus, a holistic approach to managing the economy is essential.

Despite the positive impact of measures addressing unemployment and providing loans to those in need during the pandemic, their long-term effects might create challenges for both

banks and the state treasury due to increased risks associated with excessive loan growth and potentially riskier decisions. In the event of a negative shock, such circumstances could lead to unpaid loans and a decline in collateral value, potentially triggering a financial crisis. If the government resorts to borrowing to cover public expenditures in such scenarios, it could exacerbate the growth of non-performing loans, as demonstrated in this study. Therefore, it is imperative for policymakers to enact regulations aimed at fortifying the stability of the banking system, thereby enhancing its resilience. This proactive approach can mitigate the state's necessity to amplify public spending and curtail the adverse effects on non-performing loans.

It is crucial for banks to swiftly establish capital reserves. Otherwise, in a worst-case scenario, an economic or financial sector shock, along with potential increases in the aforementioned macroeconomic variables, might impede banks from bolstering their capital, potentially leading to a crisis. Therefore, recognizing that the estimated effects of the independent variables could vary across stress variable quantiles, policymaking should account for this diversity.

Moreover, it is evident that smaller banks with lower capital and liquidity are particularly vulnerable to shocks, prompting regulators to assess consolidation practices akin to those observed globally. In the international banking sector, mergers and strategic alliances are deemed effective strategies due to weak organic growth and the necessity for large-scale investments in technological advancements. While there is a risk of potentially undermining competition within the banking sector, fostering similar concentration trends in Turkey could be contemplated as a policy measure. This move aims to strengthen the sector's position, better internalize adverse externalities, and enhance its resilience amid any possible global epidemic, thereby upholding financial stability.

2.7. Conclusion

Turkey is currently facing surges in the exchange rate, inflation rate, and both public and private debt. This situation, compounded by the erosion in capital and foreign exchange liquidity and the ongoing global energy crisis, has made Turkey more vulnerable. These circumstances have heightened macroeconomic and financial stability risks for the

Turkish banking sector, especially for banks with potentially insufficient capital ratios to confront imminent challenges. Furthermore, banks lending to industries most affected by the Covid-19 pandemic may face critical financial health issues.

Given that the destabilization of non-performing loans not only harms the banking sector but also affects the entire economy due to a feedback loop, it becomes imperative to analyze the factors that influence NPL. Consequently, this study aims to evaluate the economic challenges to facilitate the sound formulation of policy measures. The research findings underscore the profound influence of all macroeconomic variables analyzed on NPL. Therefore, ensuring a low and stable exchange rate, implementing policies to curtail unemployment, and avoiding actions that could excessively escalate public debt are crucial. Additionally, policy recommendations necessitate considering the distinctive characteristics of different bank types.

This research findings also highlight distinctions between public and private deposit banks, revealing that while the increasing exchange rate and unemployment rate have a more adverse effect on the non-performing loans of private deposit banks, the impact of the public debt to GDP ratio is more severe for public deposit banks. Additionally, the results suggest that private deposit banks may adopt credit rationing in response to interest rate hikes.

Moreover, the investigation into the differences between conventional banks and participation banks uncovers that fluctuations in macroeconomic variables and extreme conditions can impact the NPL of these two bank types differently. Conventional banks exhibit more resilience to exchange rate variability across all quantile levels of NPL but are more vulnerable to fluctuations in the interest rate. Conversely, variations in the public debt ratio and unemployment rate have a more damaging effect on higher quantile levels of NPL for conventional banks, while lower quantile levels of NPL for participation banks demonstrate increased fragility, as illustrated by the probability analysis.

The results from the first scenario analysis and the second approach of the second scenario analysis collectively indicate that, in general, participation banks are more susceptible to exceptional yet plausible scenarios associated with the exchange rate, unemployment rate, and public debt ratio. The second approach of the second scenario analysis, where

macroeconomic variables consist only of harmful tail values of simulated series, suggests that participation banks are adversely affected more than conventional banks.

It is important to acknowledge in this study, while conducting stress tests using time series, aggregated specific bank-related variables are used, which might have led to a loss of some nuanced information owing to this aggregation. As a potential area for future research, employing panel data techniques could offer more tailored results for each bank in the sample.

Furthermore, there are several aspects for expanding this research. One direction could involve the inclusion of different macroeconomic and financial variables beyond those utilized in this study as explanatory variables. Additionally, incorporating various stress variables such as the capital adequacy ratio and return on assets could offer a more comprehensive analysis.

Moreover, exploring the application of non-parametric quantile regression techniques to examine the resilience of other emerging markets and countries within the Middle East and North Africa (MENA) region could provide valuable insights. This expansion might offer a broader perspective on the robustness of different financial systems to similar stress scenarios.

3. LINKS BETWEEN U.S. AND TURKISH AGRICULTURAL COMMODITY MARKETS

3.1. Introduction

In recent years, a series of disruptive events affecting supply chains, such as the Covid-19 pandemic and global warming-induced droughts, have brought considerable attention to the interconnectedness of water, energy, and food security in global economies. The discourse surrounding deglobalization and the pursuit of self-reliance in food and energy sectors gained momentum in February 2022 with the onset of the conflict in Ukraine. With increased market interdependence, measuring and managing local market dynamics has become a more intricate task. Additionally, the integration of energy and commodity markets with financial markets, notably through derivatives based on relevant underlying assets, has been substantially completed in most developed economies. Therefore, conducting studies to measure the interdependency among markets and develop strategies to mitigate the adverse effects are imperative.

The focus on tail-dependence studies has intensified due to the potential for extreme price changes in one market to amplify fluctuations in others, or for multiple markets to experience simultaneous collapses. Consequently, numerous tail-dependence methods have emerged alongside conventional correlation-based measures to scrutinize return co-movements and interdependencies among distinct markets during extreme market conditions. However, conventional measures present notable limitations, including the symmetric estimation of tail dependence and the utilization of linear models with nonlinear datasets, potentially resulting in biased estimates (Lahiani et al., 2021). Moreover, a majority of time series exhibit nonlinear characteristics, such as nonnormality, asymmetric cycles, bimodality, and nonlinear relationships among lagged variables (Fan & Yao, 2005). Furthermore, the assumption of multivariate normality in

classical multivariate approaches is incompatible with joint tail analysis, leading to potential issues in drawing conclusions using these methods for tail-risk analysis (Krupskii & Joe, 2019). Hence, nonparametric measures, offering a superior fit to data and greater flexibility in modeling tail dependence, should be favored over parametric measures, which are inadequate for exploring nonlinear dependence structures in nonlinear time series.

Hence, a nonparametric tail-dependence measure formulated by Escanciano and Hualde (2021) is employed to capture the nonlinear linkage of dependence between markets. Unlike approaches centered on determining whether a market surpasses or falls below a specific threshold (i.e., focusing on a singular quantile value), this measure encompasses a range of quantiles, providing a more comprehensive insight into tail events. Consequently, it furnishes a more detailed perspective on how outliers instigate extreme occurrences in other markets and contribute to financial contagion. Especially, this measure addresses challenges posed by extensive variances and limited information concerning the tail risk associated with marginal expected shortfalls and exceedance correlations. Moreover, being a model-free method, it obviates the necessity for model estimation and assumptions regarding the distribution of model residuals, exhibiting greater flexibility in capturing various segments of the time series distribution. Another advantageous aspect of this measure lies in its ease of estimation and interpretation. Additionally, it circumvents smoothing by considering the integrated regression function (IRF) (Escanciano & Hualde, 2021).

The research primarily delves into the price dynamics of main food products traded between the US and Türkiye. However, it encompasses asset classes within energy and financial markets to assess the transmission of information across these different markets. The study spans periods preceding and following July 26, 2019, when the spot national agricultural commodity market commenced at the Turkish Mercantile Exchange (TMEX). Given the absence of an agricultural commodity derivatives market in Türkiye, prices from both the domestic spot market and the international derivatives market are incorporated. Concerning the transmission of information between markets, both the spot and derivatives markets collectively contribute to price discovery. Observations during

stress periods suggest potential contagion effects leading to heightened volatility and increased strain within the financial system. Nonetheless, the primary source of information spillovers appears to be the direction of price changes, specifically, return spillover (Milunovich & Joyeux, 2010).

Additionally, an examination of tail dependence between agricultural commodity markets is conducted for periods preceding and following February 24, 2022, marking the onset of Russia's invasion of Ukraine and the subsequent ongoing conflict. Notably, both Russia and Ukraine serve as major suppliers of wheat, corn, and barley, and the conflict resulted in an upsurge in agricultural commodity prices. To assess the impact of this structural shift, the dataset is partitioned into two subsets utilizing February 24, 2022, as the threshold for conducting the analysis.

The Turkish and US agricultural commodity markets are taken into account, given the global leadership and substantial benchmark status of the US market. The financialization phase of the US agricultural commodity market has already transpired through its derivatives market. The determination of prices in this market is impacted by diverse factors, encompassing international benchmarks, local and global agricultural production conditions, as well as transportation costs. Given its extensive size and depth, the US market effectively mirrors these parameters and expectations.

Nevertheless, the Turkish agricultural market heavily relies on the international market due to limited supplies within the local market. Türkiye predominantly imports agricultural commodities, particularly from the Black Sea Region, denominated in US dollars. Hence, when comparing local market prices to those in foreign markets, considerations regarding freight and insurance costs become crucial. Moreover, high levels of financialization and integration may significantly impact local prices through their association with international markets. However, comprehending the dynamics of market prices necessitates the consideration of interventions by local regulatory authorities and their incentives to bolster local agricultural production. These authorities possess the capacity to intervene in the local market by purchasing from farmers at prices above the market rate or vending to milling and animal feeding industries at prices below the market rate to stabilize food prices. During such periods, the local industry might favor

importing from more economical foreign markets due to excess demand or as reserves, arranged by local regulatory bodies such as the Turkish Grain Board. Within the private sector, decisions regarding exports are greatly influenced by fluctuations in US dollar rates concerning local currency (FX rates) and funding (interest) rates. Consequently, both local and international financial market conditions, the foreign exchange market, and regulatory frameworks have substantial impact on pricing.

The objective of this study is to investigate whether there exists dependence and simultaneous movement between the US and Turkish markets, or if the Turkish market predominantly responds to local or regional market dynamics. The insights gained from these findings have the potential not only to assist market participants in refining their portfolio management and hedging strategies but also to provide guidance to policymakers regarding pricing interventions and subsidy programs designed to stabilize food prices.

The analysis is partitioned into two distinct periods based on the TMEX launch for specific reasons. Preceding the TMEX introduction, Türkiye operated distinct local markets with constrained regional supply and demand. Most transactions within these local markets were bilateral negotiated agreements, typically reported off-exchange to local exchanges. However, with the TMEX establishment as a national exchange, these separate regional markets ceased to exist, consolidating trades into a unified order book at TMEX. This consolidation of liquidity within a single order book notably elevated the proportion of continuous auction deals, thereby enhancing the efficiency of price discovery and facilitating the establishment of benchmark prices. By segregating the analysis into periods before and after the TMEX launch, the study aims to ascertain whether this structural alteration affected market dynamics.

As far as can be determined, this study represents the initial application of the tail-restricted Integrated Regression Function (IRF) to both spot and derivatives markets concerning agricultural commodities. Despite the spot market's importance in determining prices, understanding the linkages between spot and futures markets can provide policymakers with substantial insights and consequential outcomes.

The research scrutinizes the interdependence and contagion risks among diverse markets, underscoring the necessity for a sustainable and efficient agricultural market.

Additionally, the study explores the influence of historical and current returns of US agricultural futures contracts on present TMEX spot agricultural market returns. It proposes the prospective advantages of initiating a local derivatives market within the Turkish agricultural market, aiming at enhancing price discovery mechanisms and facilitating effective risk management.

The research offers empirical evidence concerning the impact of US barley, wheat, and corn futures contract returns on TMEX spot market returns within the Turkish agricultural market. This contribution to the literature enriches the understanding of price discovery and risk management in agricultural markets by investigating the interactions between local spot markets and international derivative markets.

The research bears significant policy implications for Turkish agricultural market policymakers. It recommends that introducing a local derivative market could offer crucial hedging instruments for both price discovery and risk management. Additionally, fostering information flow between spot and derivatives markets can potentially elevate market efficiency. Moreover, the study underscores the importance of policy measures aimed at monitoring interdependencies and contagion risks, particularly during periods of stress. It advocates for policies that promote sustainability and efficiency within the agricultural market.

The research emphasizes the significance of diversifying risk management approaches to accommodate variations in tail dependence and mean dependence across markets. This contribution to the literature on risk management in agricultural markets proposes leveraging a blend of conventional risk management methods and investigating novel techniques like weather derivatives or index-based insurance. These suggestions aim to proficiently mitigate risks linked to market interdependencies.

Overall, this study contributes to the existing literature by presenting empirical evidence, outlining policy implications, and delineating risk management strategies tailored for the Turkish agricultural market. It highlights the crucial importance of sustainability and efficiency within agricultural markets.

3.2. Literature Review

This section provides an overview of the literature concerning linkages within financial markets and the connections among returns of various financial instruments. Scholars and researchers have extensively investigated the correlation between energy and commodity markets. The evolution of bioenergy has particularly intensified attention on the interplay between energy and agricultural commodity markets.

Existing literature extensively relies on autoregressive conditional heteroskedasticity (ARCH) models and their varied extensions, such as GARCH copula, BEKK-GARCH, VaR-AGARCH, and APARCH, for examining both financial and commodity markets. Studies conducted by 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 relationships existing between different financial and commodity markets.

Trabelsi (2017) utilizes the DCC-MGARCH approach alongside CoVaR measurement to explore the negative tail dependence between oil and stocks of major oil-exporting countries. The study reveals significant spillover effects.

Yousef et al. (2021a) employs the DCC-GARCH model to analyze crude oil-gold and crude oil-Bitcoin pairs. Their findings suggest diverse patterns in return spillovers before and after Covid-19. Gold emerges as a robust hedge, whereas Bitcoin functions as a diversifier for the oil market during the Covid-19 period.

Wang (2023) adopts the DCCFIGARCH model to examine tail dependence between stocks and Chinese commodity markets. The study identifies a pronounced downward trend exhibiting contagious strength at the extreme lower quantile.

Similarly, Al Rahahleh et al. (2017) utilize the DCC-GARCH model and observe bidirectional information flow between the US and Hong Kong markets, as well as between the US and Australian markets.

Hamadi et al. (2017) employ a combination of ICSS, 3 SLS, and GARCH models to assess volatility spillovers in US agricultural commodities. Their findings indicate significant bidirectional volatility spillovers.

Yousef et al. (2021b) utilize high-frequency data to examine return and volatility spillovers in Latin American stock markets and gold using VAR-AGARCH. The study highlights variations across distinct stock markets.

Davis et al. (2018) analyze the persistence of negative and positive shocks in the equity market through GARCH and APARCH models.

Islam (2016) measures volatility spillover between US and Chinese financial markets utilizing ARMA-GARCH, concluding significant and positive return and volatility spillovers from the US to China.

Joudeau (2015) establishes a multivariate noncentral t-distribution model to investigate the US stock market, revealing higher tail dependence on the downside compared to the upside.

Kondoz et al. (2019) conduct tests for volatility spillover between oil prices and the US equity market utilizing BEKK-GARCH. Their findings suggest that investors in the crude oil market can benefit from incorporating data on US equity market returns for more accurate predictions of oil market return volatility.

Kumar et al. (2018) also investigate the equity market, examining volatility spillover via ARCH-GARCH models.

Lahiani et al. (2021) utilize a novel measure of nonlinear dependence introduced by Escanciano and Hualde (2021) in analyzing cryptocurrency-stock markets.

Yuan et al. (2020) model the co-movements of six major grain commodity prices using GARCH and identify strong contagion effects, particularly stronger co-movement after the food crisis.

In general, the literature review affirms the widespread utilization of ARCH models and their extensions in studying financial and commodity markets, as well as in understanding the interrelationships among various markets.

Candelon and Tokpavi (2016) develop a kernel-based nonparametric method to examine Granger causality in distribution, focusing on causalities within the left tail, right tail, and center of the distribution for a range of 12 European daily stock market indexes. Utilizing this proposed test, Erdogan et al. (2022) explore the dependence between the clean energy stock index and precious metals prices. Their findings reveal a unidirectional causality from clean energy to precious metals for the left tail and the center of the distribution, while demonstrating bidirectional causality for the right tail.

Furthermore, among the methodologies mentioned earlier, wavelet squared coherence (WSC) stands out as a technique used to assess the lead-lag relationship between markets. Jiang et al. (2018) utilize WSC in conjunction with a wavelet-based copula to scrutinize the dependence structure of energy, agriculture, and metal commodity market indexes. Their findings indicate that stronger dependencies are more significant at the lower tails compared to the upper tails, revealing an asymmetric tail dependence.

Similarly, Mensi et al. (2017) employ WSC to investigate the dependence structure of oil, wheat, and corn commodities. Their study unveils time-varying asymmetric tail dependence among pairs across different time horizons. These studies underscore the effectiveness of WSC as a methodology for analyzing the dependence structure and lead-lag relationships among diverse markets.

Albulescu (2020) employs the copula-based local Kendall's tau method to assess nonlinear local dependence within energy, agriculture, and metal commodities using the Rogers International Commodity Index subindexes. Their findings reveal stronger dependence between energy and other commodity markets at the lower tail, suggesting heightened dependence during extreme events.

Hau (2020) investigates the relationship between crude oil and China's agricultural market, employing conventional quantile regression (QR) and quantile-on-quantile regression (QQR) techniques. Results indicate absolute volatility spillovers with an increasing trend in higher quantiles, indicating the potential for higher volatility spillovers during extreme events.

Hanif et al. (2021) utilize static and dynamic bivariate copula value-at-risk (VaR) and conditional VaR (CoVaR) methods to explore the relationship between the West Texas Intermediate (WTI) crude oil benchmark and world food price index subcategories. Their findings suggest independent movements during market upturns and downturns but highlight lower- and upper-tail dependencies between oil prices and food commodities, signifying potential contagion effects during extreme events.

Kumar et al. (2021) apply VaR and CoVaR to investigate the dependence between oil and agricultural commodity markets, identifying significant dependence in the left tail, indicating prevalent contagion during negative market conditions.

Liu et al. (2019) utilize a Markov-switching GRG copula to examine the dependence between crude oil (WTI) and Chinese agricultural commodity market prices. Their findings reveal varying degrees of positive correlation between eleven of twelve different agricultural commodity futures and WTI crude oil prices, suggesting substantial positive dependence or co-movement between these markets and implying potential linkages or spillover effects.

3.3. Methodology

Dependence measures involve computing the covariance or correlation between two random variables across their entire distribution or specific segments of the distribution, elucidating the association between these variables. Measures focusing on the complete distribution, such as mean dependence, fail to capture the relationship between extreme values of random variables. Conversely, tail-dependence measures offer insights into the dependence of the upper or lower segments of the distribution. In a bivariate distribution, tail dependence measures determine the covariance or correlation between random variables when the marginal distribution of one variable surpasses a defined threshold, under the condition that the margin of the other variable also exceeds the same threshold (AghaKouchak et al., 2013). This concept refers to the occurrence of extreme events happening simultaneously.

To evaluate both mean and tail dependence comprehensively, the analysis employs a recently developed nonlinear measure of tail dependence introduced by Escanciano and

Hualde (2021). This measure stands out due to its distinct advantages over existing methods in the literature. Unlike tail dependence measures based on copulas, this method extends traditional linear correlation measures into a nonparametric framework. It does not necessitate model estimation or assumptions regarding the distribution of model residuals, offering greater flexibility in managing various parts of the time series distribution. Additionally, it accommodates significant variances and limited information on tail risk associated with marginal expected shortfalls and exceedance correlations. Its ease of estimation and interpretation is another notable aspect. This measure covers a range of tail market events rather than solely focusing on individual occurrences, providing a more comprehensive understanding of tail dependence and systemic risk. Moreover, it avoids smoothing by incorporating the Integrated Regression Function (IRF). Subsequently, a brief explanation of the methodology behind this nonlinear tail-dependence measure follows.

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 (2019) 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:

$$\varphi_{t,h}(y, x) = Cov(1(Y_{t+h} \leq y), 1(X_t \leq x)) = K_{t,h}(y, x) - L_{t+h}(y)F_t(x), \quad (3.1)$$

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

$$\|\varphi_{t,h}\|_{y_{tail}, x_{tail}} = \sup_{y \leq y_{tail}} \sup_{x \leq x_{tail}} |\varphi_{t,h}(y, x)|. \quad (3.2)$$

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

$$\hat{\varphi}_h(y, x) = \frac{1}{n-h} \sum_{t=1}^{n-h} 1_c(Y_{t+h}, y) 1_c(X_t, x), \quad (3.3)$$

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

$$KS_{n,\bar{x}}(h) := \|\hat{\varphi}_h\|_{\bar{x}}. \quad (3.4)$$

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:

$$\hat{p}_{n,\bar{x}}(h) = \frac{1}{R} \sum_{r=1}^R 1(KS_{n,\bar{x}}^{(r)}(h) \geq KS_{n,\bar{x}}(h)). \quad (3.5)$$

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

In brief, the proposed tail-mean dependence measure computes the covariance between two variables under the condition that threshold values are met for both variables, irrespective of whether they are higher or lower. This measure, accounting for a range of quantiles, evaluates the size of covariance using the uniform (sup-) norm. To put it more clearly, initially, quantiles that establish the threshold positions are specified. Subsequently, the process involves sorting the values of the independent variable and identifying where the condition $1(X_t \leq x)$ is met, known as the outer product. Next, the computation entails generating the vector of Integrated Regression Function (IRF) at order statistics by performing matrix multiplication of the deviation from the mean of the dependent variable with the outer product. This result is then divided by the total number of observations. Following this, the values within the threshold positions are extracted from the vector of IRF, and subsequently, the absolute maximum value is determined.

This outlined procedure is implemented for each lag of conditioning variables, up to the maximum determined lag.

3.4. Data

The dataset utilized in this study comprises daily agricultural commodity prices sourced from CME/USA, CBOT/USA, NCDEX/India, TMEX/Türkiye, and Brent oil prices from ICE, representing the energy market, along with foreign exchange and overnight interest rates from the financial market. Initially, returns are calculated using logarithmic differences in price series and then analyses are performed. The selected dataset includes main food-related futures contracts for barley, corn, and wheat from advanced economies, alongside their spot market equivalents in TMEX. Data sourced outside TMEX is obtained from the Bloomberg terminal, while the TMEX dataset is directly sourced from TMEX. The study encompasses the period from January 5, 2016, to May 31, 2022. To conduct analyses for two distinct scenarios, the dataset is segmented into subsamples corresponding to periods before and after the TMEX launch (July 26, 2019) and before and after the onset of the Ukraine war (February 24, 2022) for each scenario.

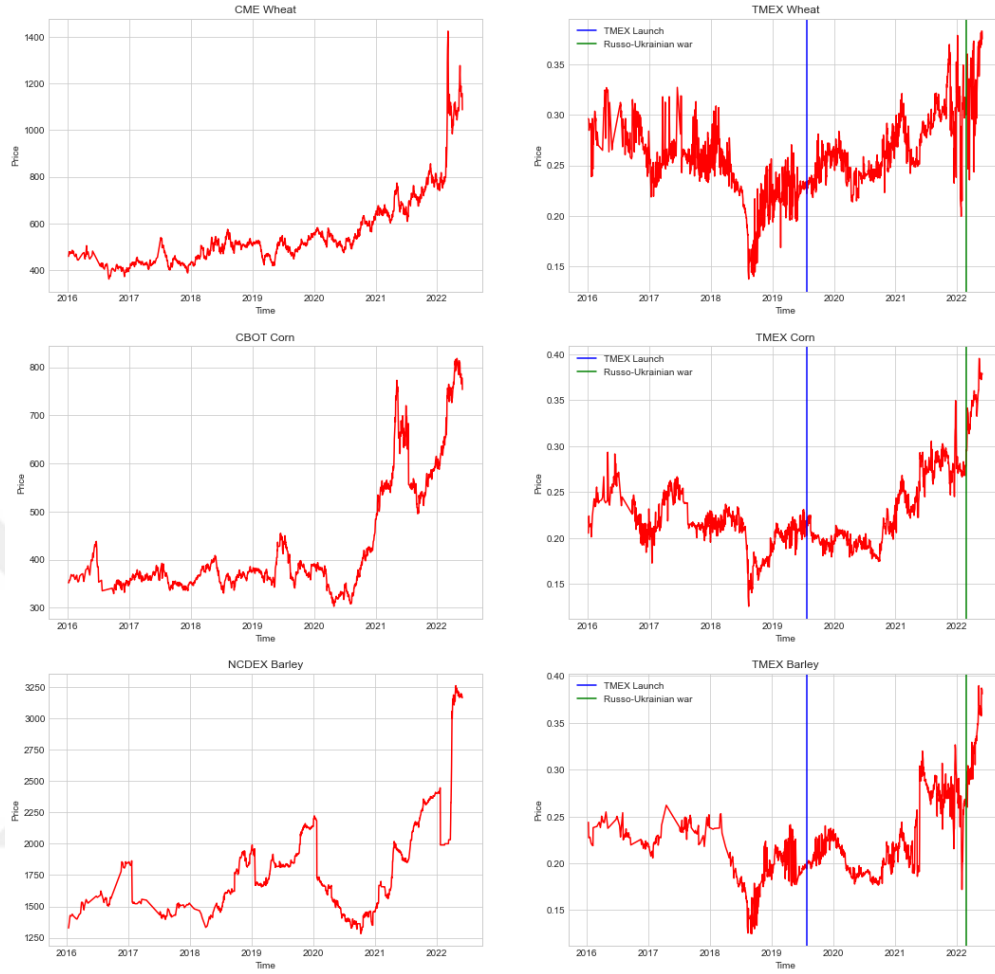


Figure 3.1 : Time series of commodity prices in terms of US dollars

Table 3.1 : Data set

Series*	Details	Data period
TMEX <u>Barley</u>	TMEX <u>Barley</u> spot	13.01.2016 – 31.05.2022
TMEX <u>Wheat</u>	TMEX <u>Wheat</u> spot	05.01.2016 – 31.05.2022
TMEX <u>Corn</u>	TMEX <u>Corn</u> spot	05.01.2016 – 31.05.2022
CBOT <u>Corn</u>	CBOT <u>Corn</u> futures	05.01.2016 – 31.05.2022
CME <u>Wheat</u>	CME <u>Wheat</u>	05.01.2016 – 31.05.2022
NCDEX <u>Barley</u>	NCDEX <u>Barley</u>	05.01.2016 – 31.05.2022
Brent <u>Oil</u>	ICE Brent <u>futures</u>	05.01.2016 – 31.05.2022
USDTRY	CBRT USD/TRY	05.01.2016 – 31.05.2022
TRLIBOR	TRLIBOR O/N	05.01.2016 – 31.05.2022

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 Turkey.

Table 3.2 : Descriptive statistics

Variable	Number of Obs.	Mean	Std. Dev.	Min	Max	Skew	Kurt	JB	BDS	ADF	ABP
<i>Panel A- Before TMEX Launch</i>											
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
<i>Panel B- After TMEX Launch</i>											
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***
<i>Panel C- Before War</i>											
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
<i>Panel D- After War</i>											
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: Table 3.3. 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.

Table 3.2 displays descriptive statistics concerning the returns of both dependent and conditional variables. The Jarque-Bera normality test reveals the nonnormality of these variables. Furthermore, the BDS test (Brock et al., 1987) rejects linearity for most variables, thereby endorsing the utilization of nonparametric analysis methods.

3.5. Empirical Results

Tail and mean dependence are measured from the US agricultural market, Brent oil, currency rates, and overnight interest rates to the Turkish agricultural market. This assessment allows the examination of asymmetric risk spillovers in both upward and downward directions concerning tail dependence. To cover a range of quantiles, the analysis incorporates all quantiles ranging from 1 percent to 5 percent for the lower tail and from 95 percent to 99 percent for the upper tail. For mean dependence, the entire distribution is taken into account. The analyses are conducted using 300 moving block bootstraps.

Figures 3.2-3.25 illustrate the nonlinear correlograms representing the magnitude and persistence of tail and mean dependence from conditioning variables to Turkish agricultural commodities. These plots display the IRF cross-coefficients $K_n(h) = \|\hat{\phi}_h\|_\infty$, indicating the size $\hat{\phi}_h$ of a function of h , along with 95 percent marginal bootstrap critical values. The algorithm stops if 1(A) becomes zero, despite setting h to 300 lags.

3.5.1. Pre-and post-TMEX launch

3.5.1.1. Findings on tail dependence

Figures 3.2-3.9 depict the nonlinear correlograms concerning the period preceding the TMEX launch, while Figures 3.10-3.17 showcase outcomes post the TMEX launch. Across both periods, the initial four graphs (Figures 3.2-3.5 and 3.10-3.13) present lower-tail dependence outcomes, whereas the subsequent four graphs (Figures 3.6-3.9 and 3.14-3.17) portray higher-tail dependence results.

Before the TMEX launch period, significant and persistent lower and upper-tail dependence is identified from US commodity markets to Turkish agricultural commodities. This highlights return co-movements, particularly evident for wheat and corn. The significant lags on current returns of TMEX wheat and corn persist even beyond 200 days, as evidenced in Figures 3.2 and 3.6. There exists persistent tail dependence from Brent oil to Turkish agricultural commodities across both lower and upper quantiles (depicted in Figures 3 and 7). Examination of the USD/TRY exchange rate demonstrates

persistent tail dependence across both quantile continuums for each commodity, as illustrated in Figures 4 and 8. Additionally, significant and persistent lower and upper tail dependence is observed from TRLIBOR to TMEX corn and wheat (as shown in Figures 3.5 and 3.9). Although fewer significant lags are evident for tail dependence from TRLIBOR to TMEX barley, effects of extreme events are still discernible even after 240 days. These findings suggest that both low and high values of the US Agricultural market, Brent oil, USDTRY, and TRLIBOR contribute to driving TMEX commodity returns.

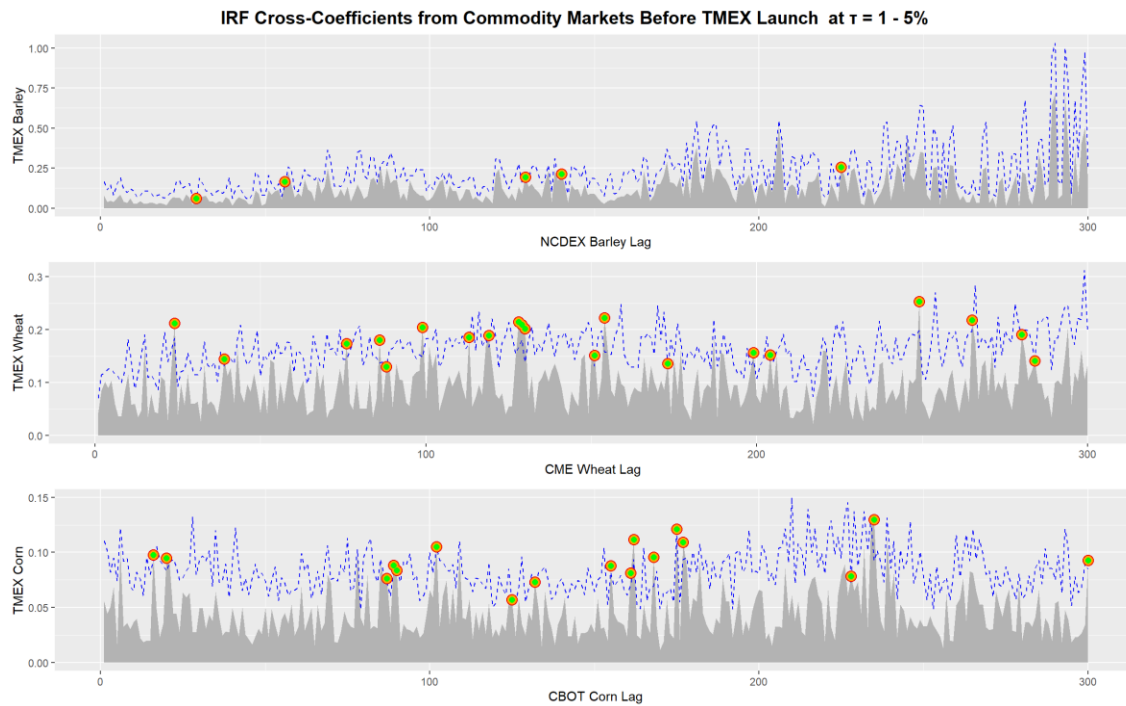


Figure 3.2 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 1%-5% (block 95% bootstrap critical values represented by dashed lines)

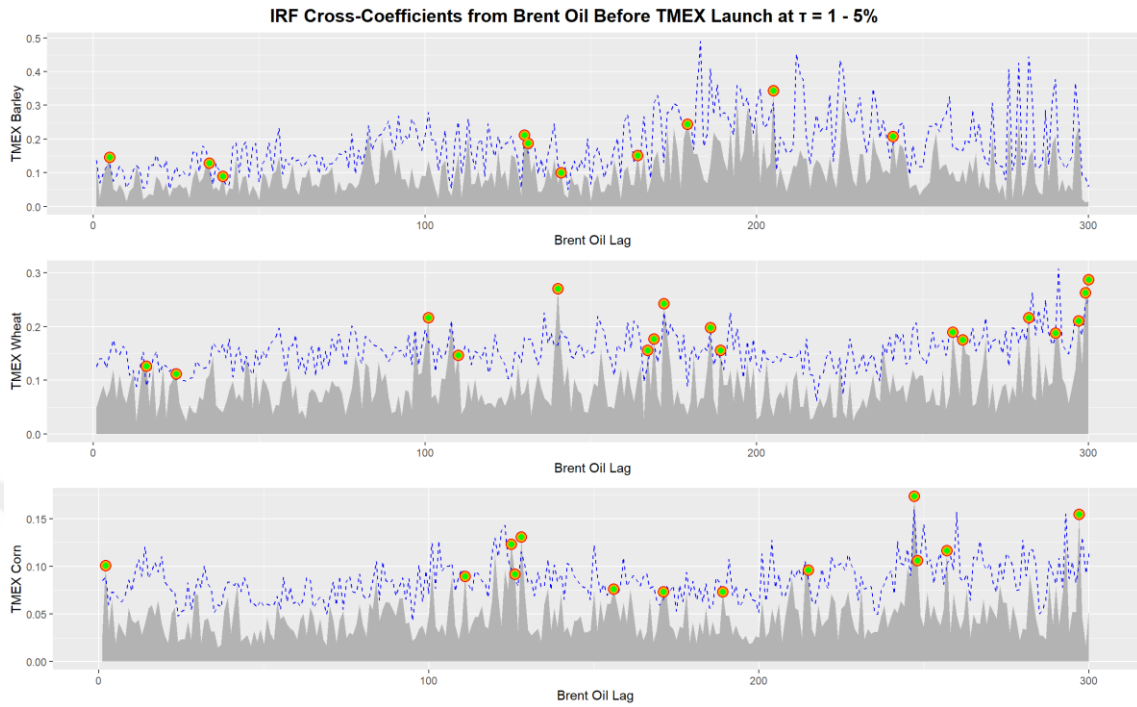


Figure 3.3 : IRF cross-coefficients from lagged Brent Oil to Turkish agricultural commodities market measured at quantiles 1%-5%

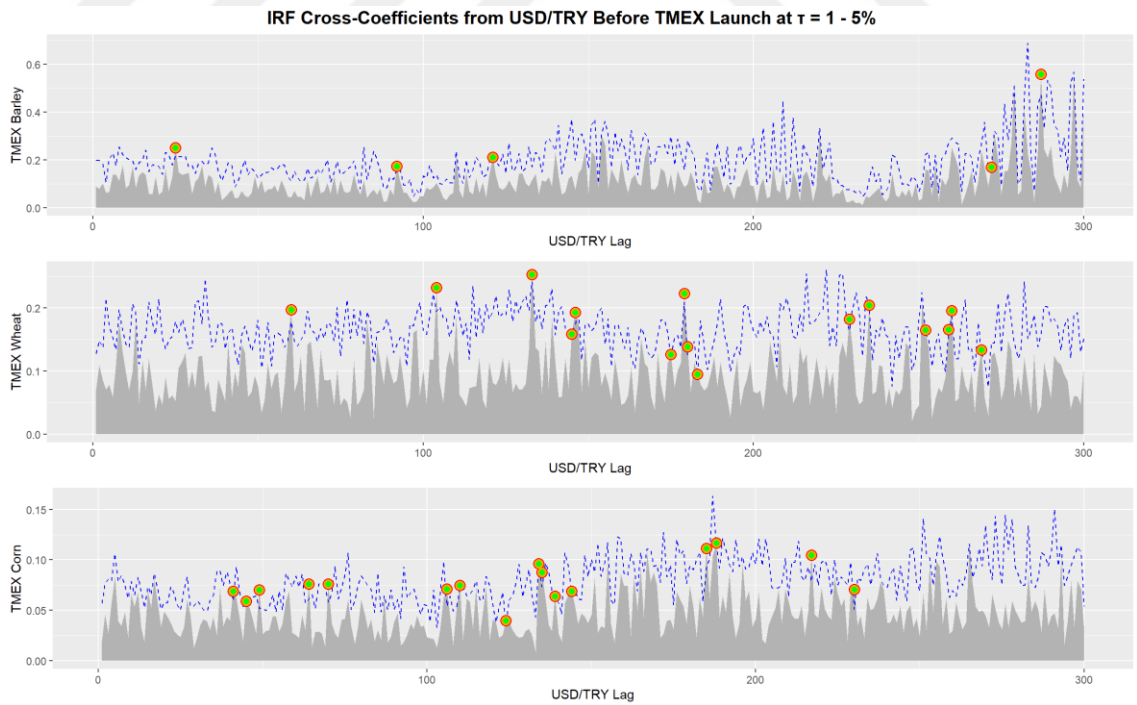


Figure 3.4 : IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 1%-5%

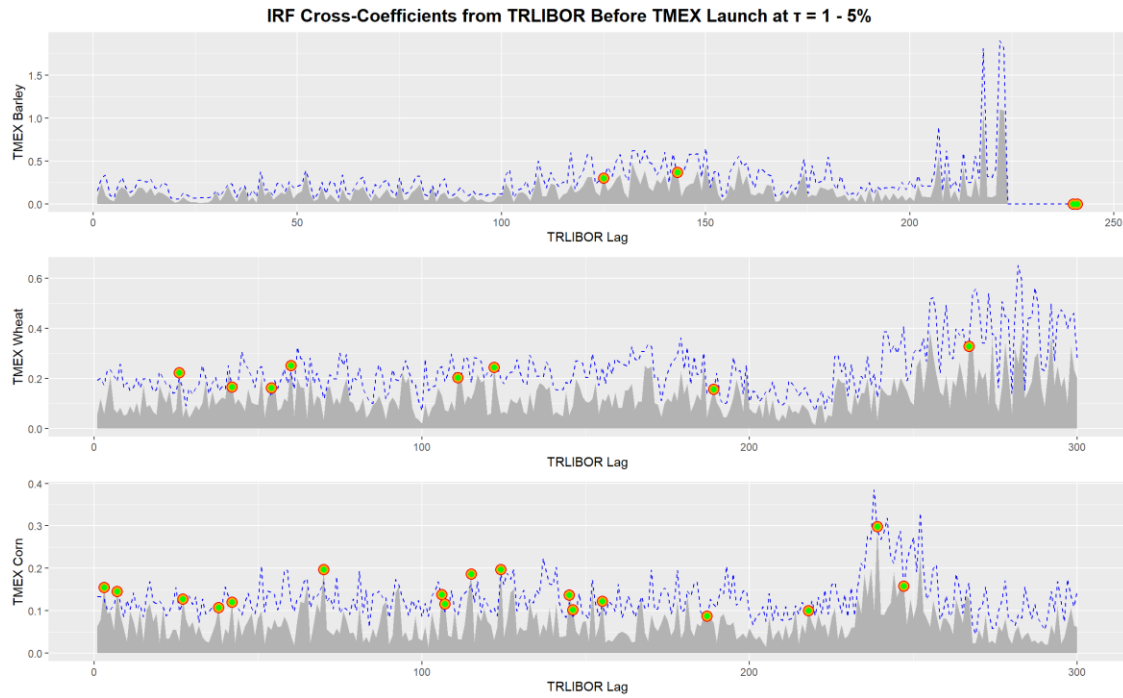


Figure 3.5: IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 1%-5%

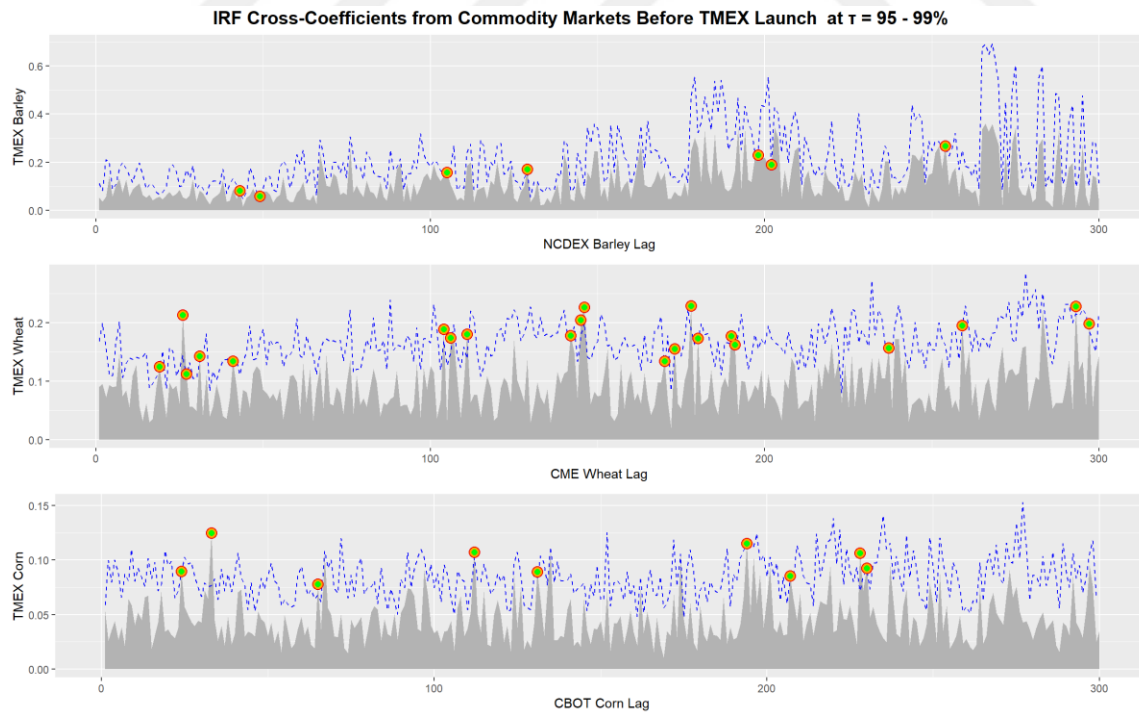


Figure 3.6 : IRF cross-coefficients from lagged Commodity Markets to Turkish agricultural commodities market measured at quantiles 95%-99%

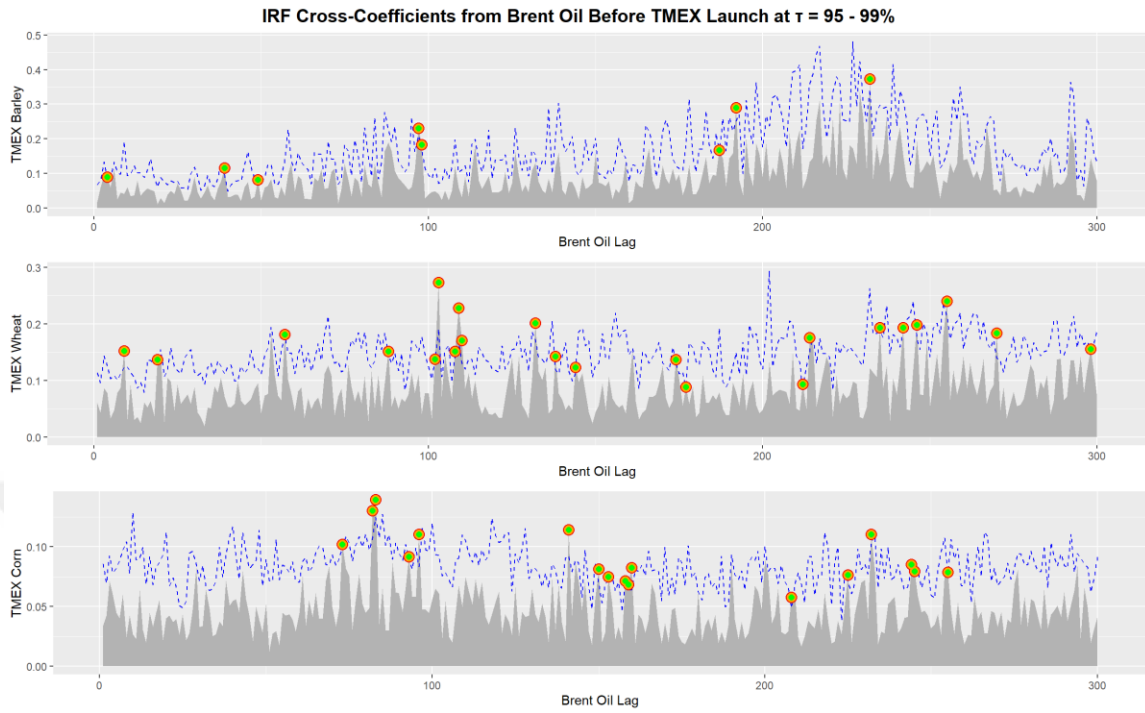


Figure 3.7 : IRF cross-coefficients from lagged Brent Oil to Turkish agricultural commodities market measured at quantiles 95%-99%

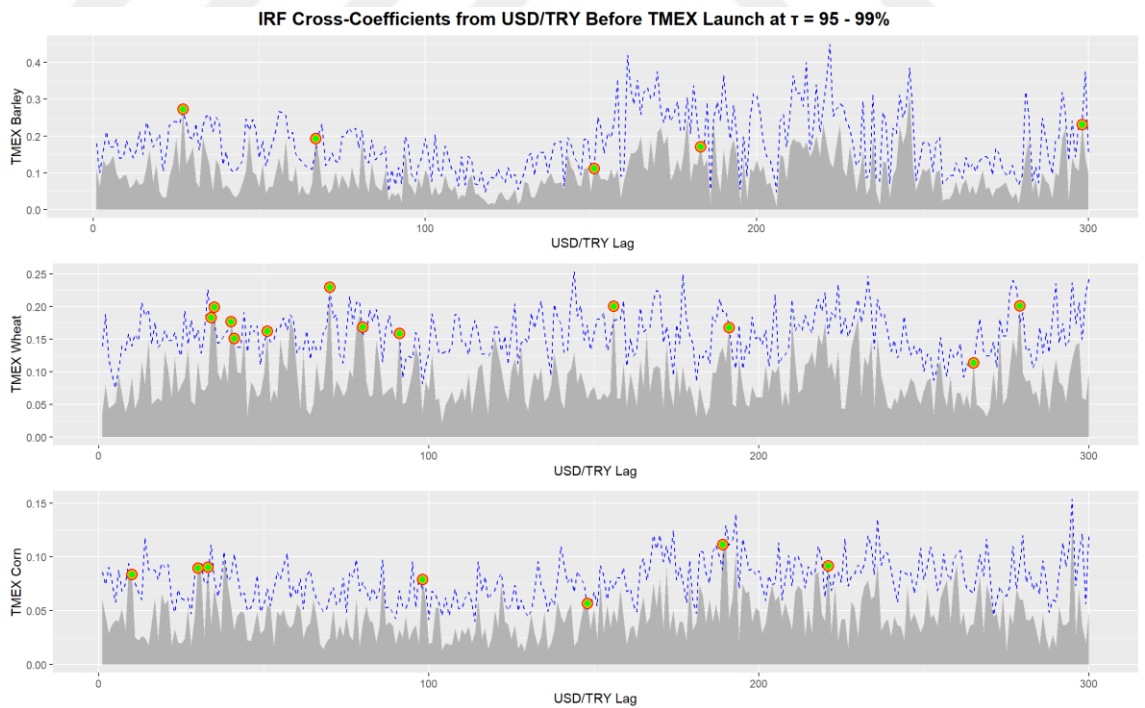


Figure 3.8 : IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 95%-99%

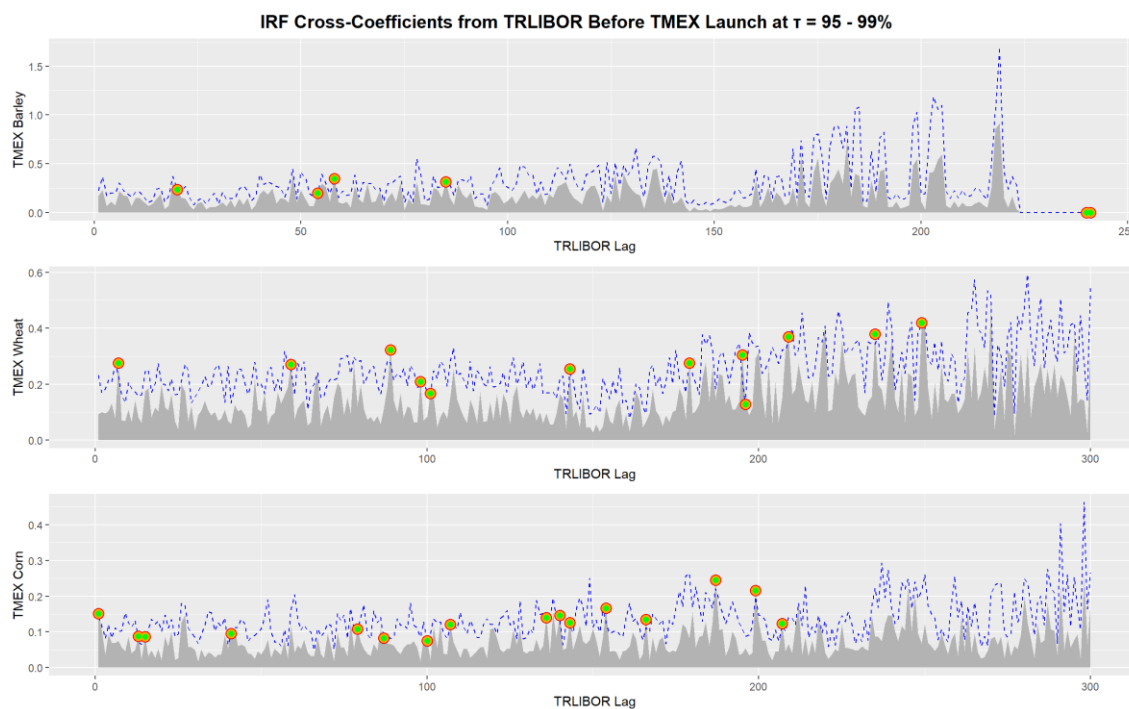


Figure 3.9 : IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 95%-99%

The outcomes observed after the TMEX launch period reveal significant and persistent tail dependence across both quantile continuums for each pair of agricultural commodities, as demonstrated in Figures 3.10 and 3.14. Specifically, for barley, significant lags persist up to the 260th lag, while for corn, they endure up to nearly the 300th lag for the lower tail. Initial lags for wheat and corn also display significance, indicating an impact of recent US wheat and corn returns on current TMEX wheat and corn returns. Moreover, concerning the upper tail, numerous significant lags are noticeable after 200 days. Notably, for wheat and corn, significant lags are evident up to nearly the 300th lag. The calculated measure of tail dependence presents compelling evidence for both lower and upper tail dependence from Brent oil retruns and USD/TRY exchange rates to the Turkish commodities market. These effects endure persistently for almost 300 days (highlighted in Figures 3.11-3.12 and 3.15-3.16). Additionally, the findings underscore strong evidence of tail dependence from TRLIBOR to TMEX corn across both tails, depicted in Figures 3.13 and 3.17. However, concerning tail dependence from TRLIBOR to both TMEX barley and wheat, only a few significant lags signify notable co-movement in these markets.

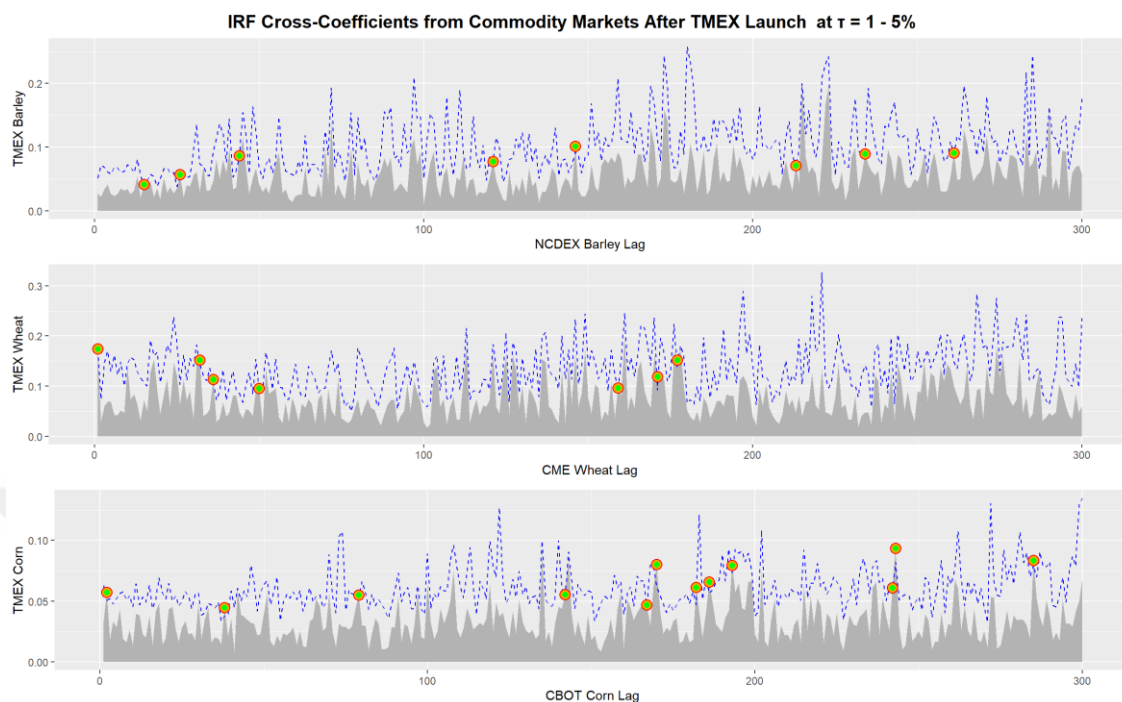


Figure 3.10 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 1%-5%

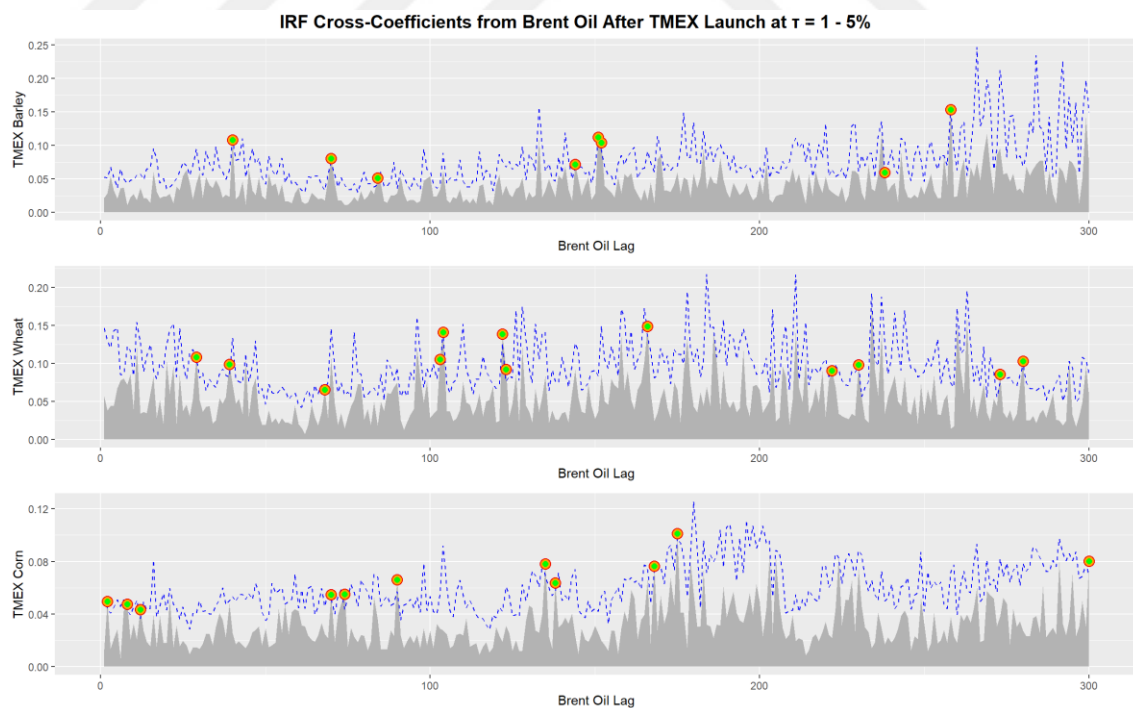


Figure 3.11 : IRF cross-coefficients from lagged Brent Oil to Turkish agricultural commodities markets measured at quantiles 1%-5%

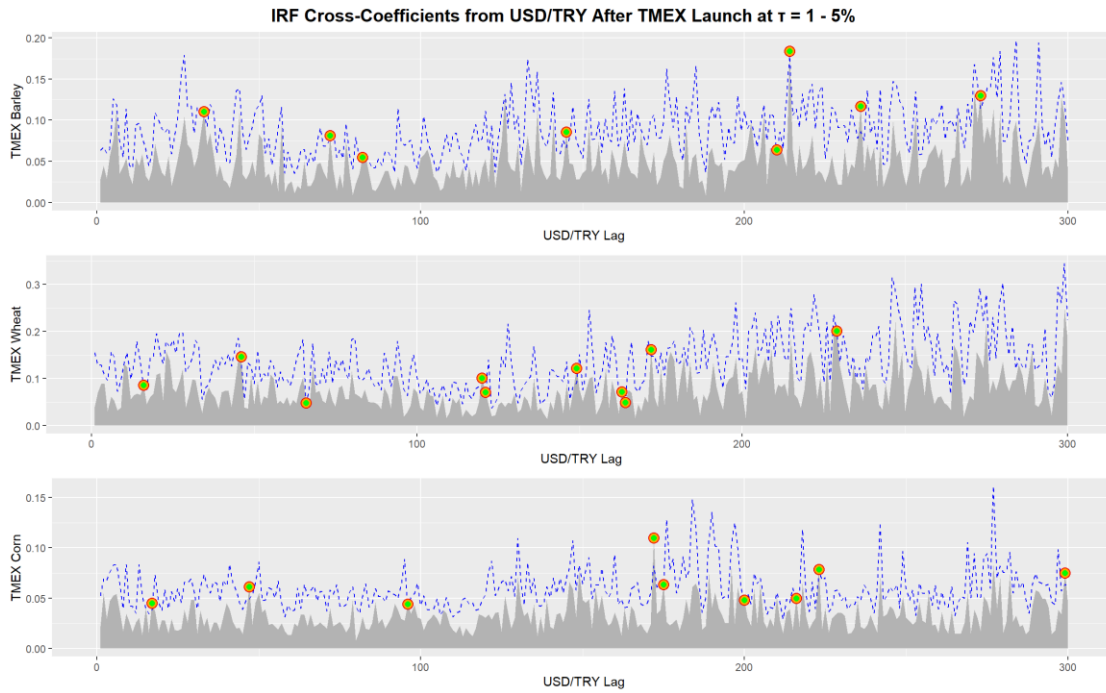


Figure 3.12 : IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 1%-5%

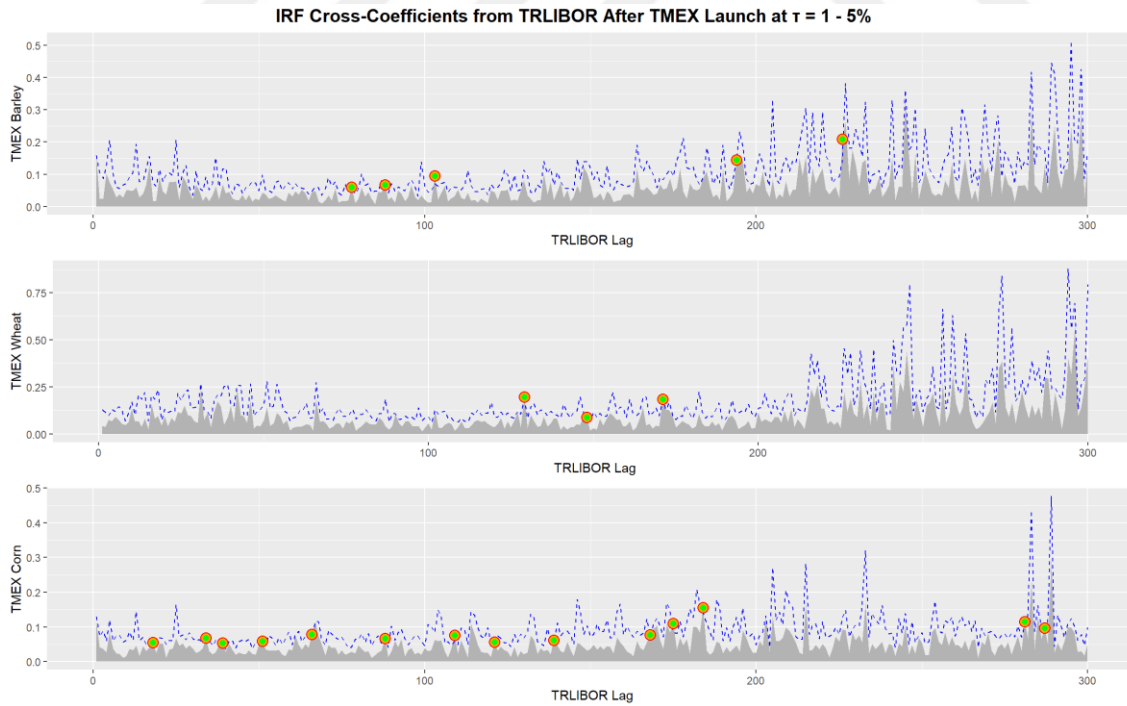


Figure 3.13 : IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 1%-5%

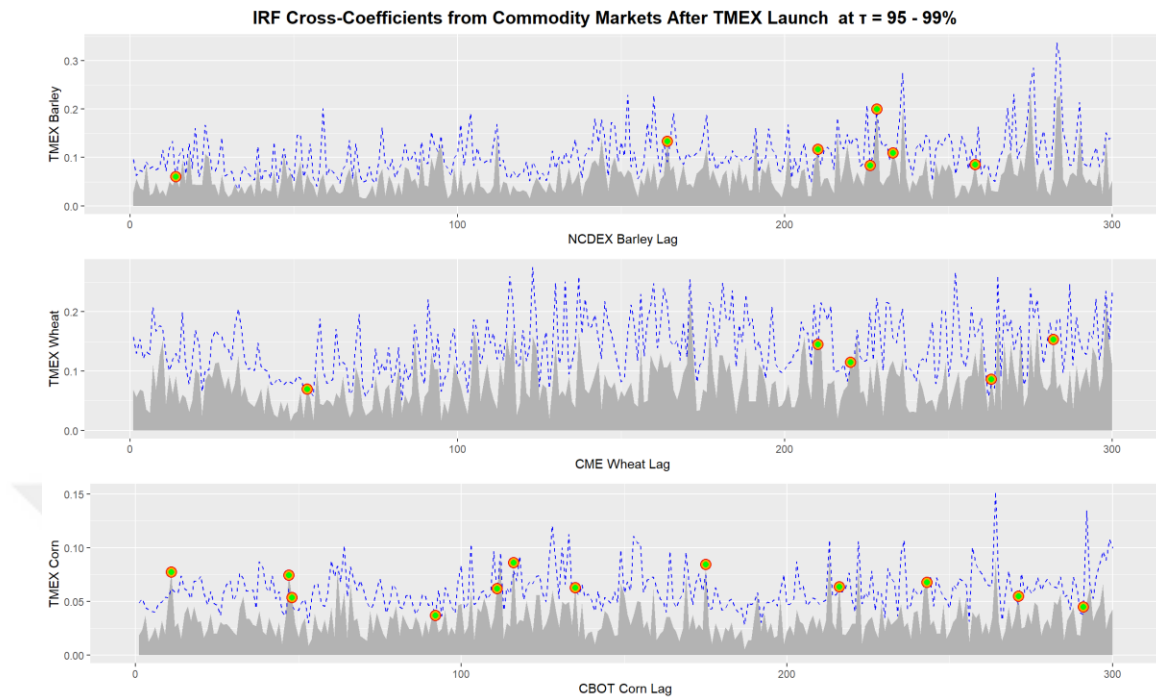


Figure 3.14 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 95%-99%

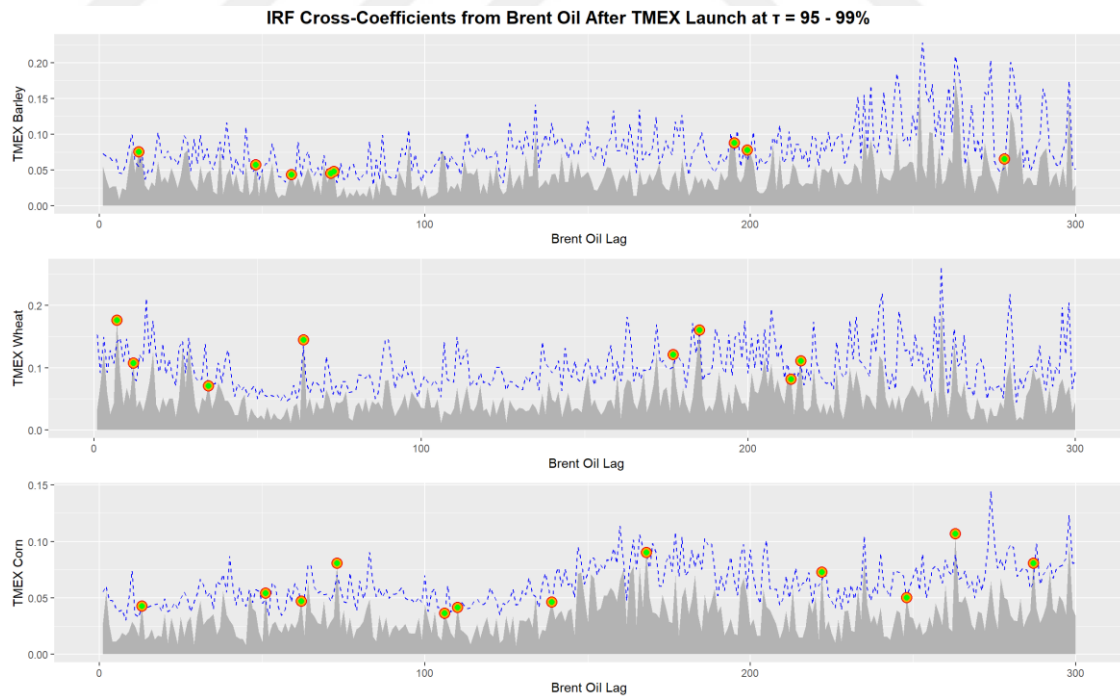


Figure 3.15 : IRF cross-coefficients from lagged Brent oil to Turkish agricultural commodities market measured at quantiles 95%-99%

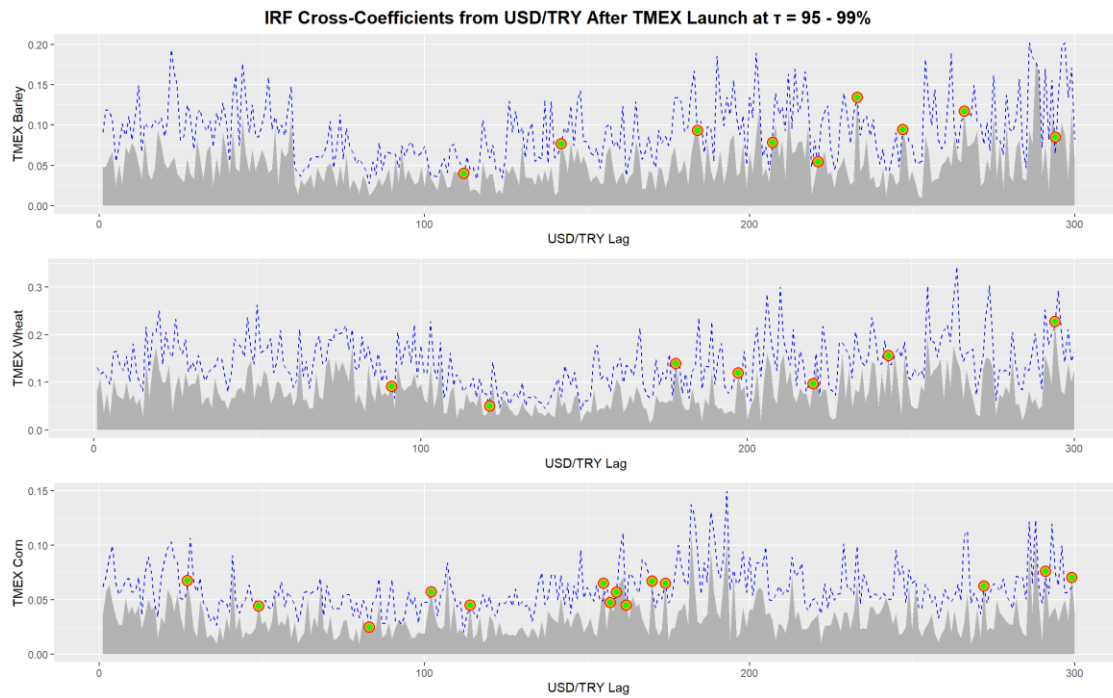


Figure 3.16 : IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 95%-99%

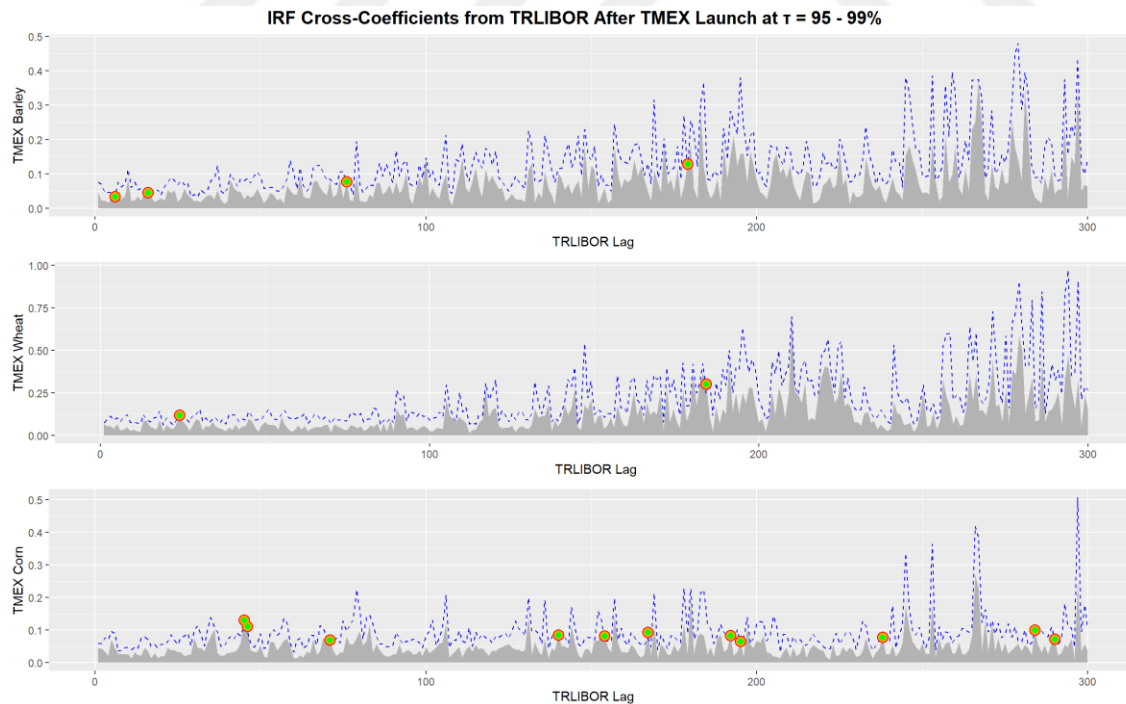


Figure 3.17 : Figure 3.17. IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 95%-99%

3.5.1.2. Findings on mean dependence

Figures 3.18-3.21 illustrate mean dependence during the period before the TMEX launch, while Figures 3.22-3.25 represent mean dependence after the TMEX launch. The findings underline the persistence of mean dependence from US commodities to Turkish commodities in both periods (depicted in Figures 3.18 and 3.22). Notably, following the TMEX launch (Figure 3.22), there is an escalation in co-movement observed in the barley and wheat pairs. Additionally, mean dependence from Brent oil and the USD/TRY exchange rate to Turkish commodities displays high significance and persistence in both periods (evident in Figures 3.19-3.20 and 3.23-3.24). The impact of TRLIBOR on the Turkish commodities market remains significant for an extended duration. However, mean dependence appears stronger for wheat and corn before the TMEX launch (Figure 3.21) compared to the period following the TMEX introduction (Figure 3.25).

Furthermore, the figures indicate the significance of recent lags, providing insights into mean predictability. For instance, recent lag values of CME wheat and CME corn, along with Brent oil for corn return prediction, should be considered in their respective models to predict future values of TMEX wheat and TMEX corn, as highlighted in Figures 3.22 and 3.23, respectively.

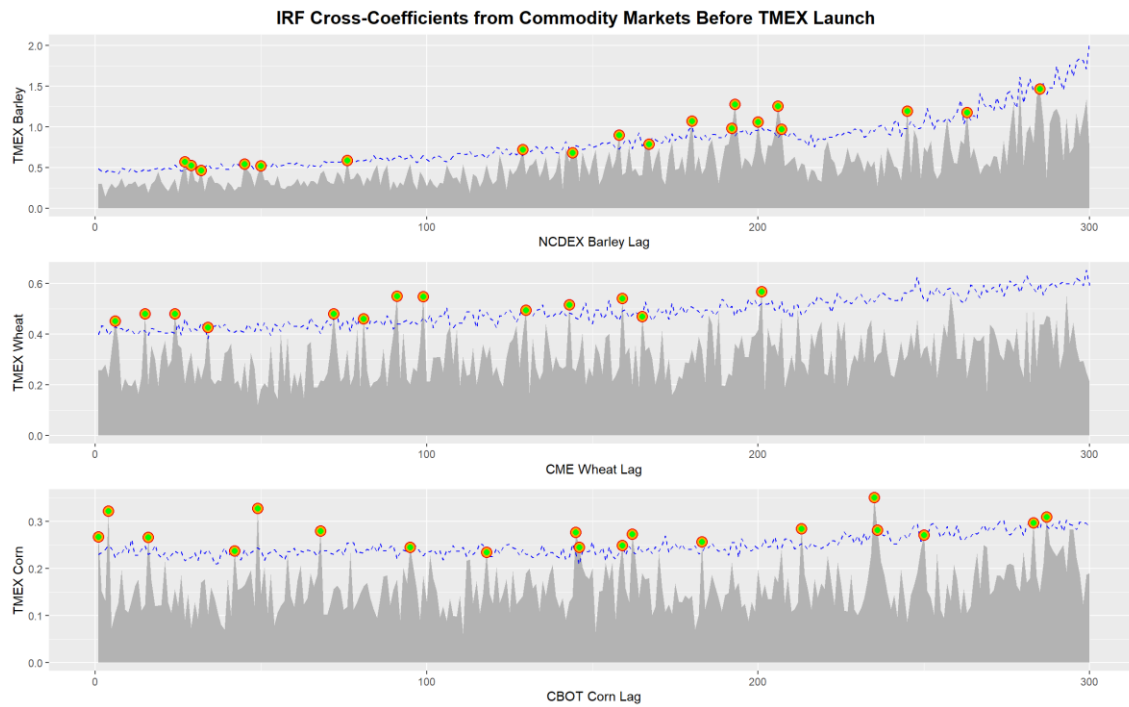


Figure 3.18 IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 0-100%

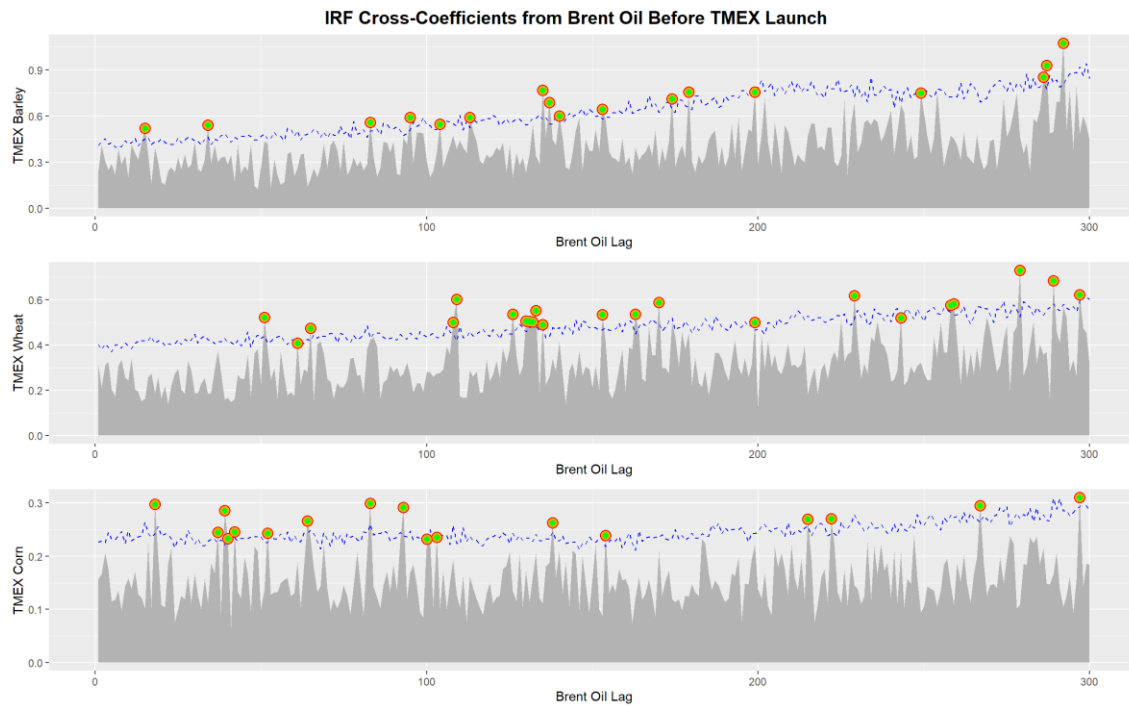


Figure 3.19 : IRF cross-coefficients from lagged Brent oil to Turkish agricultural commodities market measured at quantiles 0-100%

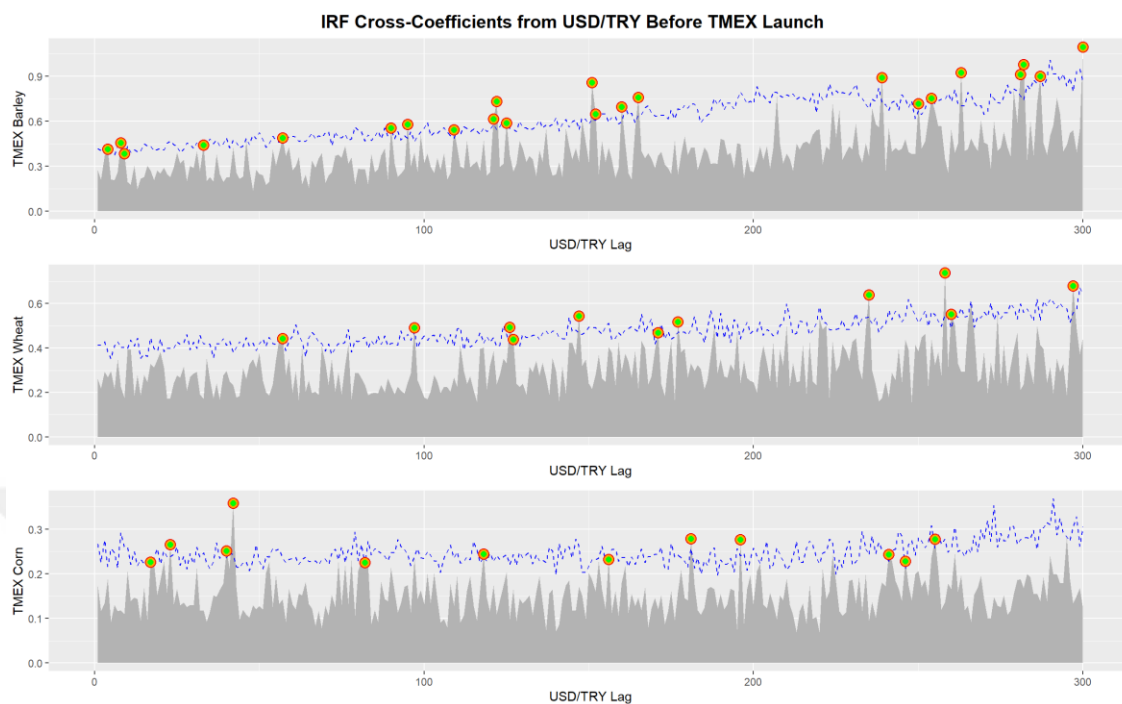


Figure 3.20 : IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 0-100%

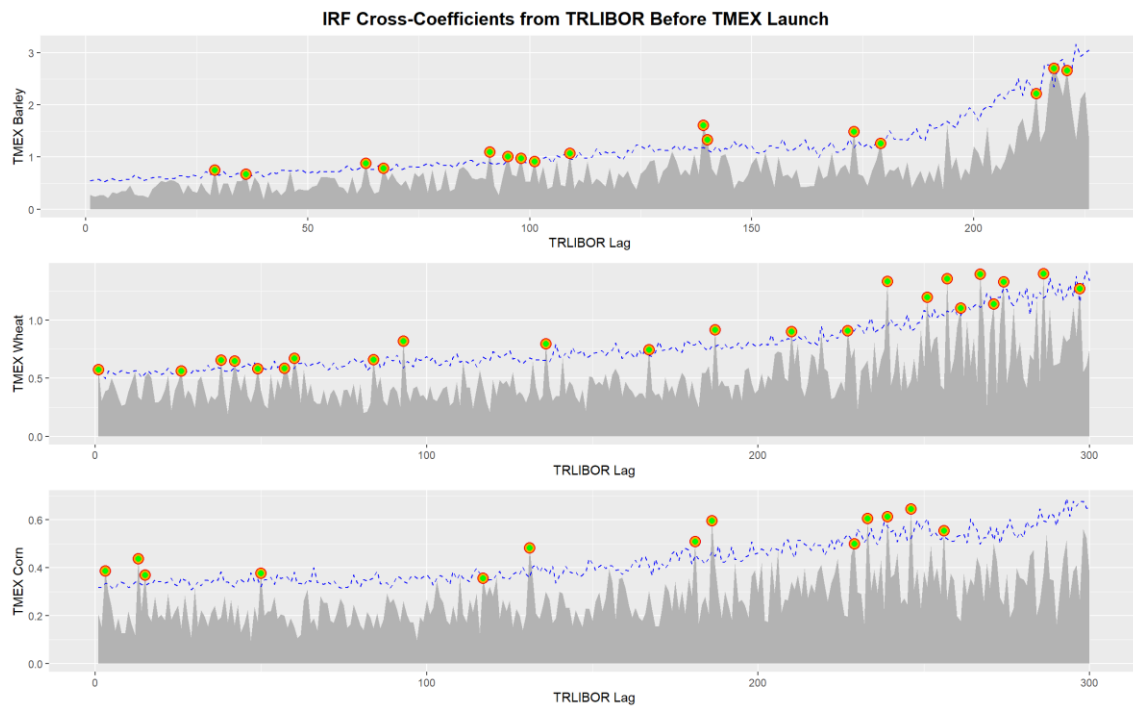


Figure 3.21 : IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 0-100%

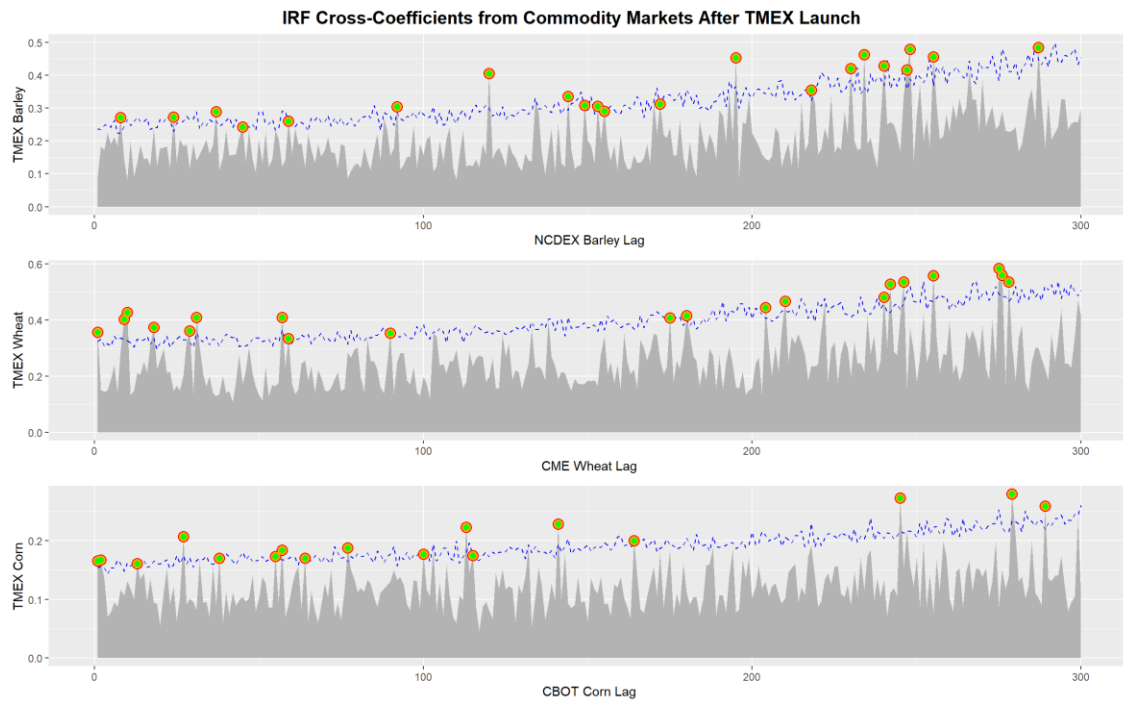


Figure 3.22 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 0-100%



Figure 3.23 : IRF cross-coefficients from lagged Brent oil to Turkish agricultural commodities market measured at quantiles 0-100%

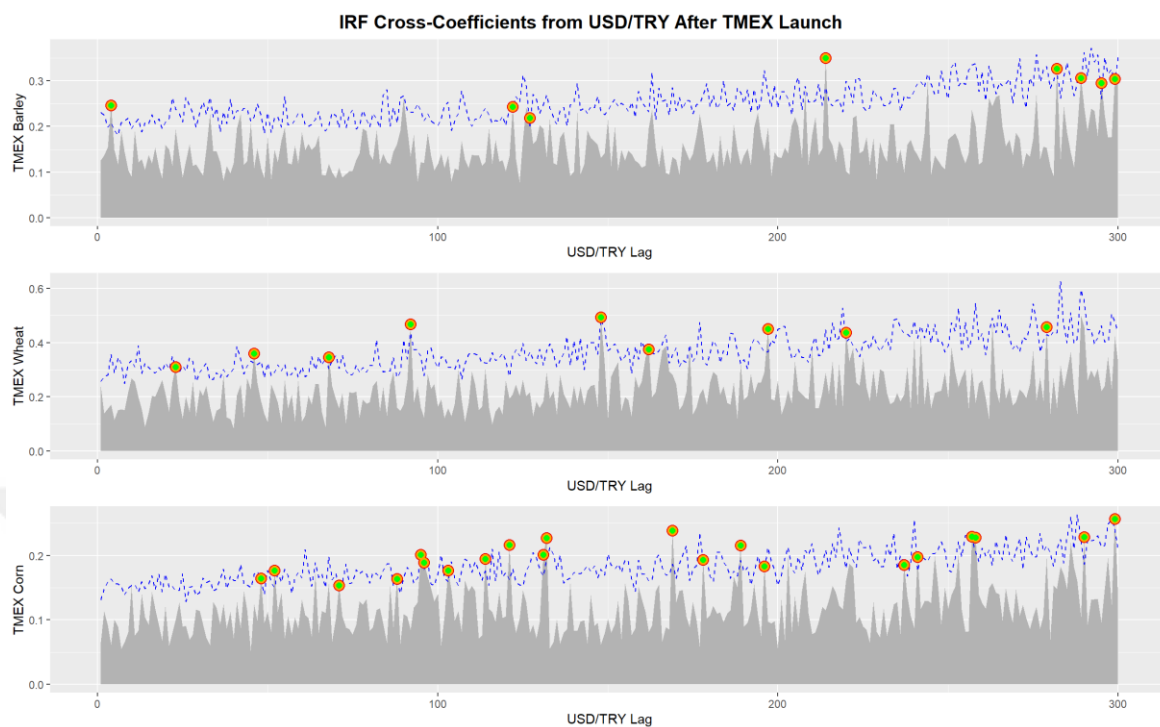


Figure 3.24 : IRF cross-coefficients from lagged USD/TRY exchange rate to Turkish agricultural commodities market measured at quantiles 0-100%

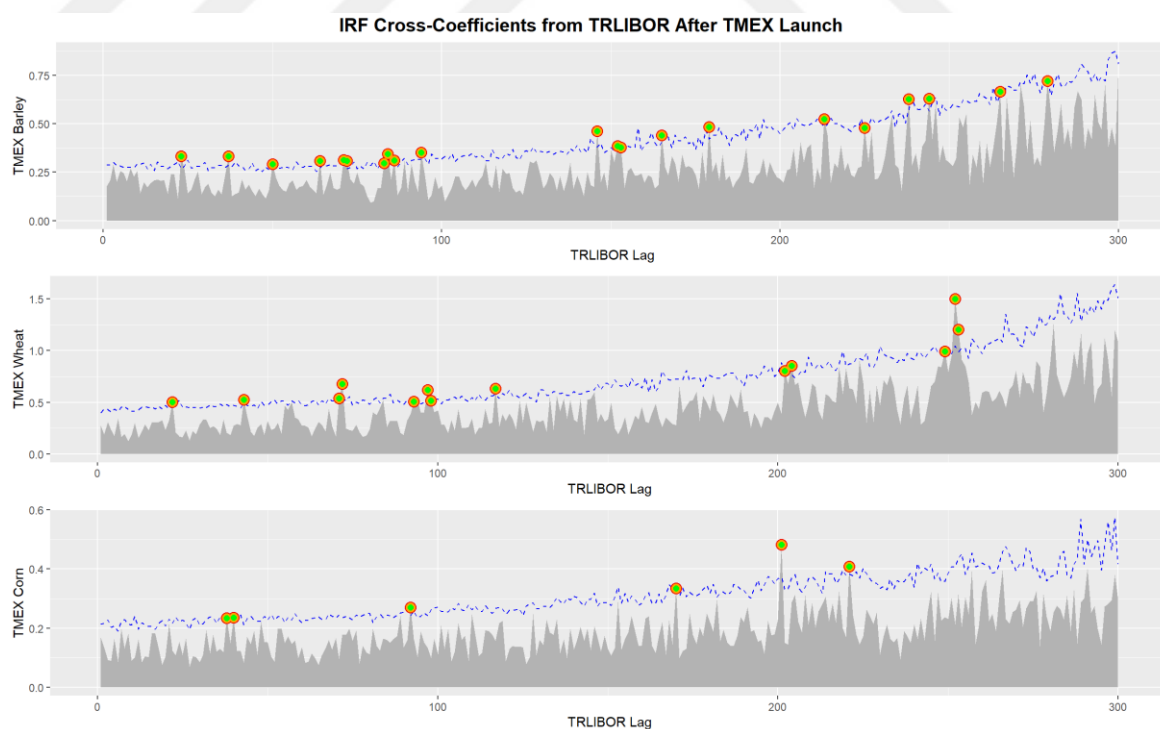


Figure 3.25 : IRF cross-coefficients from lagged TRLIBOR to Turkish agricultural commodities market measured at quantiles 0-100%

3.5.2. Before and after the war in Ukraine

The conflict between Russia and Ukraine significantly impacted commodity prices, especially agricultural commodities, causing disruptions in the supply chain and trade. This conflict led to a global food crisis, resulting in vessels being stranded in Black Sea ports and a surge in commodity prices. The FAO Food Price Index increased swiftly from approximately 140 (February 2022) before the Russian invasion to 160 (March 2022). However, the resolution brought about by the signing of the Black Sea Grain Corridor Agreement between Russia and Ukraine on July 22, 2022, played a pivotal role in alleviating the food crisis during the 2022/2023 harvest season. Consequently, the FAO Food Price Index witnessed a decline, reaching a level even lower than its value in February 2022. Similarly, the IGC Wheat Index experienced a significant decrease, dropping below its value at the beginning of 2022.

In the TMEX market, the average price of wheat initially surged to over TL/ton 5000 (USD 301), significantly higher than the value of approximately TL/ton 4000 (USD 290) observed before February 2022. Due to geopolitical risks and apprehensions regarding the accessibility of grains from the Black Sea region, prices hovered around TL/ton 6500 (USD 360) during the harvest season in June and July. This was an unexpected scenario despite the increase in supply. However, following the Grain Corridor Agreement in July, prices stabilized, maintaining levels around TL/ton 6500–7,000 (USD 360–390), aligning with the support purchase price set by the Turkish Grain Board.

To explore this impact, the data was divided into two segments: pre and post-February 2022. Figures 3.26-3.28 display nonlinear correlograms for the period preceding this date, while Figures 3.29-3.31 portray the correlograms for the period following February 2022. Before February 2022, the lasting impact of US commodity return lags is evident, affecting current returns for Turkish commodities in both the lower and upper tails, as illustrated in Figures 3.26 and 3.27. Furthermore, Figure 3.28 demonstrates significant and persistent mean dependence among commodity markets during this period. Post-February 2022, persistent left- and right-tail dependence is observed for corn (Figures 3.29 and 3.30), although this dependence is not as pronounced for wheat and barley. This observation may be attributed to the brevity of the period and, consequently, the operating

logic of the methodology. Nonetheless, the findings demonstrate a significant and persistent mean dependence for each commodity.

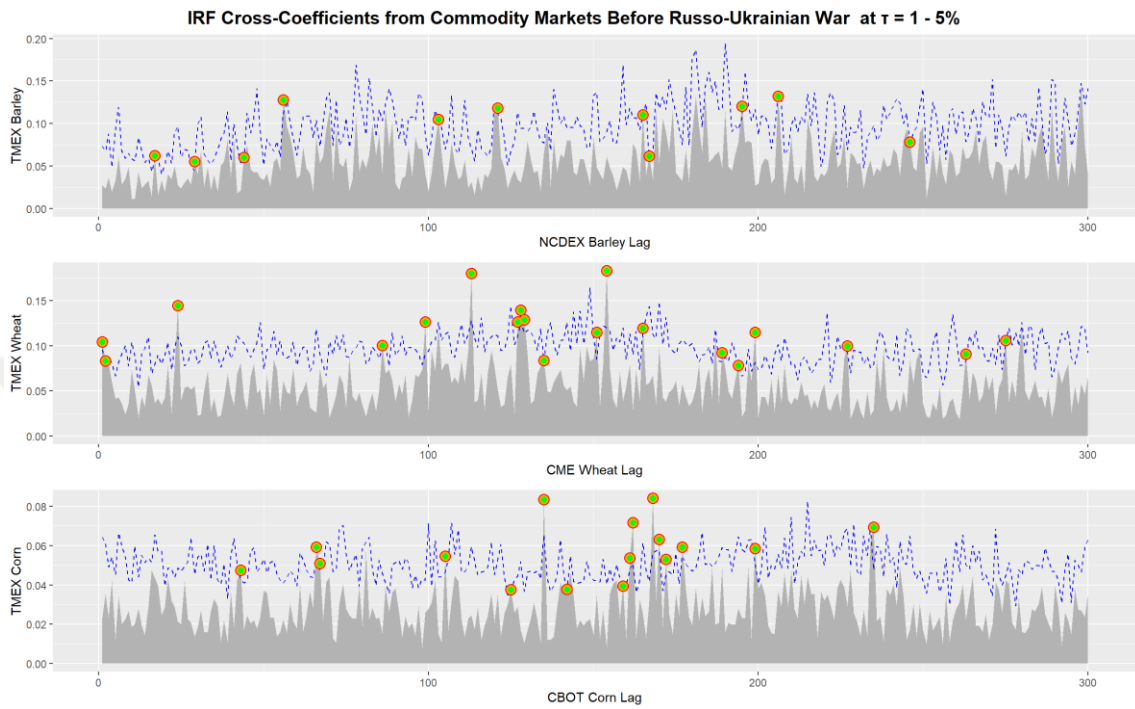


Figure 3.26 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 1-5%

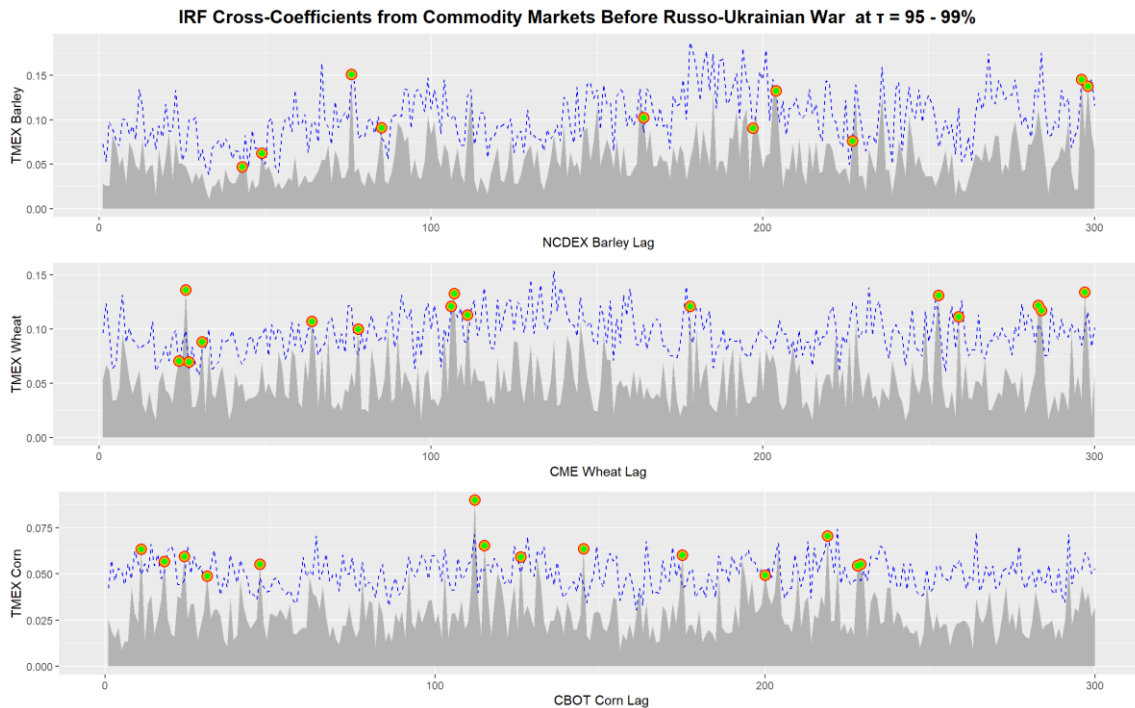


Figure 3.27 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 95-99%

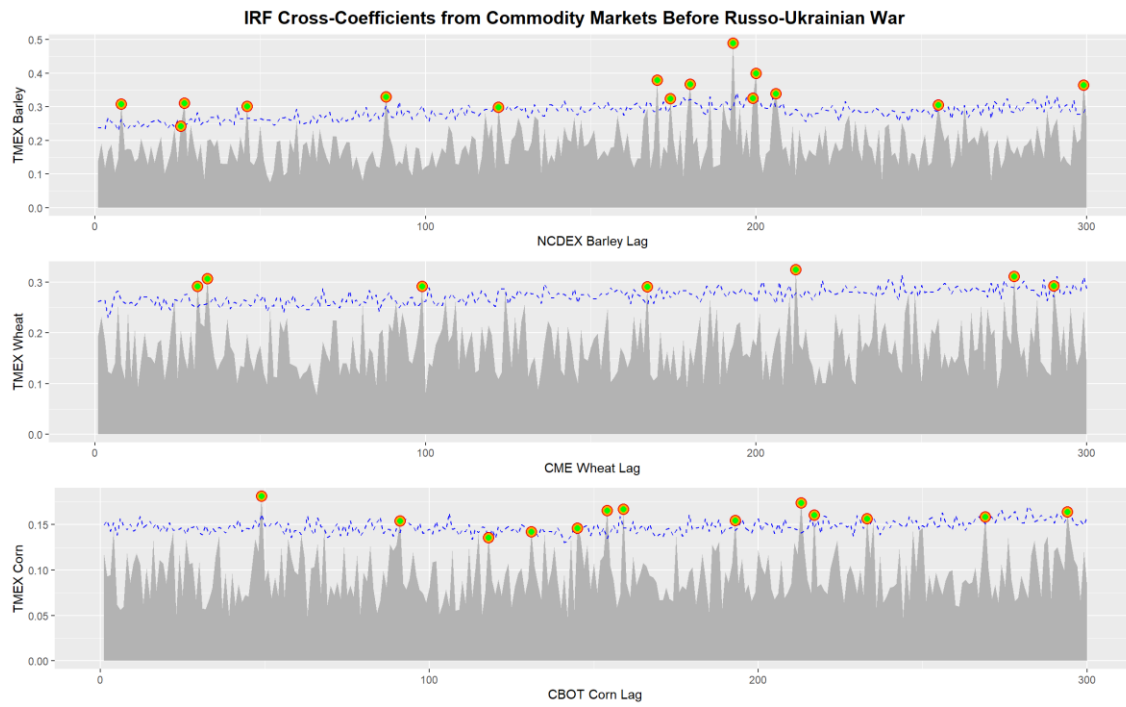


Figure 3.28 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 0-100%

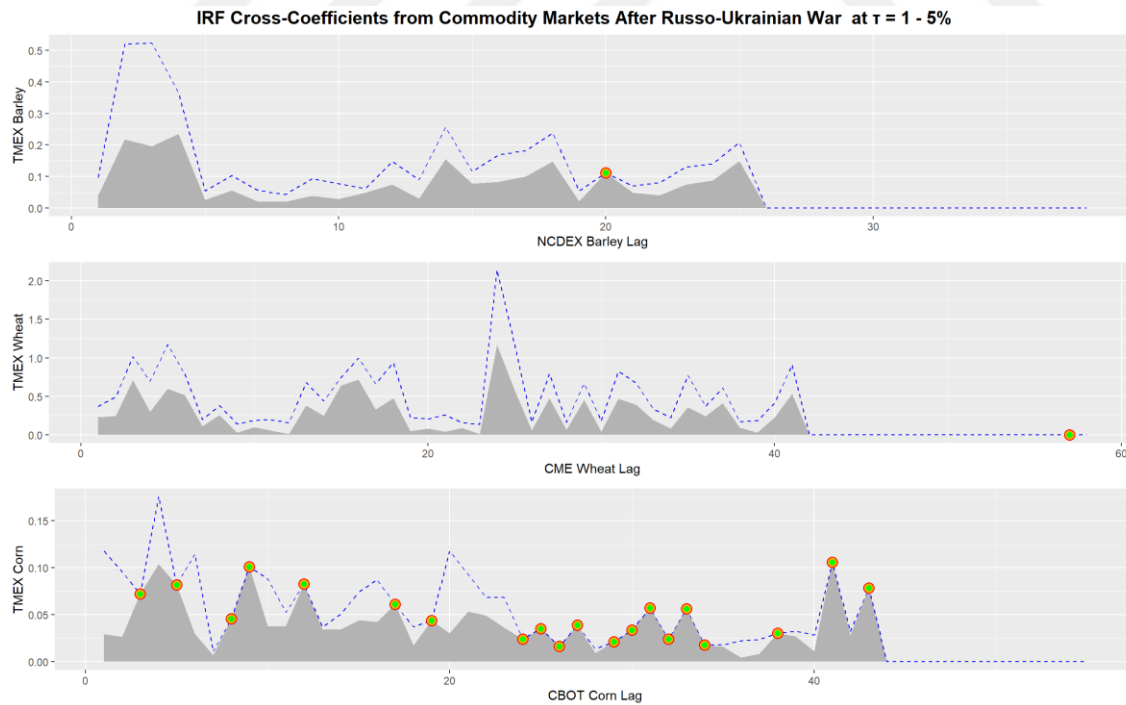


Figure 3.29 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 1-5%

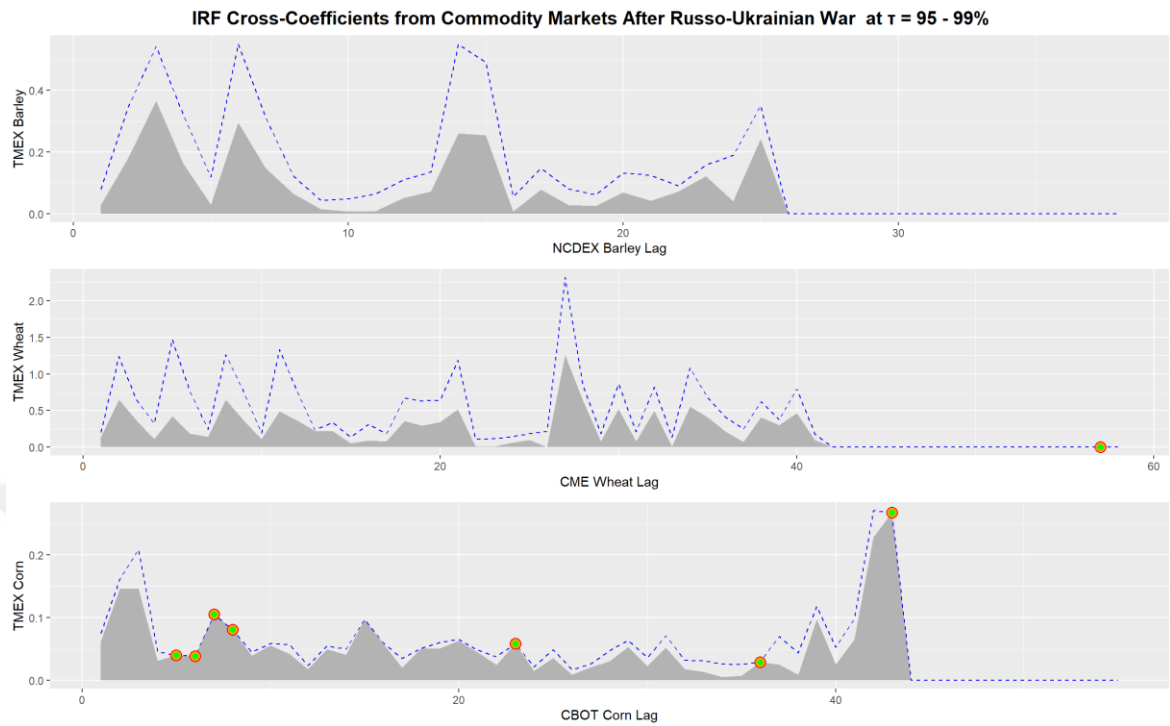


Figure 3.30 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 95-99%

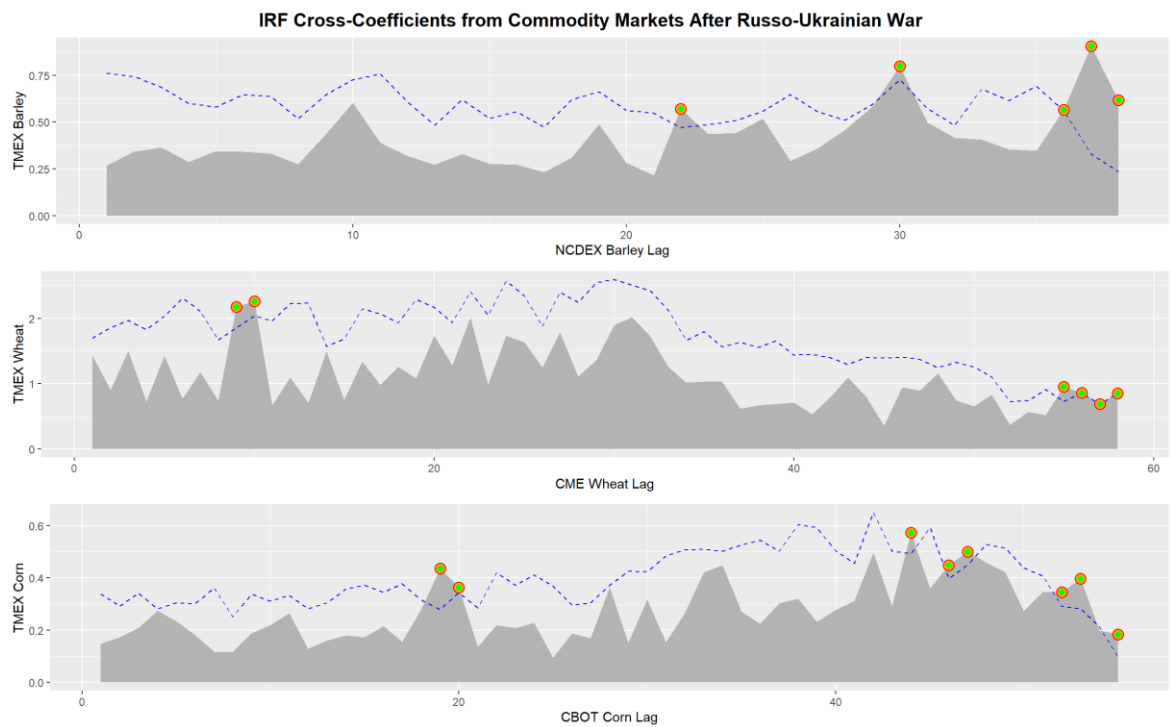


Figure 3.31 : IRF cross-coefficients from lagged commodity markets to Turkish agricultural commodities market measured at quantiles 0-100%

3.6. Robustness Check

For a robustness check, the nonparametric test for Granger causality in distribution, which extends the kernel-based Granger-causality test in a tail event by Candelon and Tokpavi (2016), is employed. This flexible test determines Granger causality or predictability within specific parts of a series distribution, such as the tails or the center. Following the methodology of Candelon and Tokpavi (2016), an AR(1)-GARCH(1,1) model is utilized to evaluate time-varying VaR for conducting the test. The 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, are set. The choice of truncation parameter M followed the $[1.5T^{0.3}]$ definition, where T represents the number of observations.

Tables 3.3 and 3.4 present the test statistics indicating the rejection of the null hypothesis of no Granger predictability. The outcomes reveal both upside and downside risk spillovers, or contagion, from US agricultural commodities, Brent oil, and macroeconomic variables to Turkish agricultural commodities. Additionally, the findings demonstrate dynamic interactions among commodities during normal days, as represented by the center of the distribution, which reflects predictability-in-mean.

Table 3.3 : Test statistics of Granger-causality test for agricultural commodity markets

Predictability direction	Before <u>TMEX</u> Launch	After <u>TMEX</u> Launch	Before Russo- Ukrainian War	After Russo- Ukrainian War
CME Wheat ^L → TMEX Wheat ^L	629.9852***	-938.4193***	-1707.8***	-11253.75***
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***	-10169.66***	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***	11782.83***
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 3.4 : 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	Predictability direction	Before Tmex Launch	After Tmex Launch
Brent Oil ^L → TMEX Wheat ^L	-391.673***	-1591.672***	USD/TRY ^L → TMEX Wheat ^L	-41.6831***	-69.08312***	TRLIBOR ^L → TMEX Wheat ^L	-40.8105***	529.6349***
Brent Oil ^R → TMEX Wheat ^R	-576.0026***	347.8277***	USD/TRY ^R → TMEX Wheat ^R	-15.51461***	-1504.436***	TRLIBOR ^R → TMEX Wheat ^R	397.509***	-11.22755***
Brent Oil ^C → TMEX Wheat ^C	-326.6098***	356.3131***	USD/TRY ^C → TMEX Wheat ^C	1353.317***	846.7028***	TRLIBOR ^C → TMEX Wheat ^C	79.387***	572.077***
Brent Oil ^L → TMEX Barley ^L	724.5868***	376.9838***	USD/TRY ^L → TMEX Barley ^L	1364.604***	655.5472***	TRLIBOR ^L → TMEX Barley ^L	724.5868***	-663.2243***
Brent Oil ^R → TMEX Barley ^R	-169.6636***	-620.7078***	USD/TRY ^R → TMEX Barley ^R	523.9209***	-620.7078***	TRLIBOR ^R → TMEX Barley ^R	-859.064***	-1155.733***
Brent Oil ^C → TMEX Barley ^C	234.5062***	934.2144***	USD/TRY ^C → TMEX Barley ^C	2921.266***	2656.313***	TRLIBOR ^C → TMEX Barley ^C	225.3087***	117.7063***
Brent Oil ^L → TMEX Corn ^L	594.7447***	-1155.733***	USD/TRY ^L → TMEX Corn ^L	1047.987***	-69.35334***	TRLIBOR ^L → TMEX Corn ^L	1354.986***	-971.3194***
Brent Oil ^R → TMEX Corn ^R	-514.6347***	331.0896***	USD/TRY ^R → TMEX Corn ^R	847.5424***	331.0896***	TRLIBOR ^R → TMEX Corn ^R	-91.1036***	-111.7116***
Brent Oil ^C → TMEX Corn ^C	188.2887***	645.7794***	USD/TRY ^C → TMEX Corn ^C	1154.008***	2000.264***	TRLIBOR ^C → TMEX Corn ^C	781.9038***	275.9746***

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.

3.7. Discussion and Policy Suggestion

The introduction of TMEX on July 26, 2019, marked a series of subsequent events: the onset of the Covid-19 pandemic in 2020, a severe drought aggravated by global warming in 2021, and the Russian invasion of Ukraine in 2022. These occurrences reveal that the agricultural commodity market behaves similarly to the financial market in times of stress. Heightened interdependence and potential contagion amplify volatility and escalate tension within the financial and commodity markets.

The derivatives market presents essential tools for managing risks in price discovery and future market conditions. Both spot and derivatives markets play significant roles in discovering spot and forward prices. The study findings indicate that previous and recent returns of US barley, wheat, and corn futures exert influence on current TMEX spot market returns for these commodities. Hence, initiating a local derivative market could be a prudent move for policymakers aiming to establish an effective local commodity market and enhance risk management strategies. Integrating both spot and derivatives markets contributes to local market efficiency and enhances the analysis of price discovery, offering policymakers and market participants valuable insights. These insights can aid in crafting incentives that improve sustainability and efficiency within the agricultural

market. Based on the empirical results, the following comprehensive policy recommendations are proposed.

The research findings indicate that previous and recent returns of US barley, wheat, and corn futures significantly impact the current TMEX spot market returns for barley, wheat, and corn. Thus, initiating a local derivatives market could serve as crucial instruments for managing risks associated with future price discovery and risk management within the Turkish agricultural market. This step would assist market participants in more effectively mitigating price risks while boosting the overall efficiency of the market.

The study underlines the contribution of both spot and derivatives markets to spot and forward price discovery. To improve price discovery and efficiency in the agricultural market, policymakers should concentrate on fostering the flow of information between these markets. This can be accomplished through measures such as enhancing market infrastructure, increasing market transparency, and facilitating market participants' access to both spot and derivatives markets.

The analyses show significant and persistent tail dependence and mean dependence among different markets, encompassing US agricultural markets, Brent oil, USD/TRY exchange rates, and TRLIBOR, concerning the Turkish agricultural market. During challenging periods like the Covid-19 pandemic, instances of global warming-induced drought, and geopolitical tensions, policymakers must diligently oversee these interconnectedness and contagion risks. This proactive monitoring approach can assist in recognizing potential weaknesses, implementing measures, and formulating policies to effectively manage risks. It will also contribute to stabilizing the agricultural market and averting systematic crisis.

The results indicate that different commodities display varying degrees of tail dependence and mean dependence with other markets. To address these differences, policymakers and market participants need to diversify their risk management strategies. This diversification might involve employing a blend of conventional risk management tools like futures contracts and insurance, along with exploring innovative risk management approaches like weather derivatives or index-based insurance. These methods are crucial for effectively handling risks associated with tail and mean dependence among markets.

The establishment of TMEX and the subsequent occurrences emphasize the necessity for a sustainable and effective agricultural market. Policymakers ought to concentrate on implementing incentives and initiatives that advance sustainability and efficiency in this market. These may encompass bolstering agricultural research and development, advocating sustainable farming techniques, upgrading market infrastructure, fostering transparency within the market, and delivering education and training opportunities for market participants.

Given the significant tail dependence found among variables, especially concerning the market cap size, book-to-market ratio, and momentum portfolios, policymakers and practitioners should prioritize the adoption of robust risk management practices. Insights into directional connectedness and understanding the markets' roles in transmitting and receiving risk will assist in formulating suitable policies (Derindere Köseoğlu, 2023). Strategies might involve diversifying investments, employing risk mitigation techniques, and utilizing risk management tools to alleviate potential downside risks.

In light of the significant return and volatility spillovers observed across various markets, policymakers and regulators ought to strengthen their monitoring and surveillance initiatives to meticulously observe interconnections between markets and potential contagion effects. This may involve routine monitoring of market dynamics, recognizing early indicators of potential risks, and promptly taking measures to alleviate them.

3.8. Conclusion

The tail-dependence methodology is utilized to measure tail and mean dependence from the US agricultural market, Brent oil, USD/TRY currency rate, and overnight interest rates to the Turkish agricultural market. These analyses allow for the assessment of both upside and downside asymmetric risk spillovers concerning tail dependence within the period spanning January 5, 2016, to May 31, 2022, which covers periods both prior to and following the TMEX launch on July 26, 2019, as well as before and after the Russian invasion of Ukraine on February 24, 2022.

Significant and persistent lower and upper tail dependence is evident from US commodity markets to Turkish agricultural commodities during the period preceding the TMEX

launch. Both lower and upper quantiles display persistent tail dependence between Brent oil and Turkish agricultural commodities. Notably, we detect robust and sustained tail dependence between the USD/TRY exchange rate and various commodities, especially in the lower quantile for each. Specifically, the USD/TRY exchange rate significantly impacts TMEX wheat and TMEX corn within the upper quantile over an extended period. Furthermore, the analysis of tail dependence indicates substantial and persistent lower and upper tail relationships from TRLIBOR to TMEX corn, and a pronounced upper tail dependence to TMEX wheat. However, there is relatively limited evidence of tail dependence from TRLIBOR to TMEX barley for both tails.

In the period preceding the TMEX launch, significant and persistent lower and upper tail dependence are observed from the US commodity markets to Turkish agricultural commodities. Brent oil displays persistent tail dependence on Turkish agricultural commodities for both lower and upper quantiles. The USD/TRY exchange rate exhibits significant and persistent tail dependence, particularly affecting TMEX wheat and TMEX corn in the upper quantile for a prolonged period. Further analysis demonstrates significant and persistent lower and upper tail dependence from TRLIBOR to TMEX corn, while displaying strong upper tail dependence on TMEX wheat. However, the evidence of tail dependence from TRLIBOR to TMEX barley for both tails is relatively scarce.

The results following the TMEX launch reveal significant and persistent tail dependence between each agricultural commodity pair in both the lower and upper quantiles. Significant initial lags in wheat and corn indicate that recent US wheat and corn returns affects current TMEX wheat and corn returns. Moreover, there is evidence of lower and upper tail dependence from both Brent oil returns and the USD/TRY exchange rate to the Turkish commodities market. Additionally, the study indicates pronounced tail dependence from TRLIBOR to TMEX corn, particularly in both tails.

The results regarding mean dependence indicate persistent mean dependence from US commodities to Turkish commodities for the pre-TMEX launch period. Following the TMEX launch, mean dependence amplifies, especially for barley and wheat. Similarly, the mean dependence from Brent oil and the USD/TRY exchange rate to Turkish commodities is also significant and persistent for both periods. Furthermore, there is a

significant and persistent impact of TRLIBOR on the Turkish commodities market. However, the strength of mean dependence for wheat and corn is more pronounced before the TMEX launch compared to the period afterward.

The IRF results during the period preceding the Russian invasion in February 2022 indicate significant and persistent tail and mean dependence from US commodities to Turkish commodities. Following February 2022, strong tail dependence is observed in both tails specifically for corn. Moreover, significant mean dependence is identified across all pairs of agricultural commodities. Additionally, the nonparametric test of Granger causality in distribution demonstrates significant outcomes, indicating Granger predictability for each commodity and period.

The results show an impact from past and recent US wheat and corn future contract price changes on current TMEX spot market wheat and corn returns. This highlights the potential benefits of initiating a local derivatives market for hedging and managing risks within the Turkish agricultural market. Policymakers should prioritize fostering information flow between spot and derivatives markets to improve the market's overall efficiency. Notably, significant and persistent tail dependence and mean dependence exist among various markets, urging policymakers to closely monitor these interconnections and contagion risks, especially during challenging periods. As commodities display varying degrees of dependence on other markets, it might be essential to devise strategies for diversifying risk management.

Events following the introduction of TMEX emphasize the necessity for a sustainable and efficient agricultural market. The empirical findings indicate the importance for policymakers to concentrate on instituting a local derivatives market, facilitating information flow between spot and derivatives markets, monitoring tail and mean dependence across markets, and diversifying risk management strategies. These steps are crucial for advancing sustainability and enhancing overall market efficiency within the Turkish agricultural sector.



4. NONLINEAR TAIL DEPENDENCE FROM ENERGY TO AGRICULTURAL COMMODITIES

4.1. Introduction

The world faces an energy and food security crisis alongside disruptions in supply chains. Climate change, extreme weather conditions, and the conflict between Ukraine and Russia have driven up agricultural commodity prices. The disruption in food import and export channels has also contributed to the global surge in food prices and increased volatility (Espitia et al., 2022). Rising energy prices have further amplified these price surges, pushing them to unprecedented levels. As agricultural facilities, vehicles, and machinery necessitate higher energy consumption during production, the upsurge in energy commodity prices has increased the overall cost of farming, consequently elevating agricultural commodity prices. Consequently, food prices surged by 84 percent from April 2020 to March 2022, marking the most substantial increase since 2008 (CMO, 2022).

Disruptions in the global food system have significant ramifications as fluctuations or increases in food prices profoundly impact household purchasing power, particularly among the most impoverished, exacerbating global hunger issues. Countries facing food insecurity, low-income nations, and those heavily reliant on food, fuel, and agricultural input imports are particularly susceptible (FAO, 2022). According to the Global Report on Food Crises (2022), hunger levels in 2021 surpassed all historical records, with approximately 193 million individuals experiencing severe food insecurity—an increase of around 40 million from the previous peak in 2020. Moreover, past research studies (Choi et al., 2018; Lòpez-Villavicencio and Pourroy, 2019; Yilmazkuday, 2021, etc.) have illustrated a positive correlation between energy prices and consumer prices, heightening the vulnerability of at-risk groups. For instance, Yilmazkuday (2021) demonstrated that

the estimated transmission of oil prices to consumer prices stands at approximately 4.2% in the long term.

Given that agricultural commodity prices significantly impact food security and malnutrition, while energy commodities play a pivotal role in agricultural production, understanding the interdependence between energy and agricultural commodities is crucial in devising proactive measures to safeguard the well-being of nations.

Moreover, as demand for the commodity derivative market grows, it becomes an essential part of portfolios, offering diversification and hedging advantages, which contributes to the financialization of the agricultural commodity market. This increased interconnections among agricultural commodities and other markets leads to heightened risk transmission and contagion effects. Additionally, as global market integration deepens, the agricultural commodity market becomes more exposed to speculation and heightened price volatility. Understanding the relationship between energy and agricultural products holds considerable importance for financial entities in managing price risks. The concept of tail dependence has garnered significant attention due to its potential in extreme market scenarios where significant price movements in one market might impact prices in others or cause simultaneous collapses across multiple markets. Hence, besides traditional correlation-based measures, a multitude of tail dependence measures has emerged to scrutinize price dynamics and interdependence during extreme market events. Conventional correlation-based methods have limitations, assessing tail dependence symmetrically and employing linear models on nonlinear data. Many time series exhibit nonlinear characteristics such as nonnormality, asymmetric cycles, bimodality, and nonlinearity among lagged variables (Fan and Yao, 2005). Furthermore, conventional multivariate approaches might struggle in tail risk assessment, given that joint tail analysis contradicts the assumption of multivariate normality underpinning these methods. (Krupskii and Joe, 2019). In this respect, utilizing parametric measures in nonlinear time series for examining nonlinear dependence patterns may be inadequate; therefore, employing nonparametric measures is crucial as they offer a better fit to the data and greater flexibility in modeling tail dependence.

In this study, Escanciano and Hualde's (2021) nonparametric tail dependence measure is utilized to examine the nonlinear linkage between energy and agricultural commodities. This method offers a comprehensive understanding of tail events by considering a continuum of quantiles, rather than solely focusing on whether a market surpasses or falls below a certain quantile value. The measure addresses significant variations and the limited information about tail risk concerning marginal expected shortfalls and exceedance correlations. Importantly, this approach avoids the need for model estimation or assumptions regarding the distribution of model residuals. Its adaptability across different parts of the time series distribution is another noteworthy advantage. Furthermore, it provides an easy-to-calculate measure that is interpretable. Notably, it does not rely on smoothing techniques through the employment of Integrated Regression Function (IRF) (Escanciano and Hualde, 2021).

This chapter offers several contributions to empirical literature. Firstly, it examines the tail dependence between energy and agricultural commodity returns, tracing the effects of extreme energy returns on agricultural returns. This investigation employs a recent technique introduced by Escanciano and Hualde (2021), which presents several advantages over existing methods, as detailed earlier. Secondly, it presents significant policy implications not only for researchers and policymakers but also for investors and portfolio managers aiming to diversify and hedge their portfolios. Thirdly, to the best of our knowledge, this study marks the first exploration focusing on tail dependence between energy and agricultural returns across pre-, during, and post-Covid-19 periods and conducts analyses for both the lower and upper quantile continuums.

4.2. Literature Review

The review of existing literature reveals the increasing concerns surrounding rising agricultural commodity prices and their potential adverse impact on food security. Scholars have intensified their research efforts to understand the factors contributing to fluctuations in agricultural commodity prices, such as changes in exchange rates, climate change, and governmental policies. Especially, among these factors, global oil price hikes stand out as a prominent factor of changes in agricultural commodity prices. A

considerable body of literature has focused on exploring the connections between energy and agricultural commodity markets.

Since the initial surge in global oil prices during the early 1970s, researchers have extensively deliberated on the repercussions of oil price fluctuations on various sectors, including commodity prices. This extensive body of research has employed diverse methodologies to examine the correlation. The sharp increase in global food prices, which more than doubled from 2007 to 2008, has particularly attracted significant attention, resulting in a surge of scholarly works in subsequent years.

An extensive body of empirical research has thoroughly examined the relationship between energy and agricultural commodity prices across various markets. Given oil's prominent status as a primary energy commodity, its profound impact on nearly all other commodities through energy costs, ultimately shaping production costs, is evident. Consequently, oil prices have been observed to exhibit a spillover effect on all commodity markets, yet the findings have been mixed. Some studies indicate dependence between oil and different commodities, while others suggest interdependence. For instance, Esmaili and Shokoohi (2011) explored the relationship between the food price index, oil price index, and macroeconomic index, identifying significant impacts of both oil price and macroeconomic indices on the food price index. Nazlioglu and Soytas (2011) delved into the nonlinear causality between oil and specific agricultural commodities, discovering persistent nonlinear causality from oil to certain agricultural commodities. Additionally, Nazlioglu et al. (2013) examined volatility spillover between oil and specific agricultural commodities before and after the 2006–2008 crisis, indicating no risk transmission during the pre-crisis period but substantial shifts in volatility dynamics post-crisis. Similarly, Wang et al. (2014) suggested that oil shocks could potentially explain minor changes in agricultural commodity prices pre-crisis, while its explanatory power significantly increased during and after the crisis. The demand side predominantly drove fluctuations in agricultural prices pre-crisis. Avalos (2014) highlighted that oil prices became a significant factor in specific agricultural commodity markets after the enactment of the Energy Policy Act of 2015 in the US, establishing a tangible connection between oil and agricultural commodity markets and fostering bidirectional feedback causality.

Moreover, Koirala et al. (2015) emphasized the influence of biodiesel, diesel, corn oil, and gasoline prices on energy producers, which indicated a high correlation between agricultural and energy futures, signifying a substantial relationship. Correspondingly, an increase in energy prices has been linked to a rise in agricultural commodity prices. Additionally, Kapusuzoğlu and Ulusoy (2015) observed a causal relationship from Europe Brent and WTI oil to specific agricultural commodities. Lucotte (2016) and De Nicola et al. (2016) documented positive co-movement between crude oil and agricultural commodity prices, particularly post-crisis, underlining a strong correlation. Similarly, Pal and Mitra (2017, 2018) noted substantial co-movements and positive interdependence between crude oil and global food prices. Other works by Meyer et al. (2018), Fasanya et al. (2019), and Judit et al. (2017) also highlighted significant and positive relationships between global oil price increases and agricultural commodity prices. However, Zmami and Ben-Salha (2019) indicated that only positive long-run oil price shocks affect global food prices, while Zafeiriou et al. (2018) found that crude oil impacts agricultural products used in bio-energies like ethanol. Additionally, Meng et al. (2020) discovered a lesser impact of upside crude oil price variations on Chinese commodity prices compared to downside variations. Mokni and Youssef (2020) revealed that the effect of lagged prices of global crude oil on agricultural commodities is lower than sudden variations.

The bounds test for cointegration conducted by Wong and Shamsudin (2017) indicated an asymmetric long-term impact of crude oil on food price changes. Similarly, Gokmenoglu et al. (2020), employing cointegration and causality tests, explored the association between Nigerian agricultural commodity prices and global oil prices. Harri et al. (2009), utilizing the cointegration test, uncovered that fluctuations in oil prices influence the prices of corn, cotton, and soybeans. Yip et al. (2020) used the VAR model and concluded that the stability of the impact of oil price fluctuations on agricultural commodities depends on the levels of volatility in oil prices. Some studies, such as those by Sun et al. (2021) and Hung (2021), detected a two-way causal link between global oil prices and agricultural commodity prices. On the other hand, Zhang and Reed (2008) investigated causality from world oil prices to China's agricultural commodity market, finding no evidence of co-movement. Fowowe (2016) found no relationship between agricultural commodity markets in South Africa, supporting the neutrality hypothesis. Considering

these studies and the methodologies employed to assess the relationship between oil price changes and agricultural commodity prices, it can be deduced that the direction and strength of the effect of global oil price fluctuations on agricultural commodity prices differ based on the country and the persistency of these effects.

Alternatively, other studies have categorized the effects of oil price fluctuations into distinct types: supply-side shocks and demand-side shocks (Yasmeen, 2019). Supply-side shocks predominantly arise from global oil price increases and the consequent rise in agricultural commodity prices due to events like droughts and climate change (Hochman et al., 2014). Conversely, demand-side shocks emerge from various factors such as population growth, increasing household incomes, currency devaluation, and the production of biofuels like ethanol (Wang et al., 2018; Lima et al., 2019). Furthermore, Garcia et al. (2020) emphasized the negative influence of the Covid-19 pandemic on global crude oil demand, resulting in subsequent price reductions. Paris (2018), on the other hand, attributes the surge in biofuel production to the rise in agricultural commodity prices.

Kaltalioglu and Soytaş (2011) conducted an analysis on the fluctuation of the oil, food consumption, and agricultural raw materials price index from 1980 to 2008. Utilizing the Cheung–Ng approach, their findings indicated the absence of Granger causality from oil to the price indices of food consumption and agricultural raw materials. Du et al. (2011) constructed stochastic volatility models and observed that after 2006, the interdependence among crude oil, corn, and wheat markets intensified. Jiang et al. (2015) investigated the fluctuations in the oil, corn, and plastics markets in the USA. Their study highlighted a similar long-term trend between corn futures prices and variations in crude oil prices affecting corn prices. Similarly, Zhang and Qu (2015) explored the impact of oil price shocks on agricultural commodities in China, revealing diverse effects of oil price shocks on different agricultural commodities. Lastly, employing a hybrid approach combining wavelet and copula methods, Mensi et al. (2017) unveiled a dependence linkage among oil, wheat, and corn.

4.3. Methodology

Dependence measures involve computing the covariance or correlation between two random variables across their entire distribution or specific segments of the distribution, elucidating the association between these variables. Measures focusing on the complete distribution, such as mean dependence, fail to capture the relationship between extreme values of random variables. Conversely, tail-dependence measures offer insights into the dependence of the upper or lower segments of the distribution. In a bivariate distribution, tail-dependence measures determine the covariance or correlation between random variables when the marginal distribution of one variable surpasses a defined threshold, under the condition that the margin of the other variable also exceeds the same threshold (AghaKouchak et al., 2013). This concept refers to the occurrence of extreme events happening simultaneously.

To evaluate tail dependence comprehensively, the analysis employs a recently developed nonlinear measure of tail dependence introduced by Escanciano and Hualde (2021). This measure stands out due to its distinct advantages over existing methods in the literature. Unlike tail-dependence measures based on copulas, this method extends traditional linear correlation measures into a nonparametric framework. It does not necessitate model estimation or assumptions regarding the distribution of model residuals, offering greater flexibility in managing various parts of the time series distribution. Additionally, it accommodates significant variances and limited information on tail risk associated with marginal expected shortfalls and exceedance correlations. Its ease of estimation and interpretation is another aspect. This measure covers a range of tail market events rather than solely focusing on individual occurrences, providing a more comprehensive understanding of tail dependence and systemic risk. Moreover, it avoids smoothing by incorporating the Integrated Regression Function (IRF). Subsequently, a brief explanation of the methodology behind this nonlinear tail-dependence measure follows.

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 (2019) 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:

$$\varphi_{t,h}(y, x) = \text{Cov}(1(Y_{t+h} \leq y), 1(X_t \leq x)) = K_{t,h}(y, x) - L_{t+h}(y)F_t(x), \quad (4.1)$$

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

$$\|\varphi_{t,h}\|_{y_{tail}, x_{tail}} = \sup_{y \leq y_{tail}} \sup_{x \leq x_{tail}} |\varphi_{t,h}(y, x)|. \quad (4.2)$$

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

$$\hat{\varphi}_h(y, x) = \frac{1}{n-h} \sum_{t=1}^{n-h} 1_c(Y_{t+h}, y) 1_c(X_t, x), \quad (4.3)$$

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

$$KS_{n,\bar{x}}(h) := \|\hat{\varphi}_h\|_{\bar{x}}. \quad (4.4)$$

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, 2019); then, the bootstrap p-values are as follows:

$$\hat{p}_{n,\bar{x}}(h) = \frac{1}{R} \sum_{r=1}^R 1(KS_{n,\bar{x}}^{(r)}(h) \geq KS_{n,\bar{x}}(h)). \quad (4.5)$$

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

In brief, the proposed tail-mean dependence measure computes the covariance between two variables under the condition that threshold values are met for both variables, irrespective of whether they are higher or lower. This measure, accounting for a range of quantiles, evaluates the size of covariance using the uniform (sup-) norm. To put it more clearly, initially, quantiles that establish the threshold positions are specified. Subsequently, the process involves sorting the values of the independent variable and identifying where the condition $1(X_t \leq x)$ is met, known as the outer product. Next, the computation entails generating the vector of Integrated Regression Function (IRF) at order statistics by performing matrix multiplication of the deviation from the mean of the dependent variable with the outer product. This result is then divided by the total number of observations. Following this, the values within the threshold positions are extracted from the vector of IRF, and subsequently, the absolute maximum value is determined. This outlined procedure is implemented for each lag of conditioning variables, up to the maximum determined lag.

4.4. Data

The study encompasses Brent oil, natural gas, and gasoline as conditioning variables, while wheat, soybean, corn, cotton, sugar, rice, oat, coffee, and cocoa are regarded as dependent variables. Analysis is conducted across three distinct periods: pre-Covid-19, Covid-19, and post-Covid-19. The sample data cover daily records for seven days a week, ranging from 01.06.2017 to 06.01.2020 for the pre-Covid-19 period, from 07.01.2020 to 26.01.2022 for the Covid-19 period, and from 27.01.2022 to 09.06.2023 for the post-Covid-19 period. The data is retrieved from Refinitiv Eikon. Initially, returns are calculated by employing the logarithmic difference in the price series, after which subsequent analyses are conducted. Detailed information regarding the series used in the study is provided in Table 4.1.

Table 4.1 : Details for data set

Commodity	Currency	Full Name	Measurement Unit
Brent Oil	USD	ICE Europe Brent Crude Electronic Energy Future	Barrel
Natural Gas	USD	NYMEX Henry Hub Natural Gas Electronic Energy Future	Million British Thermal Units
Gasoline	USD	NYMEX RBOB Gasoline Electronic Energy Future	Gallon
Wheat	USD	CBoT Wheat Composite Commodity Future	Bushels
Soybean	USD	CBoT Soybeans Composite Commodity Future	Bushels
Corn	USD	CBoT Corn Composite Commodity Future	Bushels
Cotton	USD	ICE-US Cotton No. 2 Futures Electronic Commodity Future	Weight
Sugar	USD	ICE-US Sugar No. 11 Futures Electronic Commodity Future	<u>Lbs</u>
Rice	USD	CBoT Rough Rice Composite Commodity Future	Cwt
Oat	USD	CBoT Oats Composite Commodity Future	Bushels
Coffee	USD	ICE-US Coffee C Futures Electronic Commodity Future	<u>Lbs</u>
Cocoa	USD	ICE-US Cocoa Futures Electronic Commodity Future	Metric tons

Table 4.2 : Descriptive statistics

Variable	Num. of. Obs.	Mean	Std. Dev.	Max	Min	Skew	Kurt	JB	BDS	ADF	ABP
<i>Panel A- Pre-Covid-19 Period</i>											
Brent Oil	678	0.046	1.822	13.639	-7.436	-0.053	9.285	1116.356***	0.404	-27.813***	0.142
Natural Gas	678	-0.054	2.768	16.506	-18.055	-0.265	10.776	1716.07***	6.178***	-15.271***	0.515
Gasoline	678	0.012	2.162	12.699	-20.234	-1.056	17.873	6375.07***	1.957*	-28.868***	0.367
Wheat	678	0.037	1.745	6.206	-5.716	0.285	3.804	27.45***	2.823***	-25.31***	0.515
Soybean	678	0.003	1.049	4.505	-4.817	0.048	5.034	117.10***	0.659	-26.311***	0.761
Corn	678	0.005	1.331	5.769	-6.287	0.060	5.934	243.59***	2.468**	-25.342***	0.579
Cotton	678	-0.014	1.404	5.350	-10.597	-0.500	8.564	902.76***	3.457***	-27.098***	0.310
Sugar	678	-0.012	1.735	10.814	-5.275	0.411	6.194	307.34***	1.663*	-25.253***	0.114
Rice	678	0.021	1.214	7.249	-6.654	0.168	7.346	536.84***	4.328***	-23.758***	0.058
Oat	678	0.026	2.019	9.835	-10.838	0.101	7.330	530.92***	1.220	-28.024***	0.506
Coffee	678	-0.008	1.798	6.662	-6.400	0.253	3.875	28.89***	2.518**	-27.868***	0.084*
Cocoa	676	0.026	1.820	5.819	-5.339	0.086	3.100	1.12	-0.609	-26.962***	0.235
<i>Panel B- Covid-19 Period</i>											
Brent Oil	537	0.050	3.390	19.077	-27.976	-1.770	22.987	9218.98***	8.692***	-5.518***	0.297
Natural Gas	537	0.129	3.923	19.798	-12.881	0.255	5.521	147.99***	2.570**	-11.098***	0.482
Gasoline	537	0.068	4.074	22.397	-38.535	-2.500	29.678	16483.43***	7.566***	-6.084**	0.982
Wheat	537	0.069	1.717	5.350	-4.269	0.382	3.291	14.95***	-0.384	-24.087***	0.462
Soybean	537	0.081	1.310	6.426	-8.554	-0.579	8.638	741.19***	1.968**	-23.072***	0.903
Corn	537	0.091	1.849	6.208	-19.100	-2.049	25.005	11210.26***	2.495**	-22.17***	0.315
Cotton	537	0.104	1.624	5.422	-5.467	-0.229	3.757	17.52***	1.975**	-23.399***	0.708
Sugar	537	0.055	1.841	6.255	-7.829	-0.022	4.049	24.65***	2.034**	-22.968***	0.108
Rice	537	0.030	2.186	9.802	-29.970	-4.956	71.910	108448.7***	15.061***	-9.507***	0.010**
Oat	537	0.150	1.982	6.364	-21.058	-2.251	26.930	13266.92***	1.858*	-21.335***	0.882
Coffee	537	0.125	2.246	9.557	-9.021	0.253	4.909	87.262***	2.531**	-21.484***	0.204
Cocoa	537	0.002	1.885	11.491	-8.902	-0.127	6.854	333.85***	1.064	-14.845***	0.612
<i>Panel B- Post-Covid-19 Period</i>											
Brent Oil	344	-0.082	2.757	8.429	-14.108	-0.619	5.273	95.998***	0.935	-9.266***	0.136
Natural Gas	344	-0.186	6.009	38.173	-30.048	0.153	8.721	470.537***	1.37	-24.015***	0.059*
Gasoline	344	0.008	3.017	9.920	-15.138	-0.586	5.452	105.852***	-0.448	-17.392***	0.258
Wheat	344	-0.068	2.934	19.701	-11.297	0.762	9.755	687.265***	6.504***	-10.168***	0.327
Soybean	344	-0.011	1.664	4.453	-11.092	-1.369	10.754	969.086***	4.075***	-10.764***	0.113
Corn	344	-0.011	1.813	5.881	-13.992	-1.644	13.890	1854.837***	3.872***	-11.602***	0.422
Cotton	344	-0.109	2.734	6.779	-27.292	-2.759	29.996	10882.59***	3.352***	-16.379***	0.999
Sugar	344	0.092	1.534	4.258	-7.084	-0.403	4.731	52.218***	0.033	-18.239***	0.861
Rice	344	0.068	1.256	3.937	-3.773	0.369	3.955	20.879***	5.178***	-13.030***	0.720
Oat	344	-0.176	3.291	12.659	-34.199	-3.483	37.997	18250.83***	2.068**	-10.009***	0.650
Coffee	344	-0.066	2.294	7.596	-5.873	0.294	3.186	5.466*	-0.7	-18.949***	0.712
Cocoa	344	0.068	1.522	5.445	-5.363	0.019	3.662	6.294**	-0.426	-18.360***	0.001***

Notes: This table reports the number of observations, the mean, median, standard deviation (Std. dev), minimum and maximum values, skewness (Skew), kurtosis (Kurt), and Jarque-Bera (JB) normality test statistic 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.

Table 4.2 displays descriptive statistics representing the returns of both dependent and conditioning variables throughout three distinct periods. Considering the skewness and kurtosis values, all series exhibit asymmetry and leptokurtosis, respectively. Particularly in the Covid-19 and Post-Covid-19 periods, substantial fluctuations are observed in return series, evident from the wide range between minimum and maximum values of variables.

The Jarque-Bera normality test indicates lack of normality in the variables, while the BDS test (Broock et al., 1987) indicates nonlinearity in the majority of the variables. The ADF test confirms the stationarity of all return series. For most series, the ABP (Automatic Box-Pierce) test does not reject the null hypothesis of no serial correlation.

Figure 4.1 presents plots of price series. Notably, there was a significant decline in energy commodity prices at the onset of 2020, primarily attributed to the pandemic's adverse impact on energy demand. This decrease was driven by shifts in demand resulting from economic slowdowns due to Covid-19 restrictions. Subsequent price hikes in global energy commodity prices correlated with the resurgence in energy demand as economic activities and travel gradually resumed. The price upsurge in 2021 was also influenced by supply-related issues, further exacerbated by the Russian invasion of Ukraine in early 2022 (ECB, 2022). Similar price patterns are observed in wheat, soybean, corn, sugar, oat, and coffee. Although initially following Covid-19 patterns in the early post-Covid-19 era, these agricultural and energy commodity prices later experienced declines. Figures 4.2, 4.3, and 4.4 depict correlation matrices for each period.

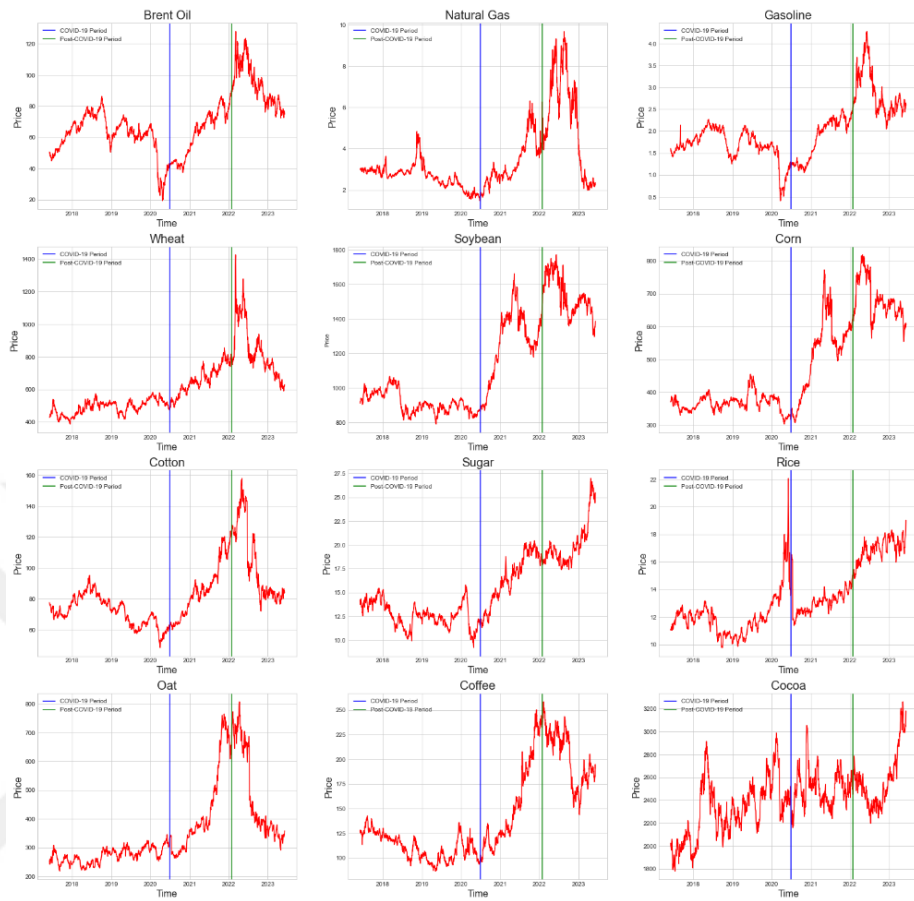


Figure 4.1 : Time series plots of price series

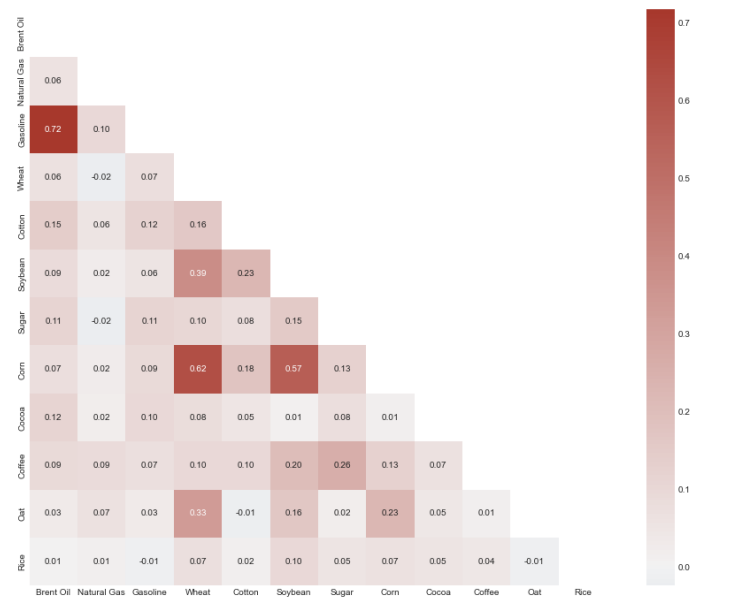


Figure 4.2 : Correlation table for the Pre-Covid-19 period

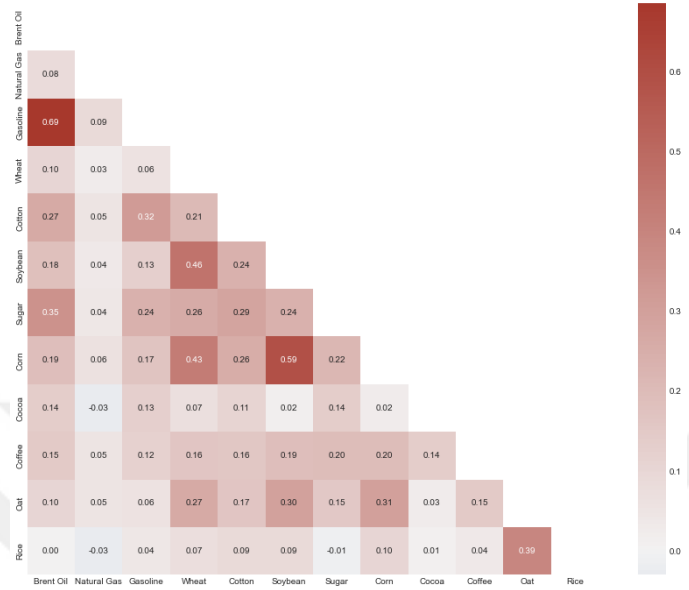


Figure 4.3 : Correlation table for the Covid-19 period

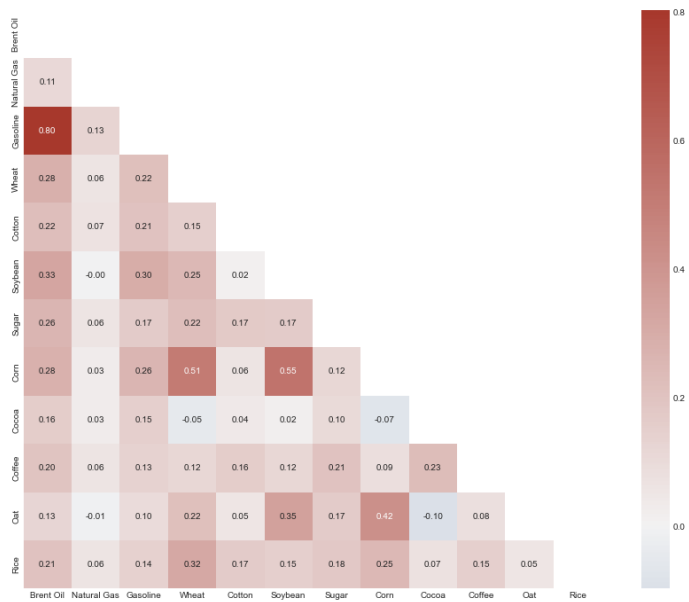


Figure 4.4 : Correlation table for the Post-Covid-19 period

4.5. Empirical Results

Tail dependence is evaluated for both the lower and upper quantiles through 300 bootstraps, considering the [0-10%] quantile range for the lower tail and the [90-100%] quantile range for the upper tail.

Figures 4.5-4.22 depict nonlinear correlograms illustrating the tail dependence between conditioning variables and dependent variables. Specifically, these figures display the IRF cross-coefficients $K_n(h) = \|\hat{\vartheta}_h\|_\infty$ which are the size of $\hat{\vartheta}_h$ as a function of h with 95% marginal bootstrap critical values. h is fixed as 300 lags for each period.

Table 4.3 : The number of significant lags on current returns

Cond. Var.	Dep. Var.	Pre-Covid-19 Period		Covid-19 Period		Post-Covid-19 Period	
		Lower Tail	Upper Tail	Lower Tail	Upper Tail	Lower Tail	Upper Tail
Brent Oil	Wheat	11	20	16	13	20	19
Brent Oil	Soybean	12	11	19	15	10	15
Brent Oil	Corn	13	18	19	7	19	18
Brent Oil	Cotton	19	15	15	9	14	10
Brent Oil	Sugar	17	11	14	11	12	13
Brent Oil	Rice	13	17	11	18	9	20
Brent Oil	Oat	17	17	6	9	13	15
Brent Oil	Coffee	29	13	26	20	17	14
Brent Oil	Cocoa	25	13	14	14	9	13
Natural Gas	Wheat	12	13	17	14	13	16
Natural Gas	Soybean	13	13	12	20	15	12
Natural Gas	Corn	18	12	16	13	11	16
Natural Gas	Cotton	26	17	14	12	21	20
Natural Gas	Sugar	15	18	14	11	18	19
Natural Gas	Rice	14	14	9	13	17	21
Natural Gas	Oat	17	18	10	14	15	10
Natural Gas	Coffee	11	11	18	19	16	32
Natural Gas	Cocoa	15	23	12	20	20	18
Gasoline	Wheat	26	18	13	16	13	22
Gasoline	Soybean	13	19	23	22	19	16
Gasoline	Corn	15	11	17	13	15	18
Gasoline	Cotton	19	16	17	17	19	16
Gasoline	Sugar	20	16	10	7	13	16
Gasoline	Rice	23	14	20	11	8	11
Gasoline	Oat	16	14	13	10	14	15
Gasoline	Coffee	13	17	17	16	21	15
Gasoline	Cocoa	21	17	12	14	19	14

Table 4.3 presents the number of rejections of the null hypothesis regarding the lack of tail dependence over a 300-day period, indicating the significant number of lags of energy commodities affecting current-day returns of agricultural commodities. As depicted in Table 4.3 and Figures A.1-A.18, the outcomes demonstrate strong and persistent tail dependence from each energy commodity to nearly all agricultural commodities across both tail events for each period. These findings imply the forecasting capability of energy commodities on agricultural commodities and suggest that extreme fluctuations in energy commodity returns contribute to fluctuations in agricultural commodity returns. Moreover, this impact of extreme energy commodity returns persists across most cases, reaching up to the 300th lag.

When analyzing the findings across periods, commodities, and tails, a consistent pattern is not discernible across different commodities and periods. In essence, while a particular energy product might wield more influence on a certain agricultural commodity in one period in contrast to other energy products, another energy product could demonstrate a more substantial effect on that agricultural commodity in a different period. This discovery implies that energy returns might exert varying periodic effects on agricultural commodities for both tail events, and the interactions are distinct for each pair of commodities.

As depicted in Figures A.1-A.6, during the pre-Covid-19 period, each energy commodity demonstrates a significant and persistent impact on all agricultural commodities. In the lower quantile continuum, the highest influence on corn and cotton appears to stem from natural gas, whereas gasoline notably affects wheat, sugar, and rice. Brent oil is prominently linked to coffee and cocoa. Conversely, in the upper tail range, cotton, sugar, oat, and cocoa display greater sensitivity to natural gas, while Brent oil significantly affects wheat, corn, and rice. Gasoline emerges as a dominant factor influencing soybean and coffee.

During the Covid-19 period (Figures A.7-A.12), Brent oil emerges as having a greater number of significant lags that impact corn, sugar, rice, coffee, and cocoa in the lower tail range. Natural gas exhibits more significant lags for wheat and sugar, while gasoline takes

the lead in effecting soybean, cotton, and rice with a higher number of significant days. Regarding upper tail events, gasoline primarily impacts wheat, soybean, corn, and cotton, while sugar, rice, and coffee are largely affected by Brent oil. Notably, natural gas stands out as the dominant factor impacting corn, sugar, oats, and cocoa. Additionally, it is important to highlight that the number of significant lags for current returns of corn is the same for both natural gas and gasoline.

In the post-Covid-19 era, as illustrated in Figures A.13-A.18, each energy commodity demonstrates a strong and persistent tail dependence on agricultural commodities. Brent oil exerts the most significant impact on the current returns of wheat and corn, whereas soybean and coffee are primarily influenced by gasoline in the lower range of quantiles. On the other hand, for the upper tail events, cotton, sugar, rice, coffee, and cocoa are predominantly affected by natural gas. Specifically, natural gas exhibits more significant lags on the present-day returns of cotton, sugar, rice, oat, and cocoa, while wheat and soybean are impacted mostly by gasoline. Notably, both Brent oil and gasoline show an equal number of significant lags on the current-day returns of corn and oats.

Furthermore, it is important to examine which agricultural commodities are most impacted by an energy commodity in terms of the number of significant lags. Brent oil demonstrates higher effects on cotton, sugar, oat, coffee, and cocoa in the lower tail range, and on wheat, corn, cotton, rice, and oat in the upper range of quantiles during the pre-Covid-19 period (as illustrated in Figures A.1 & A.5). Throughout the Covid-19 period, Brent oil notably affects coffee for both tails, as indicated in Figures A.7 and A.10. Additionally, it significantly impacts wheat, soybean, corn, and cotton in the lower tail range, and sugar and rice in the upper tail range. In the post-Covid-19 era, stronger lower tail dependence is observed for wheat, corn, and coffee. Moreover, there is stronger upper tail dependence for wheat, soybean, corn, rice, and oat.

In the pre-Covid-19 period, natural gas exhibits notably higher lower tail dependence for corn, cotton, sugar, oat, and cocoa. Similarly, in the upper quantiles, these same agricultural commodities are most affected, excluding corn. During the Covid-19 period, natural gas demonstrates significant tail dependence to wheat, corn, and coffee in the

lower tail range. In the upper tail range, its impact is more pronounced on soybean, coffee, and cocoa. In the post-Covid-19 period, natural gas showcases robust predictive power, especially for soybean, cotton, sugar, rice, oat, coffee, and cocoa in the lower quantiles. Additionally, for the upper quantiles, it displays considerable impact on cotton, sugar, rice, coffee, and cocoa.

Within the agricultural commodities, gasoline demonstrates stronger effect on wheat, corn, cotton, sugar, rice, oat, and cocoa in the lower tail range, and on wheat, soybean, cotton, sugar, coffee, and cocoa in the upper tail range in the pre-Covid-19 period. Amid the Covid-19 period, soybean, corn, cotton, rice, and coffee are the most affected commodities in the lower quantiles, while gasoline exerts a stronger impact on wheat, soybean, cotton, and coffee in the upper quantiles. In the post-Covid-19 period, the impact of gasoline is notably more significant on soybean, corn, cotton, and coffee in the lower tail range, and on wheat, soybean, corn, cotton, sugar, oat, and coffee in the upper tail range.

4.6. Robustness Check

In the robustness check, both Han et al.'s (2016) cross-quantilogram analysis and Candelon and Tokpavi's (2016) nonparametric test for Granger causality in distribution are conducted. The aim is to explore causality, with the latter test focusing on persistence. To enrich the analysis with a dynamic approach akin to Escanciano and Hualde's (2021) methodology, the cross-quantilogram technique is utilized.

The cross-quantilogram technique proposed by Han et al. (2016) involves cross-correlating quantile-hit processes to discern potential directional cross-quantile predictability between two time series using conditional quantiles. This method boasts several advantages, including its interpretational simplicity, independence from time series moment conditions, ability to capture inherent properties in joint distributions, and flexibility in considering multiple lags. While copula-based methods used to evaluate tail dependence often necessitate specifying and estimating a copula for each lag k , introducing potential misspecification errors, the cross-quantilogram method calculates

measures for all lags k simultaneously. Additionally, being a nonparametric statistic rooted in quantile hits, the cross-quantilogram inherently minimizes misspecification errors (Han et al., 2016; Cho and Han, 2021).

Instead of employing a single quantile, quantile ranges are utilized to define the lower and upper tails of the distribution. This involves measuring the dependence between two events $\{q_{1,t}(\tau_1^l) < y_{1,t} < q_{1,t}(\tau_1^h)\}$ and $\{q_{2,t-k}(\tau_2^l) < y_{2,t-k} < q_{2,t-k}(\tau_2^h)\}$ for arbitrary quantile ranges $[\tau_1^l, \tau_1^h]$ and $[\tau_2^l, \tau_2^h]$, where $q_{i,t}(\tau_i)$ is τ_i conditional quantile of $y_{i,t}$ for $i=1,2$. Specifically, the quantile range for the left tail is established as $[0, 0.10]$, and for the right tail, it is $[0.90, 1.0]$. The lag value, k , is set at 100 for each period. To determine significance, the analysis relies on the 95% bootstrap confidence intervals derived from 1000 bootstrapped replicates.

When the cross-quantilogram is positive and significant and $[\tau_1^l, \tau_1^h] = [\tau_2^l, \tau_2^h] = [0, 0.10]$, it indicates that when the conditional variable decreases, it is more likely for dependent variable largely decreases. In case of $[\tau_1^l, \tau_1^h] = [\tau_2^l, \tau_2^h] = [0.90, 1]$ and the positive and significant cross-quantilogram, this means that when conditional variable increases, the dependent variable is more likely to largely increases.

On the contrary, a negative and significant cross-quantilogram, along with quantile ranges $[\tau_1^l, \tau_1^h] = [\tau_2^l, \tau_2^h] = [0, 0.10]$, denotes that when the conditional variable decreases, it is less likely for dependent variable largely decreases. When $[\tau_1^l, \tau_1^h] = [\tau_2^l, \tau_2^h] = [0.90, 1]$ and the cross-quantilogram is negative and significant, it signifies that when conditional variable increases, the dependent variable is less likely to largely increases.

As illustrated in Figures A.19-A.36, the analysis results confirm the initial findings, providing further evidence that fluctuations in agricultural returns are influenced by extreme shifts in energy commodity returns. The observed cross-quantilograms display significance both in positive and negative directions across certain lags. When $[\tau_1^l, \tau_1^h] = [\tau_2^l, \tau_2^h] = [0, 0.10]$, the positive and significant cross-quantilograms indicate that a large drop in agricultural commodity returns corresponds to a decrease in energy commodity returns. Conversely, negative and significant cross-quantilograms imply a

decrease, albeit of a lesser magnitude. In instances where $[\tau_1^l, \tau_1^h] = [\tau_2^l, \tau_2^h] = [0.90, 1]$, significant cross-quantilograms indicate an increase in agricultural commodity returns in response to increases in energy commodity returns. However, a positive cross-quantilogram signals a greater increase in agricultural commodity returns compared to scenarios with negative cross-quantilograms.

Candelon and Tokpavi's (2016) nonparametric test for Granger causality in distribution extends the kernel-based Granger-causality test in a tail event. This flexible test determines Granger causality or predictability within specific parts of a series distribution, such as the tails or the center. Following the methodology of Candelon and Tokpavi (2016), an AR(1)-GARCH(1,1) model is utilized to evaluate time-varying VaR for conducting the test. The 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, are set. The choice of truncation parameter M followed the $[1.5T^{0.3}]$ definition, where T represents the number of observations.

Table 4.4 displays the test statistics for Granger causality. The test statistics exhibit high significance, leading to the rejection of the null hypothesis of no Granger predictability. These results illustrate the presence of both upward and downward risk transmissions from energy commodities to agricultural commodities.

Table 4.4 : Test statistics for Granger causality from energy markets to agricultural markets

	Pre-Covid-19 Era		Covid-19 Era		Post-Covid-19 Era	
	<i>Left Tail</i>	<i>Right Tail</i>	<i>Left Tail</i>	<i>Right Tail</i>	<i>Left Tail</i>	<i>Right Tail</i>
<i>Panel A- Brent Oil</i>						
Wheat	1160.59***	-2451.50***	-2723.67***	-917.92***	494.24***	6680.12***
Soybean	323.02***	1617.38***	5228.25***	20.13***	723.99***	76.02***
Corn	1806.97***	-318.93***	-442.50***	-488.56***	512.30***	332.63***
Cotton	4659.57***	2257.32***	9770.11***	-1600.37***	3413.84***	-2573.84***
Sugar	2321.56***	-1577.93***	1878.86***	-118.64***	2457.27***	-2350.43***
Rice	4779.43***	1422.50***	-956.49***	-11.49***	995.86***	6202.90***
Oat	357.47***	42.19***	-957.51***	248.25***	5554.51***	-1049.74***
Coffee	-2737.75***	593.98***	5275.01***	-2648.83***	469.41***	743.70***
Cocoa	-334.85***	-1590.84***	2082.03***	1004.49***	1801.08***	-384.36***
<i>Panel B- Natural Gas</i>						
Wheat	327.50***	1693.81***	1176.52***	-1433.43***	-2373.83***	388.02***
Soybean	-139.50***	-226.27***	242.92***	-225.71***	3593.85***	711.86***
Corn	-589.46***	-180.26***	-68.91***	7179.11***	425.73***	19.08***
Cotton	-1526.02***	306.68***	-225.71***	-782.63***	-802.70***	-1186.83***
Sugar	-589.46***	1306.92***	364.31***	-100.01***	1159.67***	1307.86***
Rice	-264.22***	-3597.91***	908.65***	186.76***	-1030.81***	388.02***
Oat	-599.31***	-432.29***	1837.21***	1344.82***	2783.35***	-704.06***
Coffee	-3267.32***	-816.45***	424.15***	-1232.89***	-1054.49***	-1030.81***
Cocoa	964.66***	1759.48***	387.10***	-1161.62***	-1197.57***	1307.86***
<i>Panel B- Gasoline</i>						
Wheat	-1018.77***	-180.26***	-2186.20***	257.23***	503.87***	-1727.29***
Soybean	-518.00***	393.50***	7772.43***	-488.56***	-1044.27***	1051.30***
Corn	2510.11***	974.23***	-85.34***	-1327.01***	2144.37***	-482.58***
Cotton	964.66***	426.29***	2267.13***	3284.40***	503.87***	-2698.03***
Sugar	-358.85***	-625.64***	2930.85***	27.16***	-3526.62***	1829.01***
Rice	213.85***	-158.76***	251.04***	-46.47***	1307.86***	431.08***
Oat	2659.08***	42.19***	-1120.39***	-225.71***	66.40***	-186.92***
Coffee	334.61***	-795.37***	2894.88***	-492.39***	5173.04***	711.86***
Cocoa	41.35***	4870.26***	7303.90***	-1510.16***	-2338.70***	-1727.29***

4.7. Conclusion and Policy Implications

It is widely acknowledged that the global community grapples with critical energy and food security challenges, leading to surges in agricultural commodity prices. The escalating energy costs have intensified these price hikes, pushing them to unprecedented levels. Moreover, energy commodities serve as pivotal elements in agricultural production. Therefore, investigating the interdependence between energy and agricultural commodities becomes crucial in devising preventive strategies for the well-being of nations. This study employs Escanciano and Hualde's (2021) new measure of nonlinear

tail dependence to examine the relationship between energy and agricultural commodities throughout pre-, during, and post-Covid-19 periods. The study findings reveal significant and persistent upper and lower tail dependence across all commodity pairs in each period. This suggests a predictive power of energy commodities on agricultural commodities. Additionally, the nonparametric Granger causality test in distribution yields significant outcomes, affirming Granger predictability for each commodity pair and period. The cross-quantilogram results validate the presence of lower and upper tail dependence from energy commodities to agricultural commodities, supporting the primary findings.

The research contributes to the existing literature in several ways. Firstly, it investigates the quantile dependence among three primary energy commodities and nine agricultural commodities. Secondly, it delves into tail risk using quantile continuums, providing a more comprehensive understanding of tail dependence beyond a single market event. Thirdly, it explores both lower and upper quantile ranges to unveil asymmetries in tail spillover effects. Lastly, it assesses risk transmissions across three distinct periods, with the Covid-19 period acting as a breaking point of analysis.

The findings provide strong but mixed evidence regarding the co-movements of commodities concerning risk transmissions during extreme upward and downward movements across different periods. For instance, in the Covid-19 period, there is stronger lower tail dependence of natural gas on wheat, yet this relationship reverses in the post-Covid-19 era. Similarly, a specific agricultural commodity might exhibit stronger left tail dependence with one energy commodity while displaying a higher right tail dependence with another energy commodity within the same period. For example, during the post-Covid-19 period, soybean demonstrates a stronger lower tail dependence from natural gas and gasoline, while exhibiting a stronger upper tail dependence from Brent oil based on the number of significant lags on current returns. Consequently, examining different major energy commodities becomes crucial. These outcomes highlight an individualized relationship for each commodity pair in the presence of extreme positive and negative shocks, rather than a certain dependence pattern. Nonetheless, the results indicate robust evidence of both upward and downward risk transmissions across each period, aligning

with recent studies (Tiwari et al., 2022; Farid et al., 2022; Wu et al., 2023; Furuoka et al., 2023).

The findings hold significant implications for policy and practical applications, offering insights crucial for devising effective market strategies and ensuring efficient portfolio management within agricultural commodity markets. Firstly, recognizing a strong and persistent interdependence between energy and agricultural markets during extreme events, policymakers can establish more resilient regulations that account for this connection, safeguarding the interests of investors, practitioners, and households. The results of this research can serve as a basis for devising strategies to stabilize markets during periods of extreme risk spillovers. Given that energy commodities transmit risks, any regulatory measures in the energy market would significantly impact agricultural commodities. Secondly, this research highlights the vulnerability of agricultural markets to energy market shocks, indicating that agricultural commodities might not be ideal substitutes for energy commodities in portfolio diversification. Investors and portfolio managers can leverage these findings to make more informed investment decisions and develop risk management strategies. Moreover, considering the asymmetries in tail spillover effects under different market conditions and the specificity of co-movements between each commodity pair, market participants can dynamically adjust portfolios, tailoring them to evolving market regimes.

For future researches, extending this methodology to encompass other energy commodities like crude oil and biofuel could provide valuable insights. Moreover, exploring the tail dependence from agricultural commodities to energy commodities would enrich our understanding of the interdependencies between these markets. Additionally, these analyses could be expanded by investigating quantile dependence between volatilities, possibly by utilizing the squared log returns as a proxy for volatility. It would also be worthwhile to conduct analyses spanning periods both before and after the Russia-Ukraine war to capture the potential impact of this event on the observed spillover effects.



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APPENDIX

APPENDIX A: Chapter 4 Apendices





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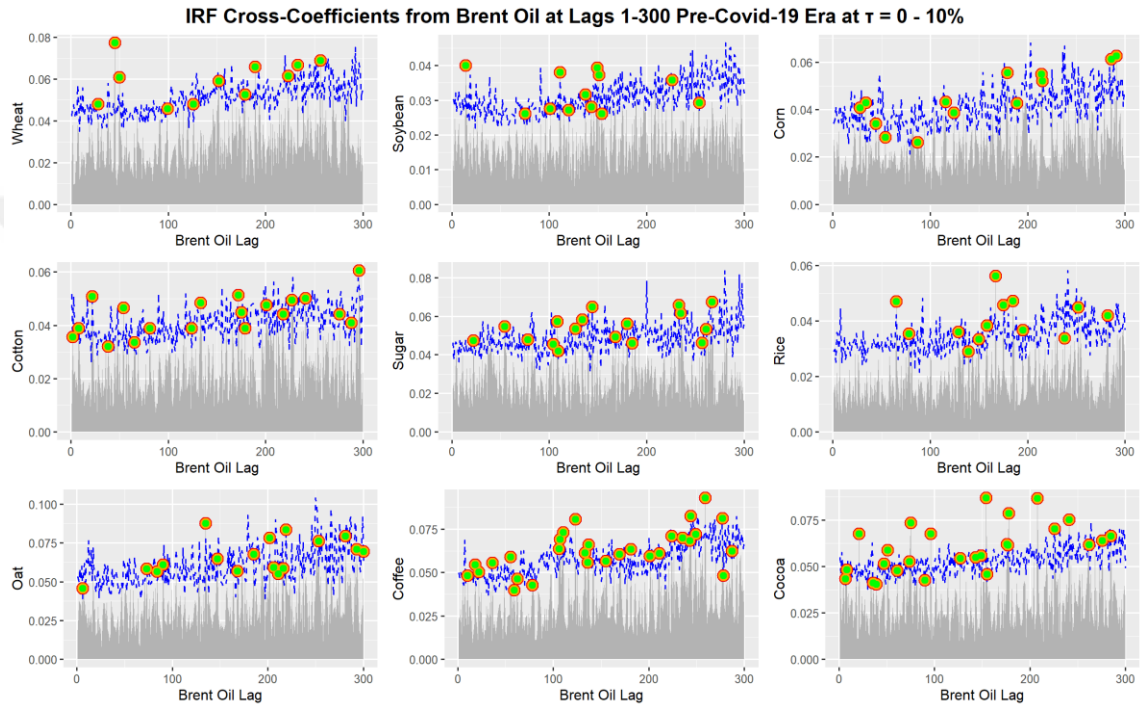


Figure A.1 : IRF cross-coefficients from lagged Brent Oil to agricultural commodities at quantiles 0-10% with block 95% bootstrap critical values (dashed lines) for Pre-Covid-19 Era

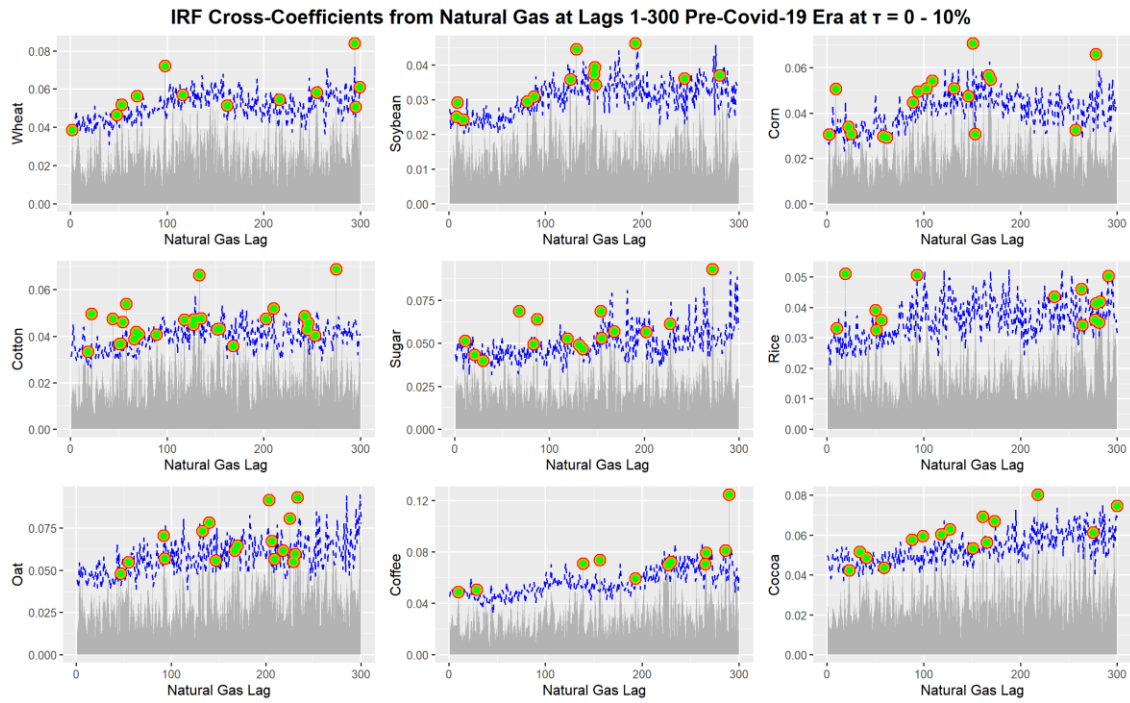


Figure A.2 : IRF cross-coefficients from lagged Natural Gas to agricultural commodities at quantiles 0-10% for Pre-Covid-19 Era

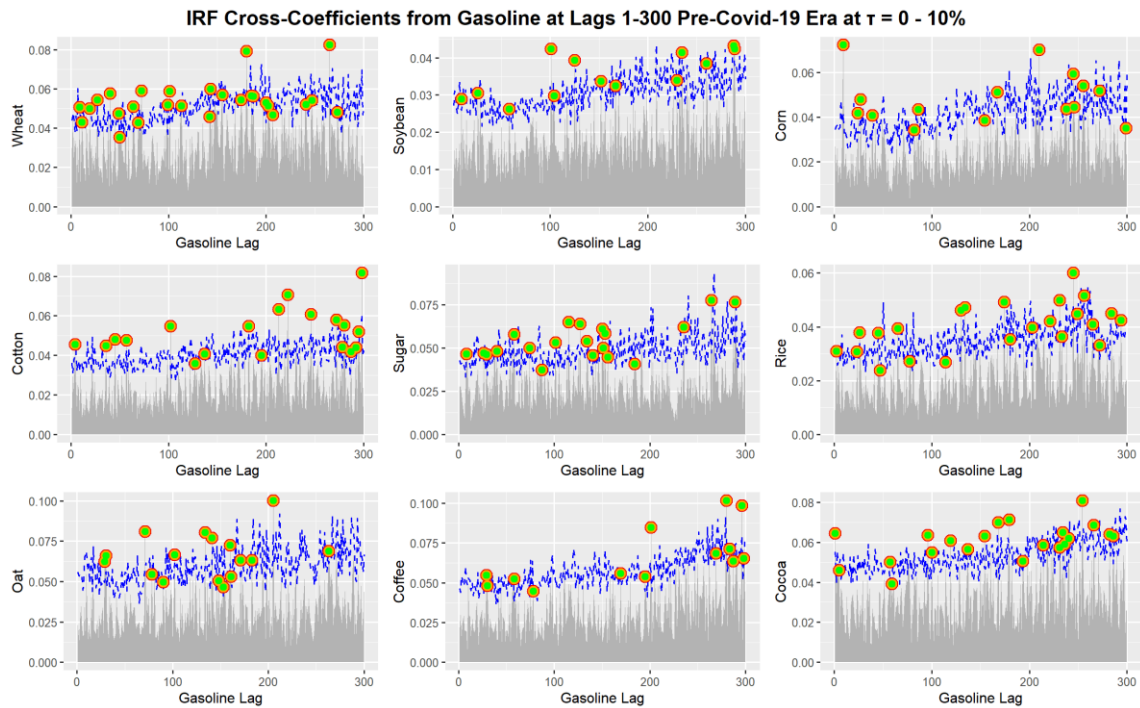


Figure A.3 : IRF cross-coefficients from lagged Gasoline to agricultural commodities market at quantiles 0-10% for Pre-Covid-19 Era

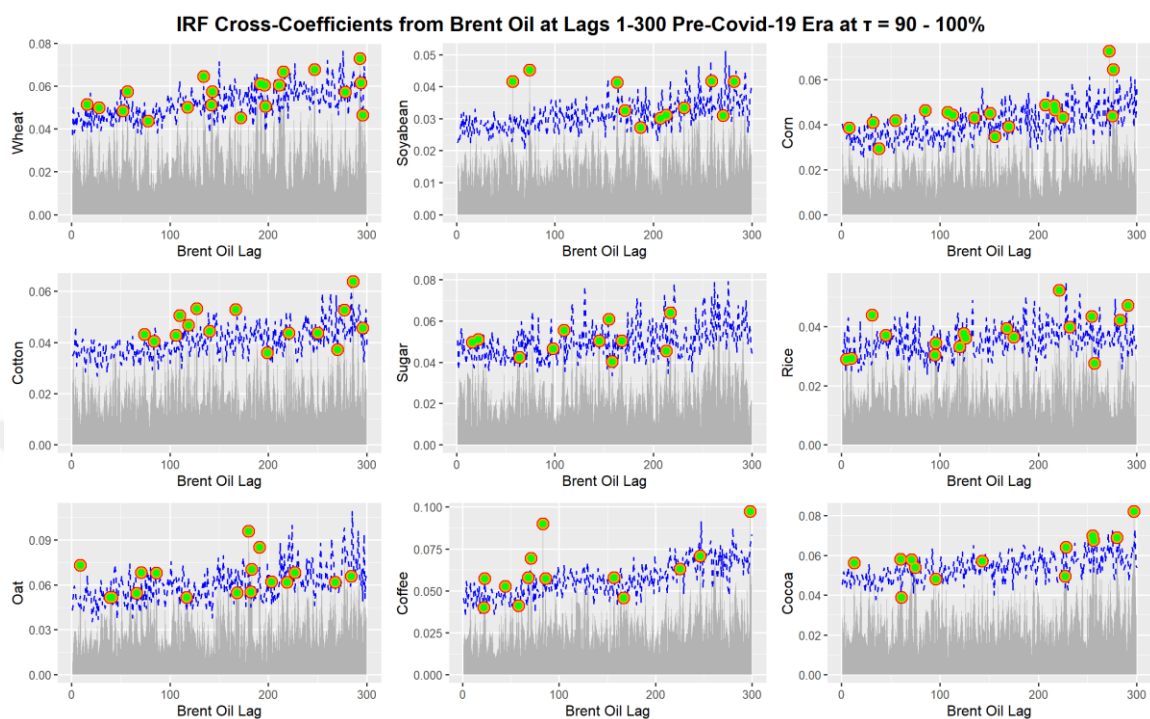


Figure A.4 : IRF cross-coefficients from lagged Brent Oil to agricultural commodities at quantiles 90-100% for Pre-Covid-19 Era

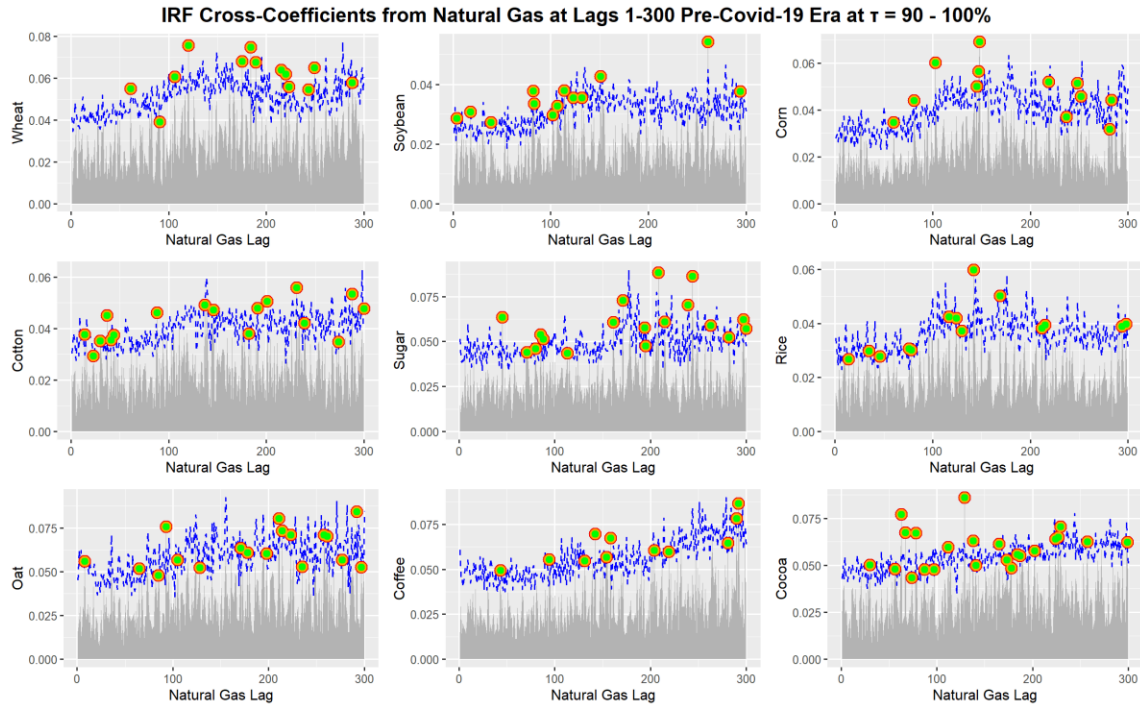


Figure A.5 : IRF cross-coefficients from lagged Natural Gas to agricultural commodities at quantiles 90-100% for Pre-Covid-19 Era

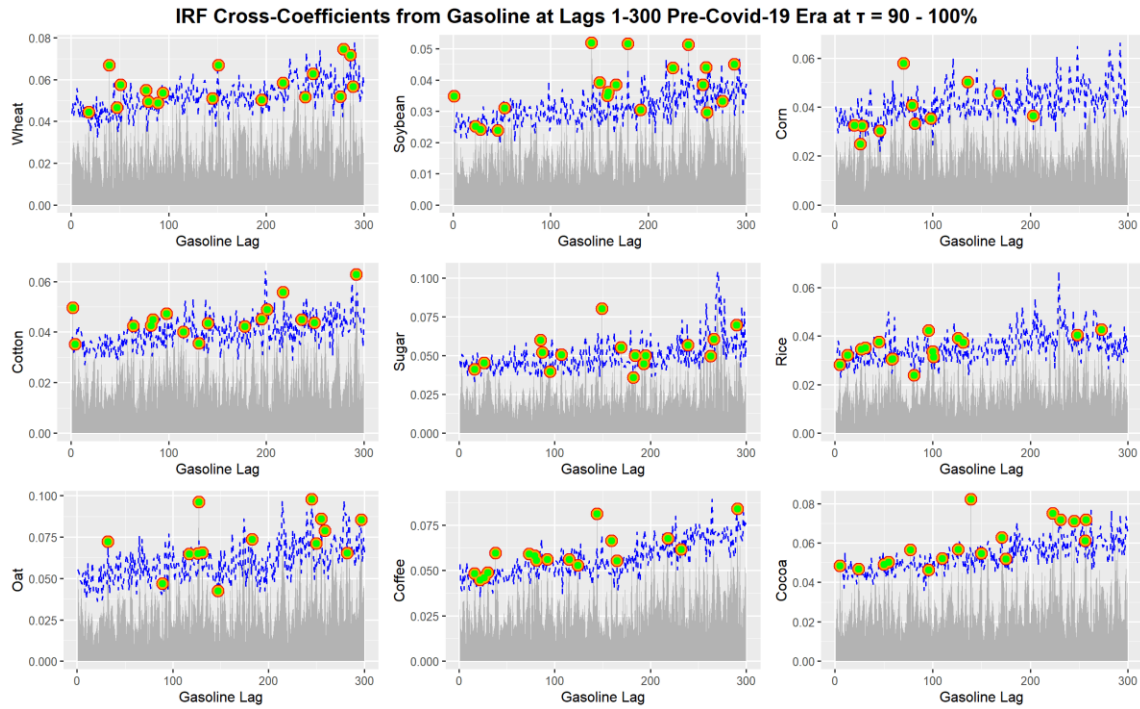


Figure A.6 : IRF cross-coefficients from lagged Gasoline to agricultural commodities market at quantiles 90-100% for Pre-Covid-19 Era

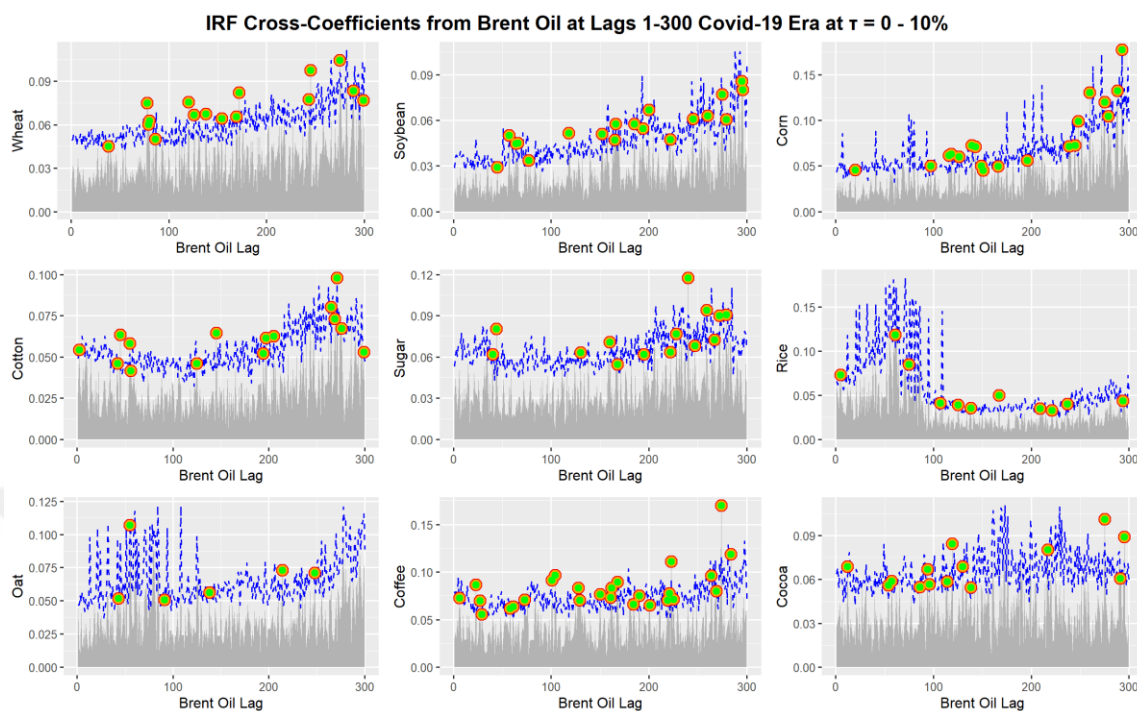


Figure A.7 : IRF cross-coefficients from lagged Brent Oil to agricultural commodities at quantiles 0-10% for Covid-19 Era

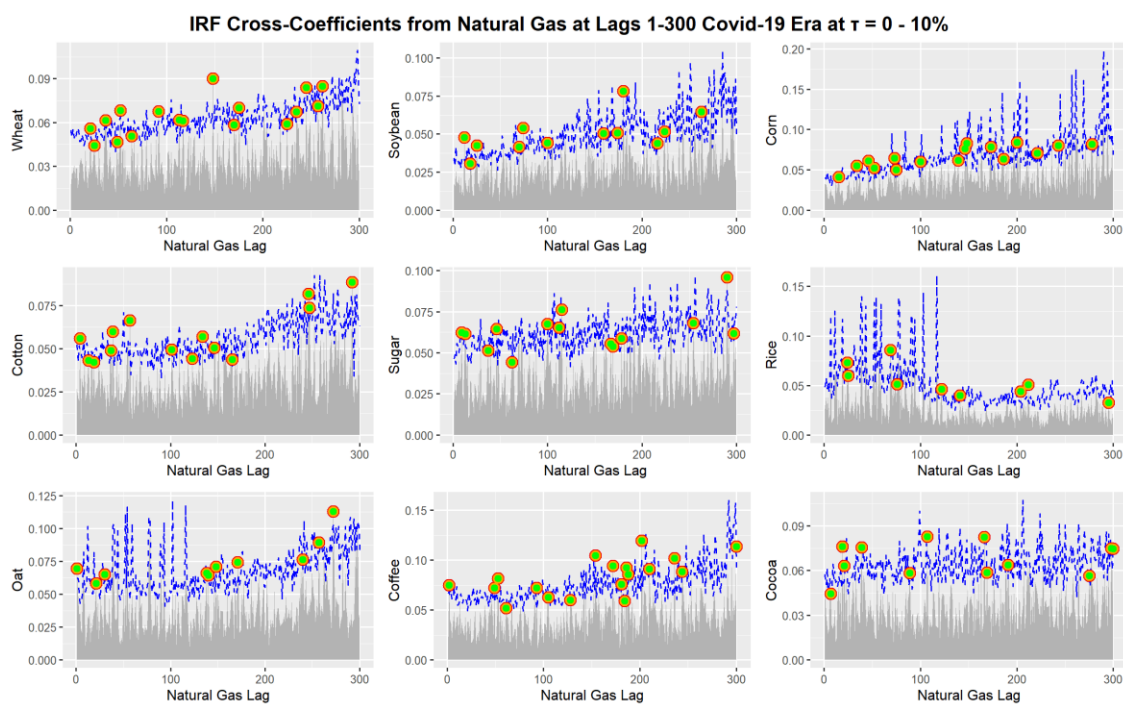


Figure A.8 : IRF cross-coefficients from lagged Natural Gas to agricultural commodities at quantiles 0-10% for Covid-19 Era

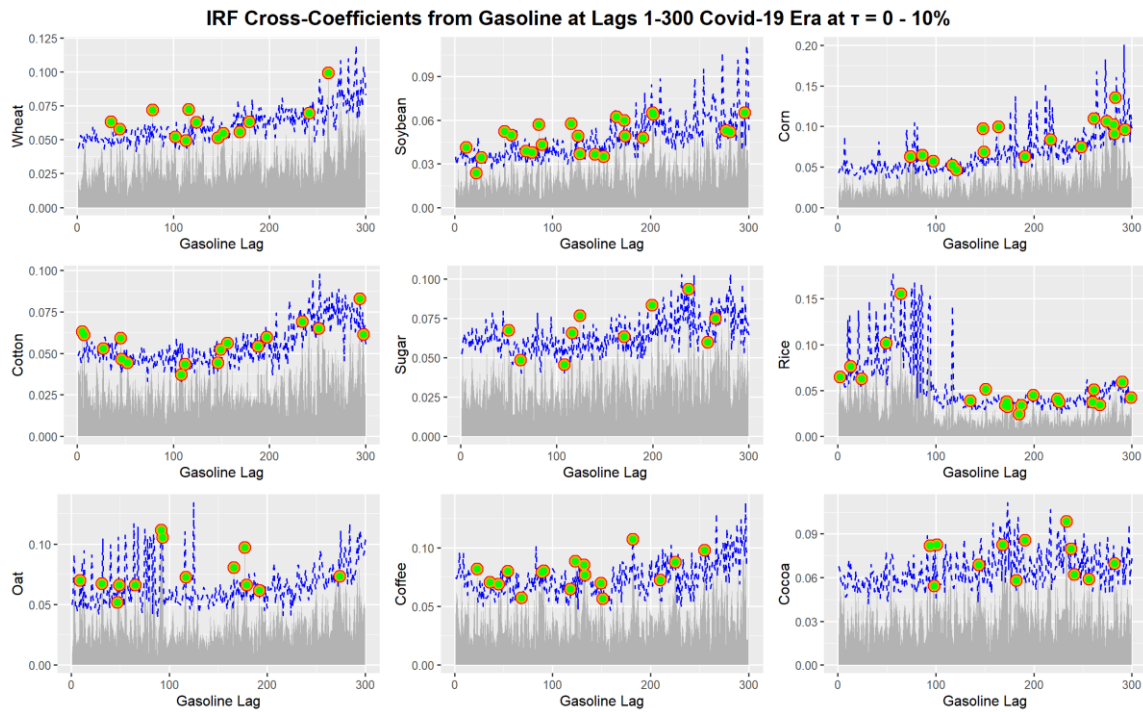


Figure A.9 : IRF cross-coefficients from lagged Gasoline to agricultural commodities market at quantiles 0-10% for Covid-19 Era

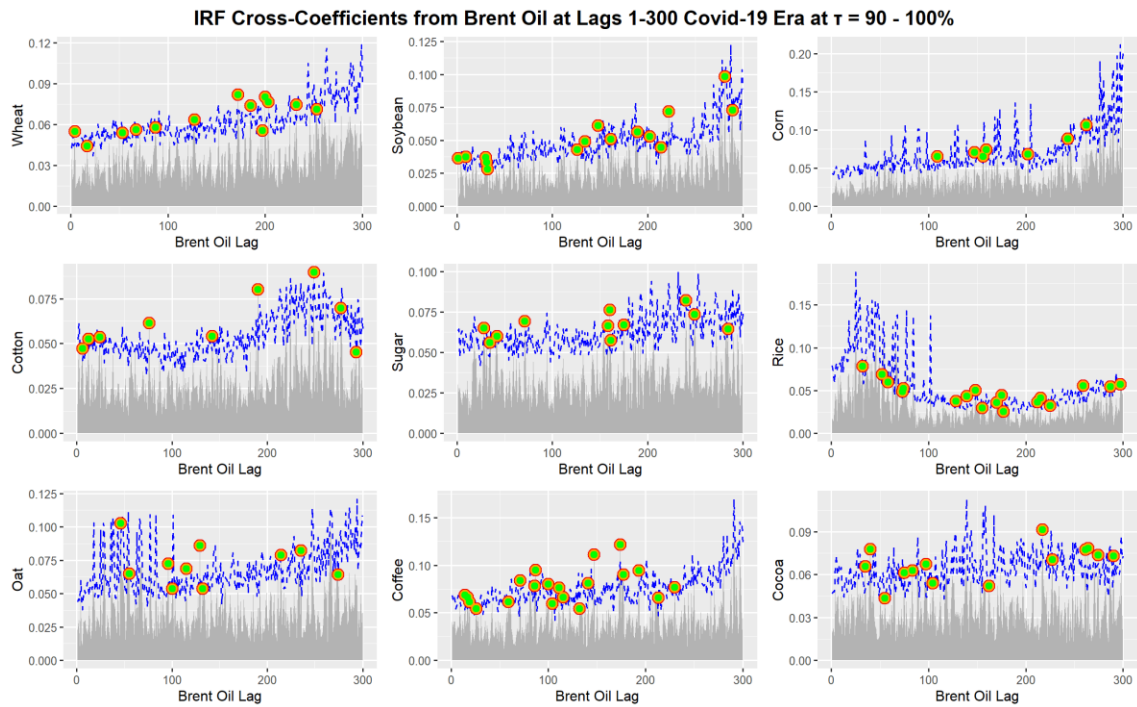


Figure A.10 : IRF cross-coefficients from lagged Brent Oil to agricultural commodities at quantiles 90-100% for Covid-19 Era

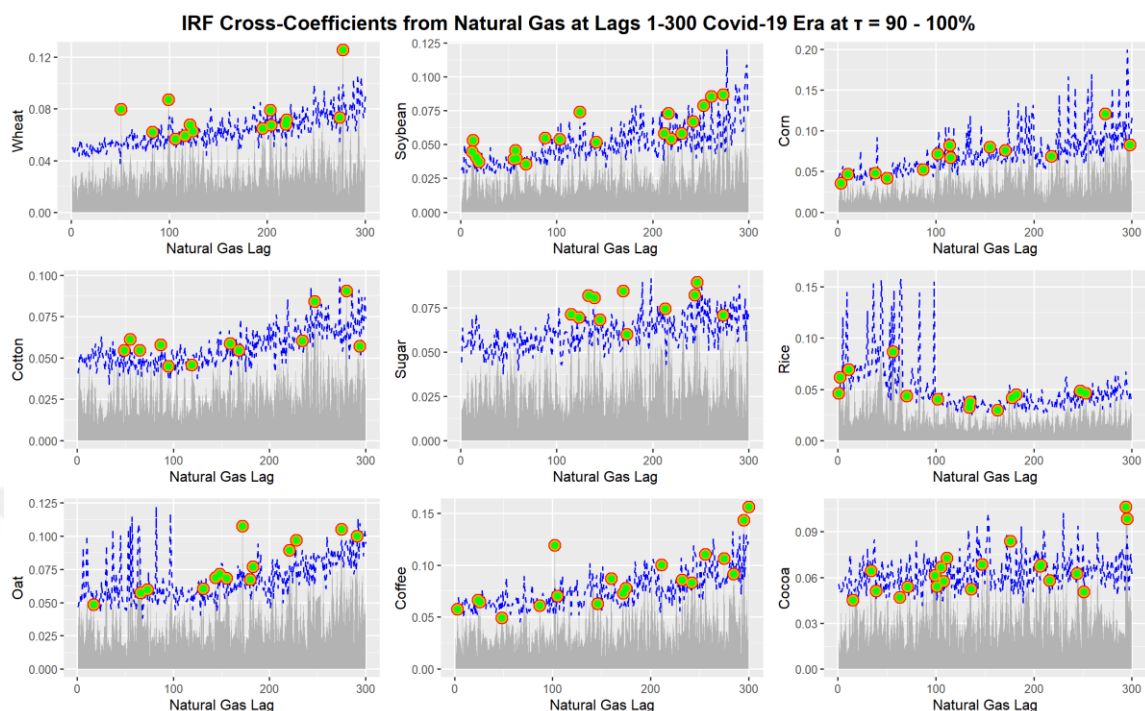


Figure A.11 : IRF cross-coefficients from lagged Natural Gas to agricultural commodities at quantiles 90-100% for Covid-19 Era

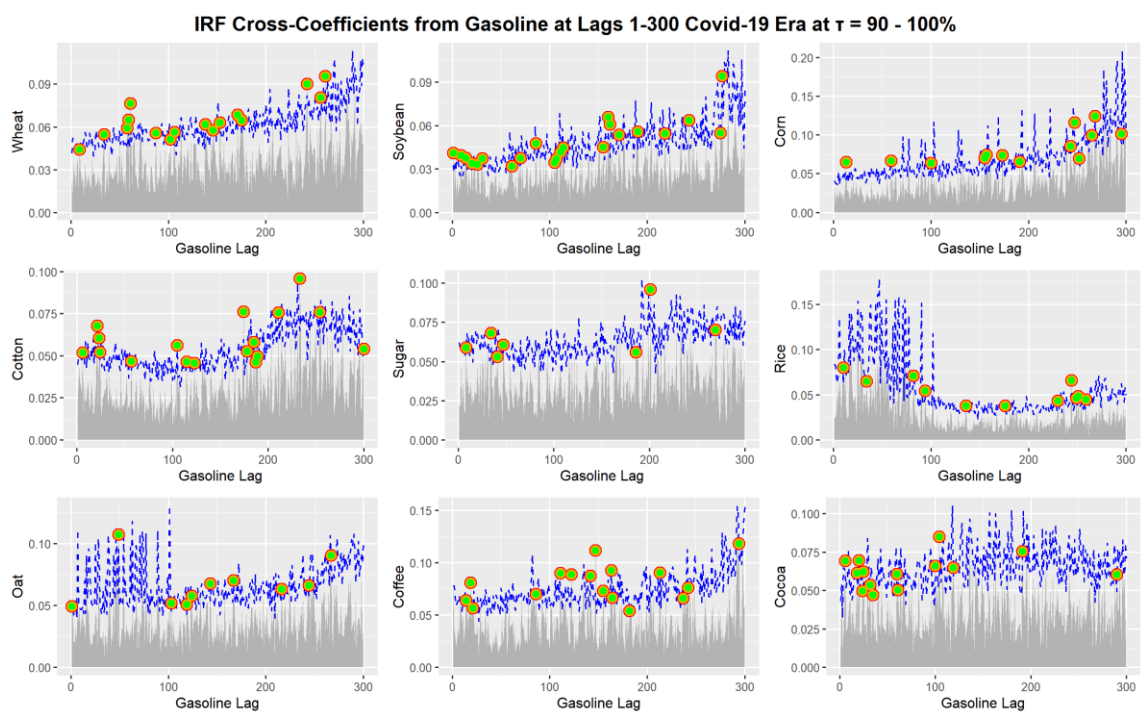


Figure A.12 : IRF cross-coefficients from lagged Gasoline to agricultural commodities market at quantiles 90-100% for Covid-19 Era

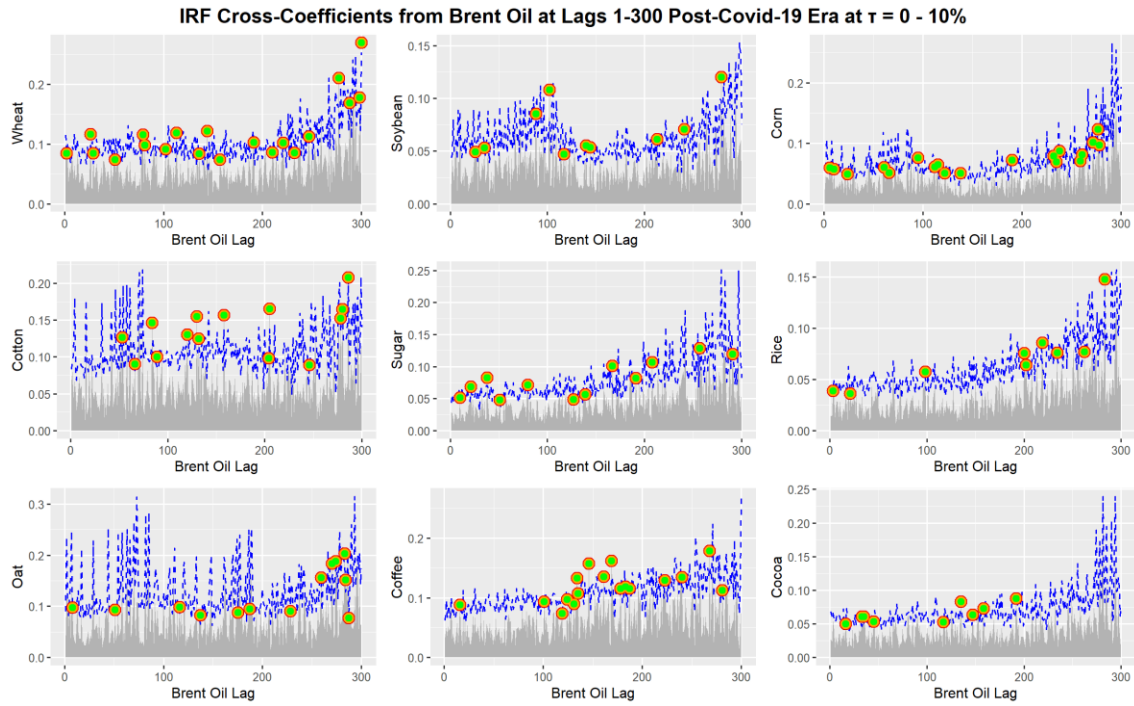


Figure A.13 : IRF cross-coefficients from lagged Brent Oil to agricultural commodities at quantiles 0-10% for Post-Covid-19 Era

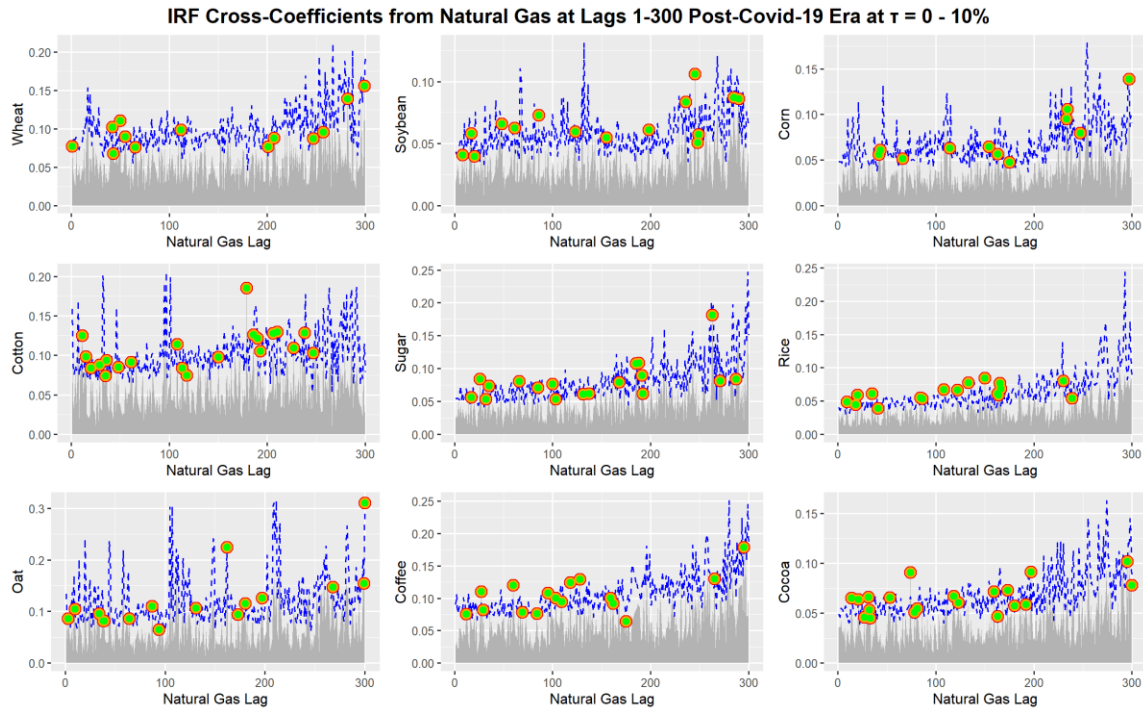


Figure A.14 : IRF cross-coefficients from lagged Natural Gas to agricultural commodities at quantiles 0-10% for Post-Covid-19 Era

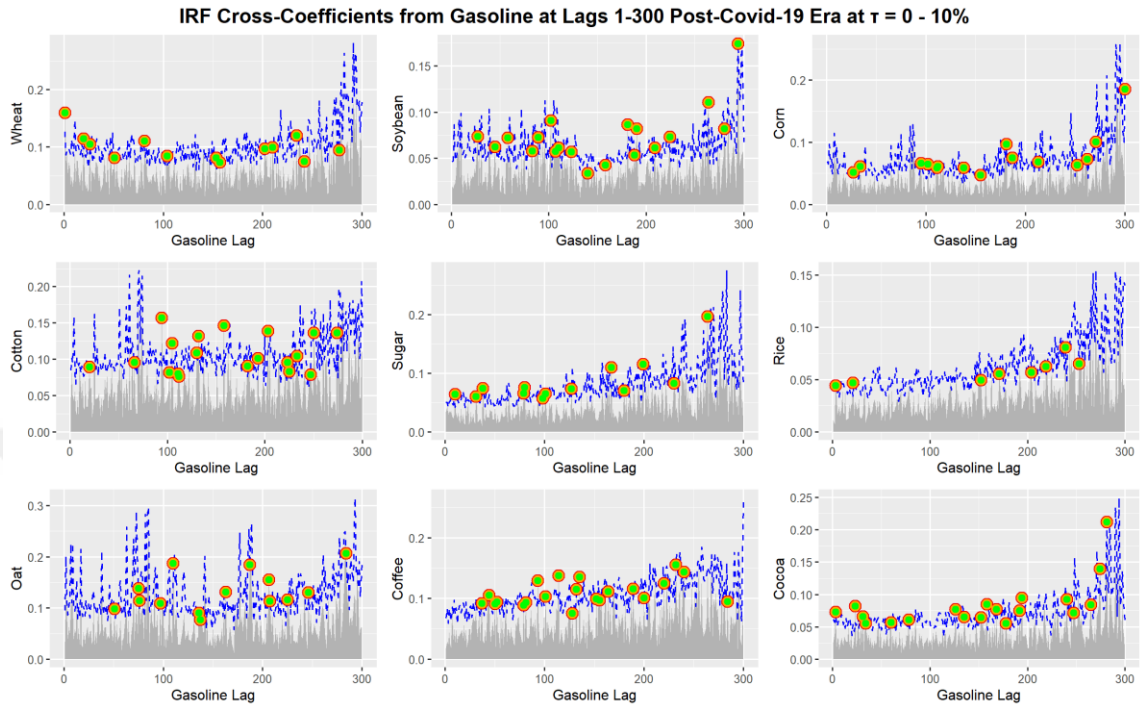


Figure A.15 : IRF cross-coefficients from lagged Gasoline to agricultural commodities market at quantiles 0-10% for Post-Covid-19 Era

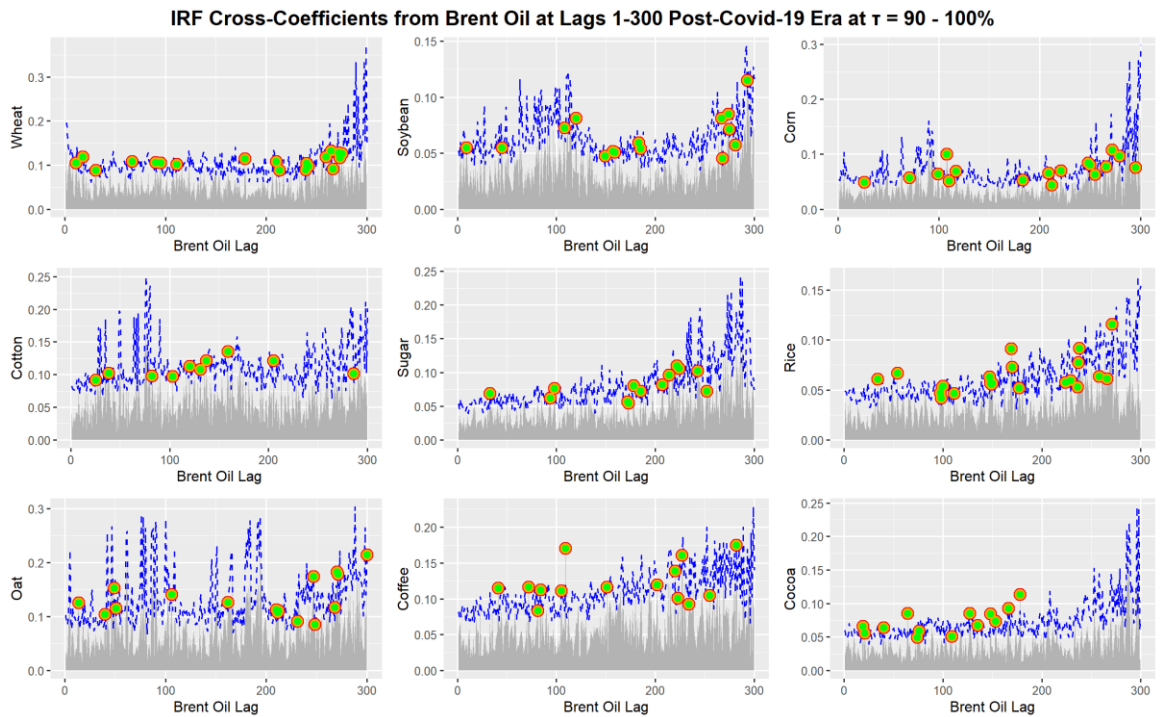


Figure A.16 : IRF cross-coefficients from lagged Brent Oil to agricultural commodities at quantiles 90-100% for Post-Covid-19 Era

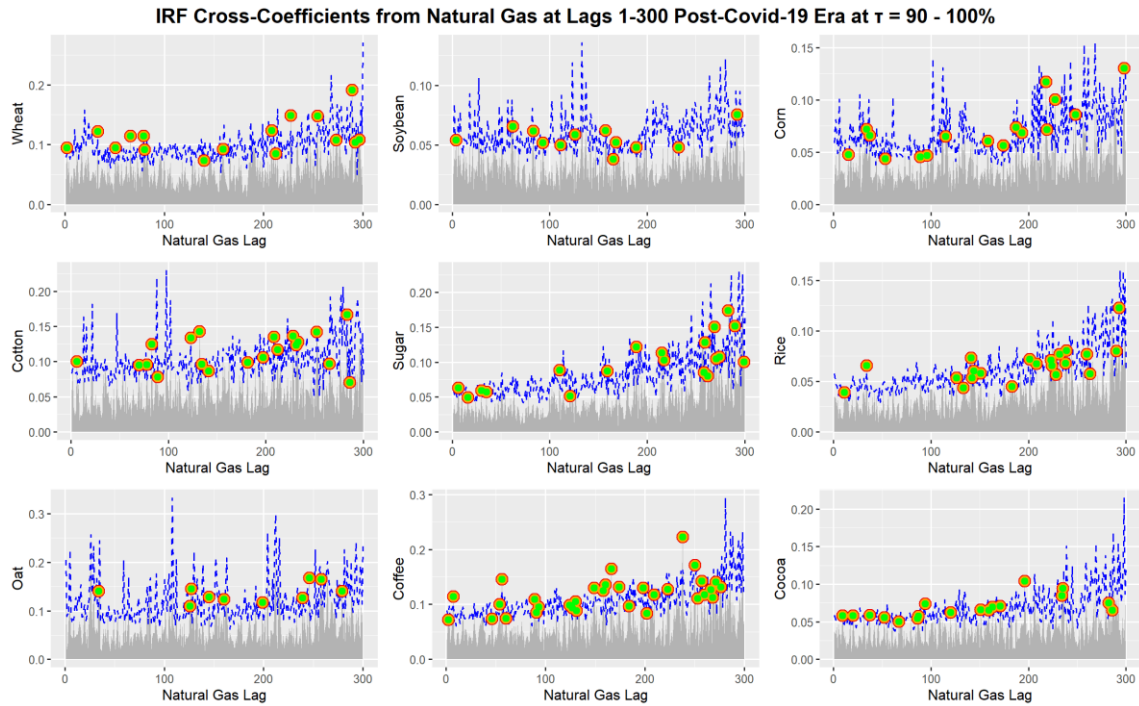


Figure A.17 : IRF cross-coefficients from lagged Natural Gas to agricultural commodities at quantiles 90-100% for Post-Covid-19 Era

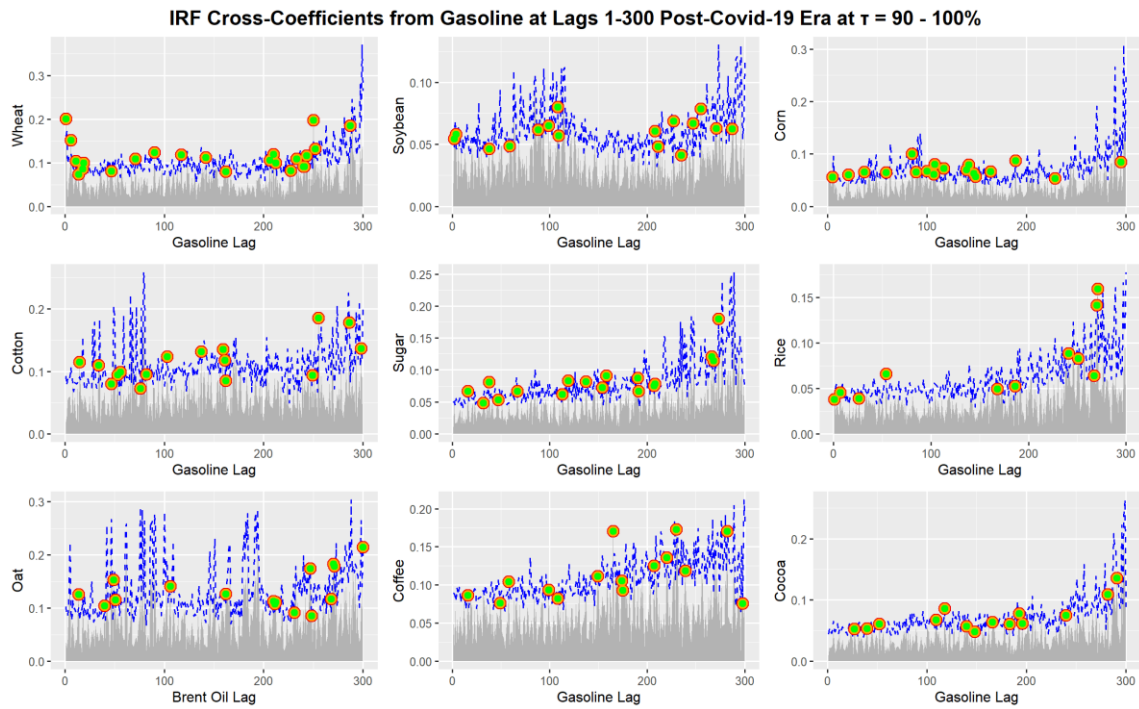


Figure A.18 : IRF cross-coefficients from lagged Gasoline to agricultural commodities market at quantiles 90-100% for Post-Covid-19 Era

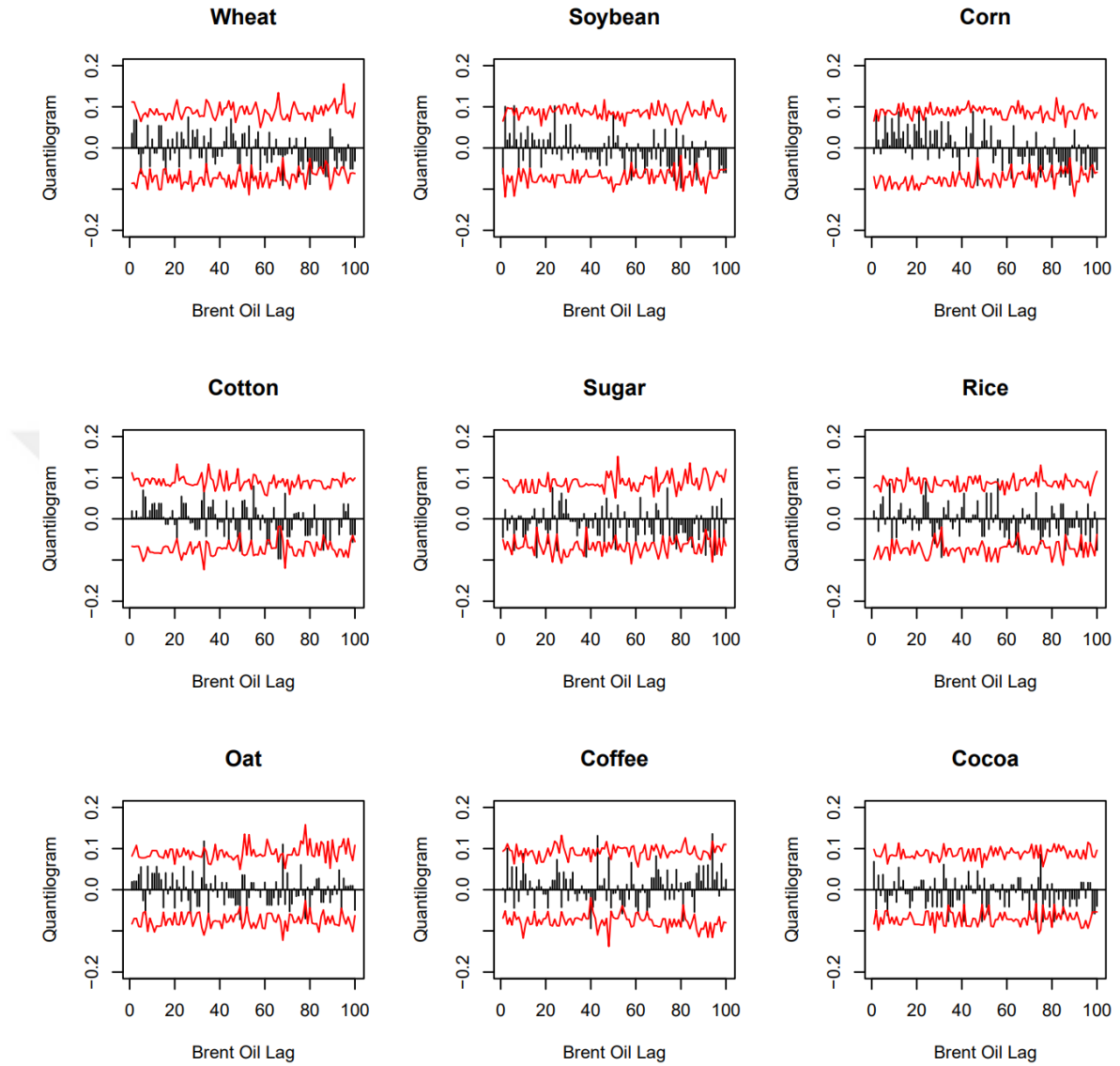


Figure A.19 : The cross-quantilogram results for Brent oil at lags 1-100 Pre-Covid-19 Era $\tau=[0-0.10]$

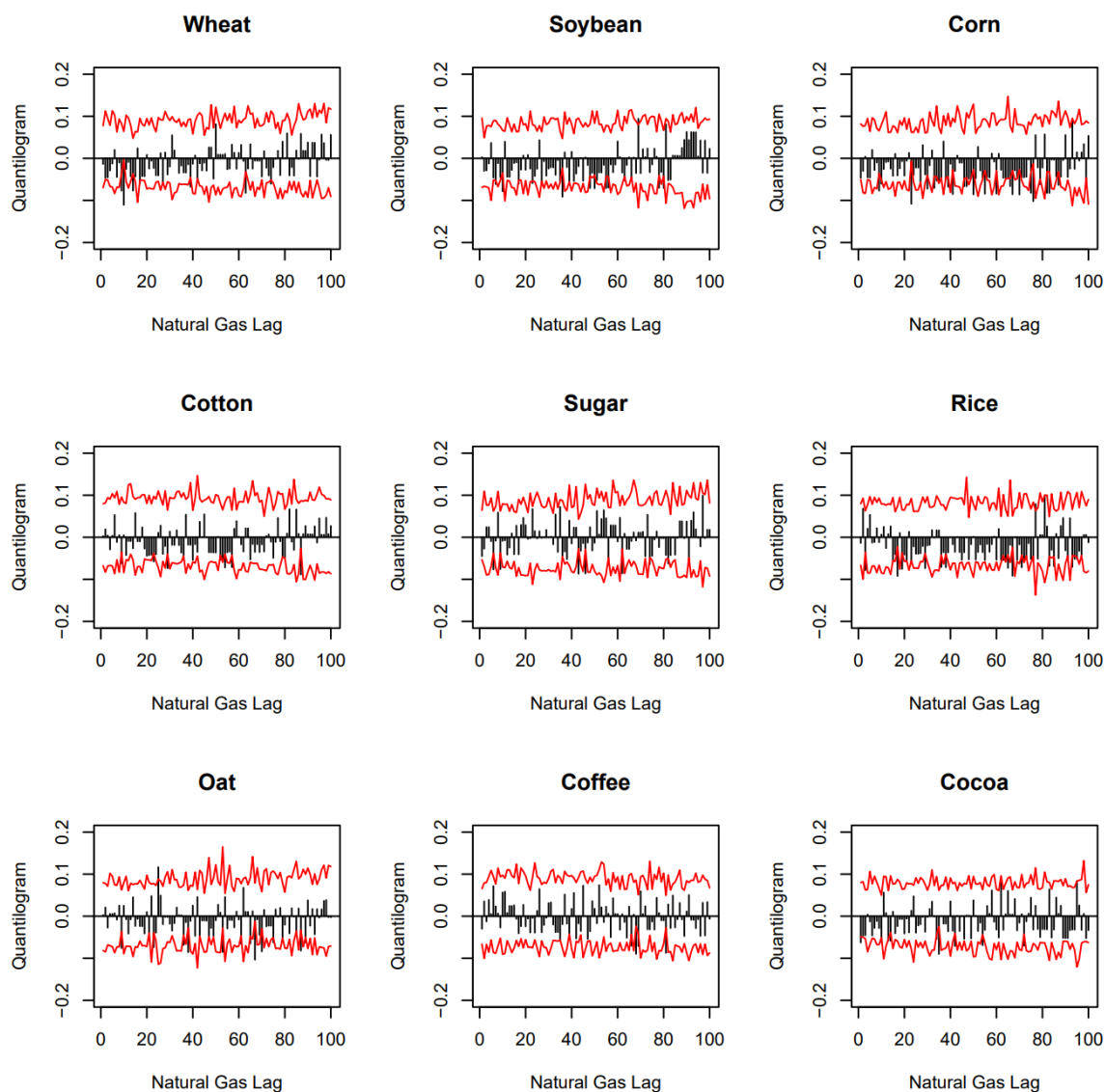


Figure A.20 : The cross-quantilogram results for Natural gas at lags 1-100 Pre-Covid-19 Era $\tau=[0-0.10]$

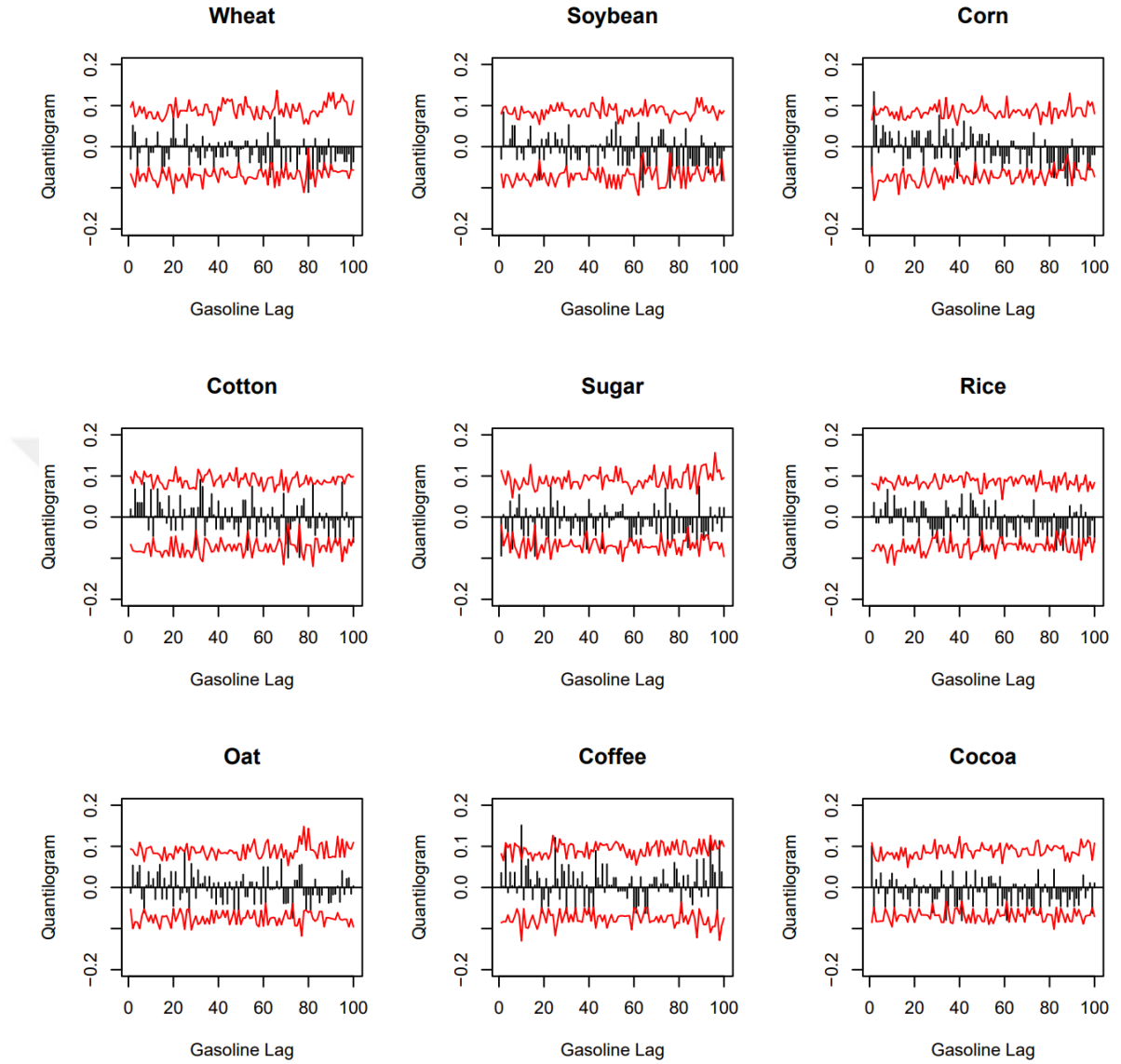


Figure A.21 : The cross-quantilogram results for Gasoline at lags 1-100 Pre-Covid-19
Era $\tau=[0-0.10]$

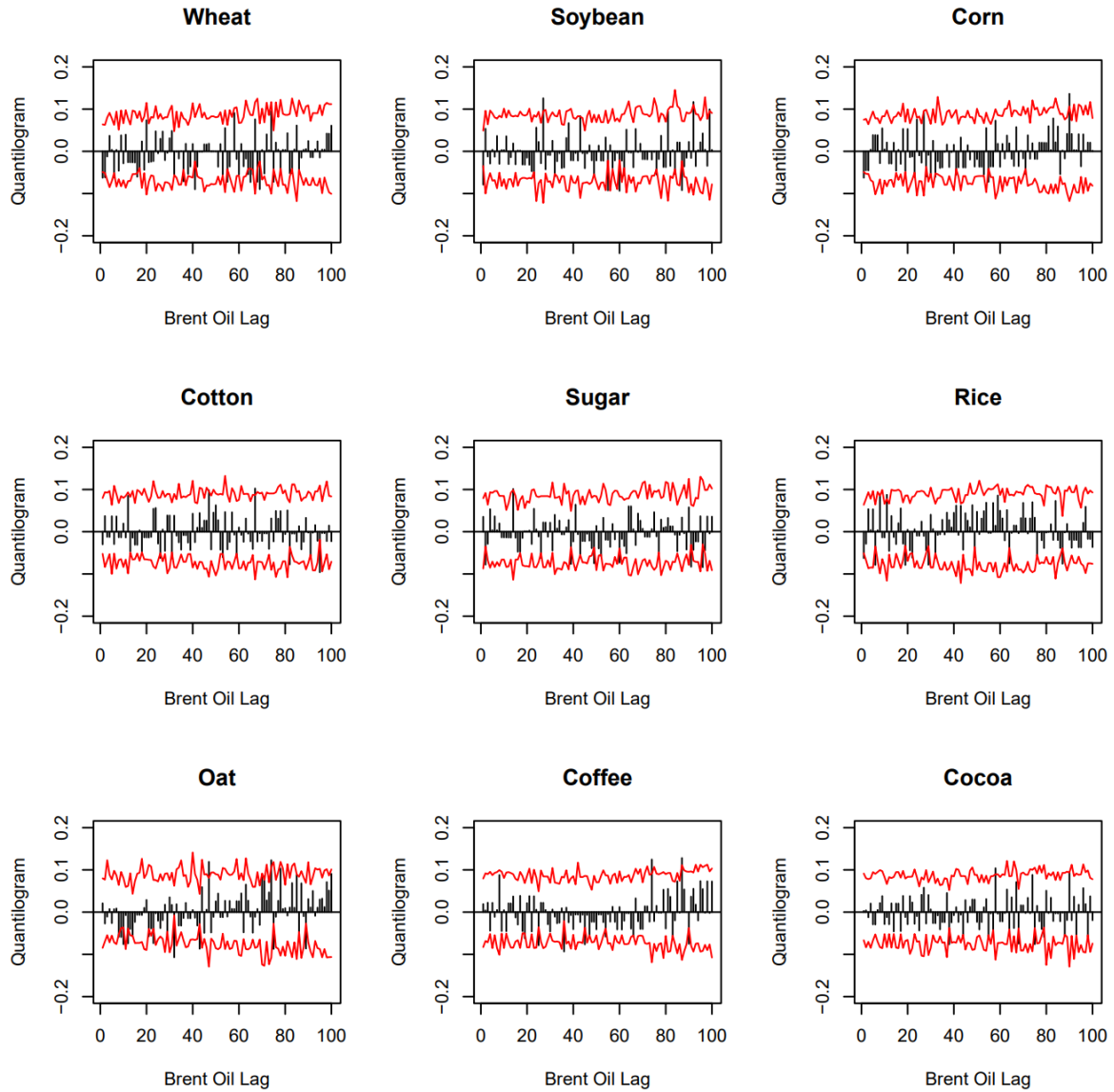


Figure A.22 : The cross-quantilogram results for Brent oil at lags 1-100 Pre-Covid-19 Era $\tau=[0.90-1]$

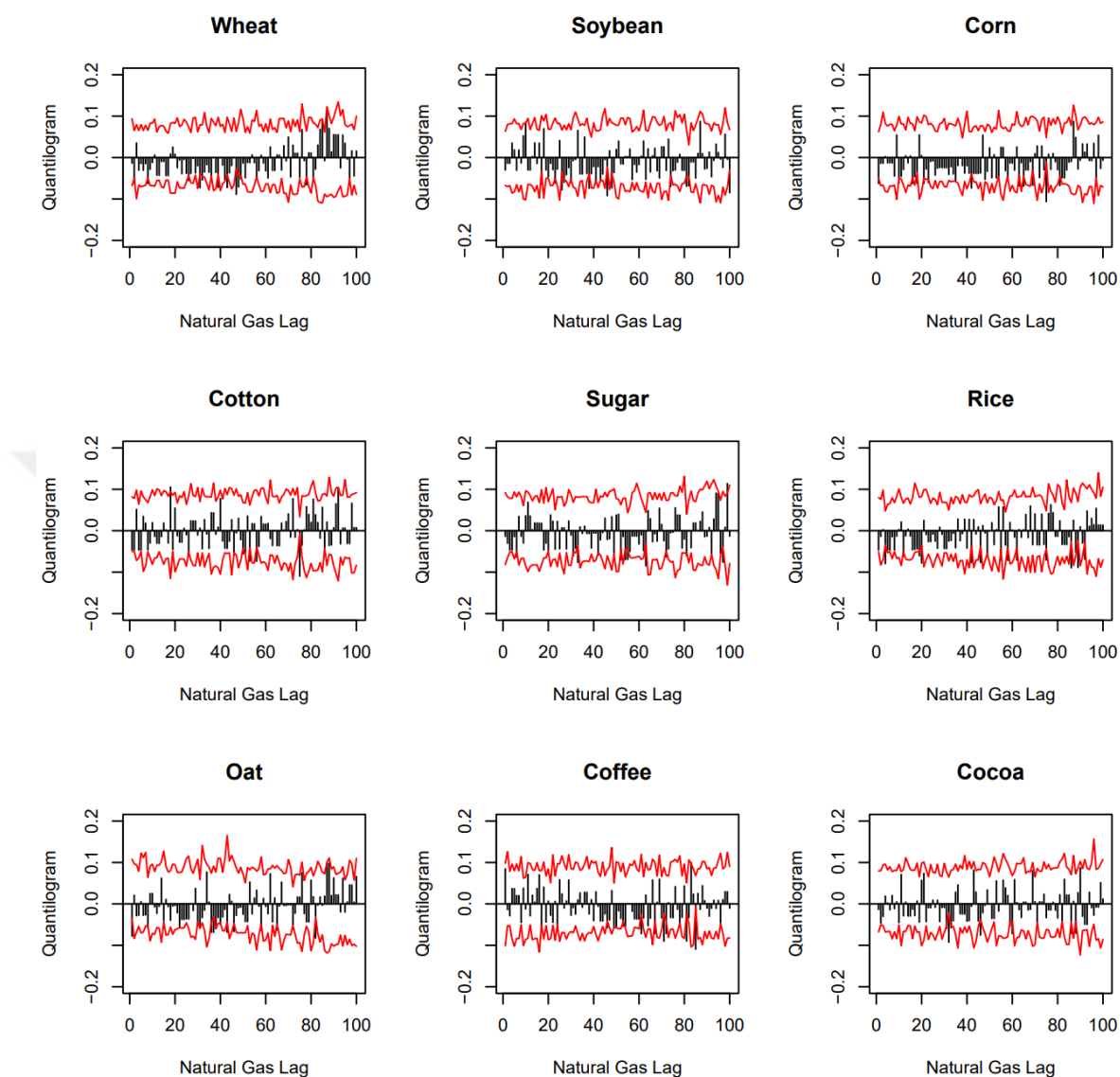


Figure A.23 : The cross-quantilogram results for Natural gas at lags 1-100 Pre-Covid-19 Era $\tau=[0.90-1]$

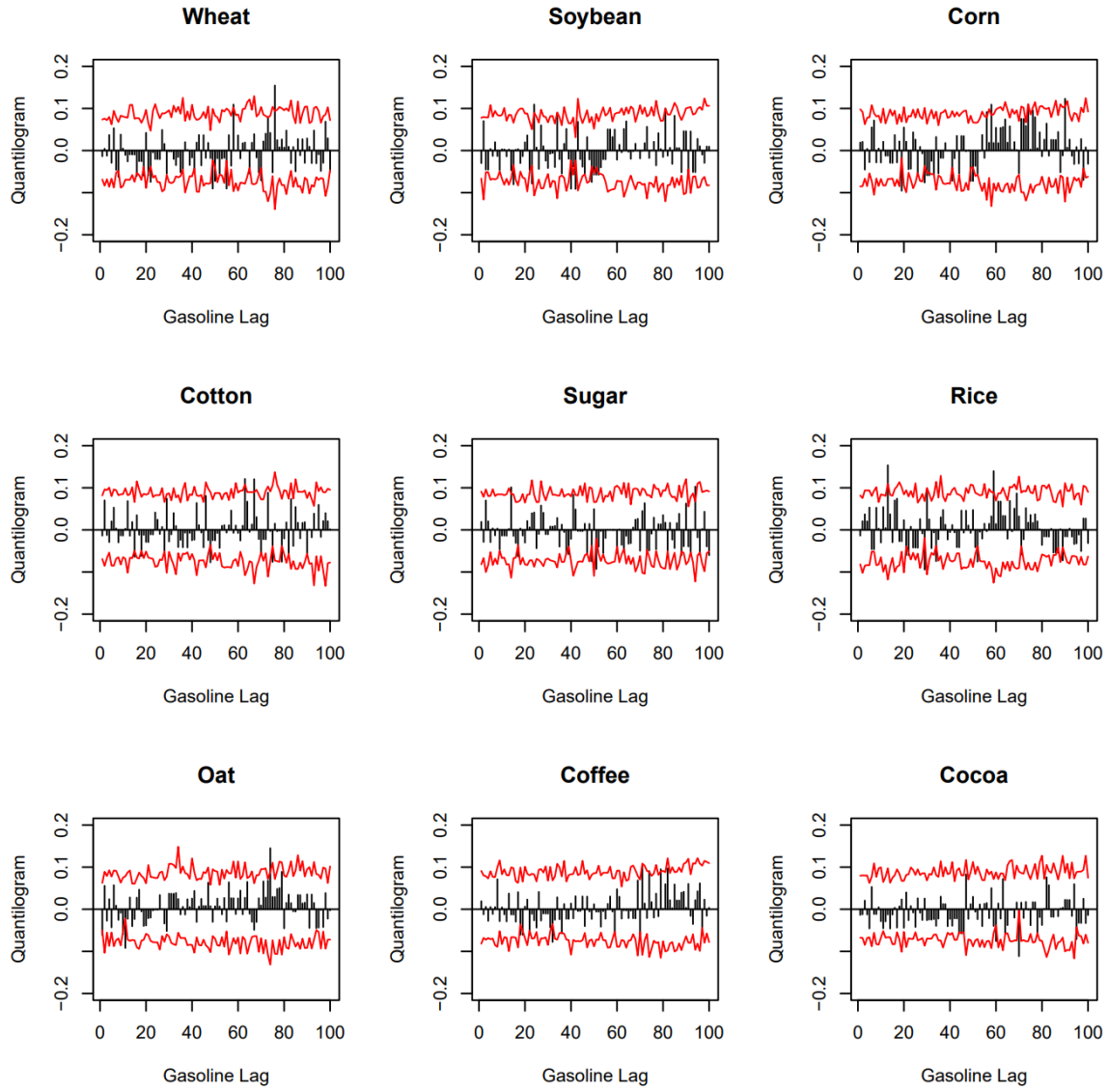


Figure A.24 : The cross-quantilogram results for Gasoline at lags 1-100 Pre-Covid-19 Era $\tau=[0.90-1]$

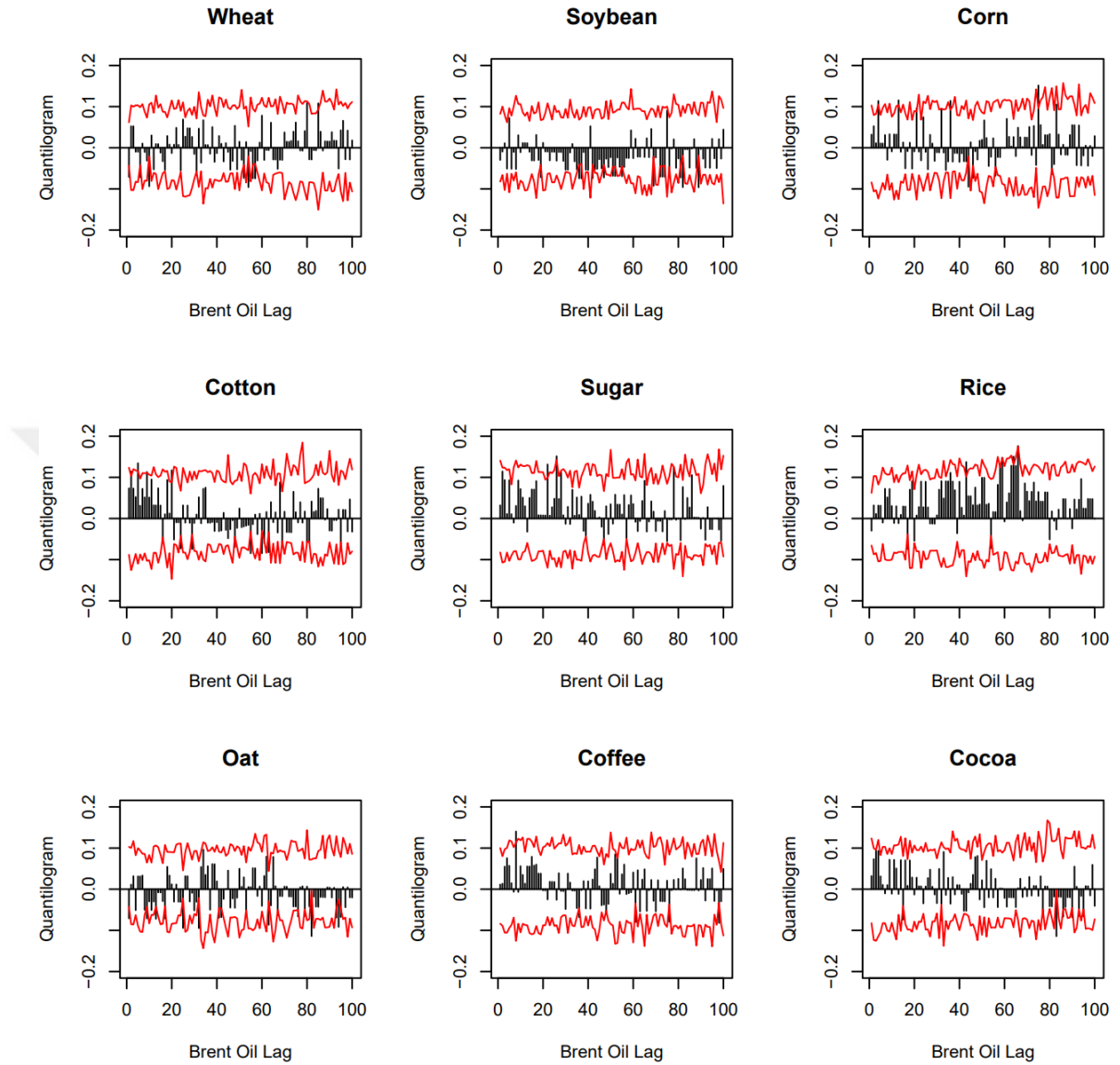


Figure A.25 : The cross-quantilogram results for Brent oil at lags 1-100 Covid-19 Era $\tau=[0-0.10]$

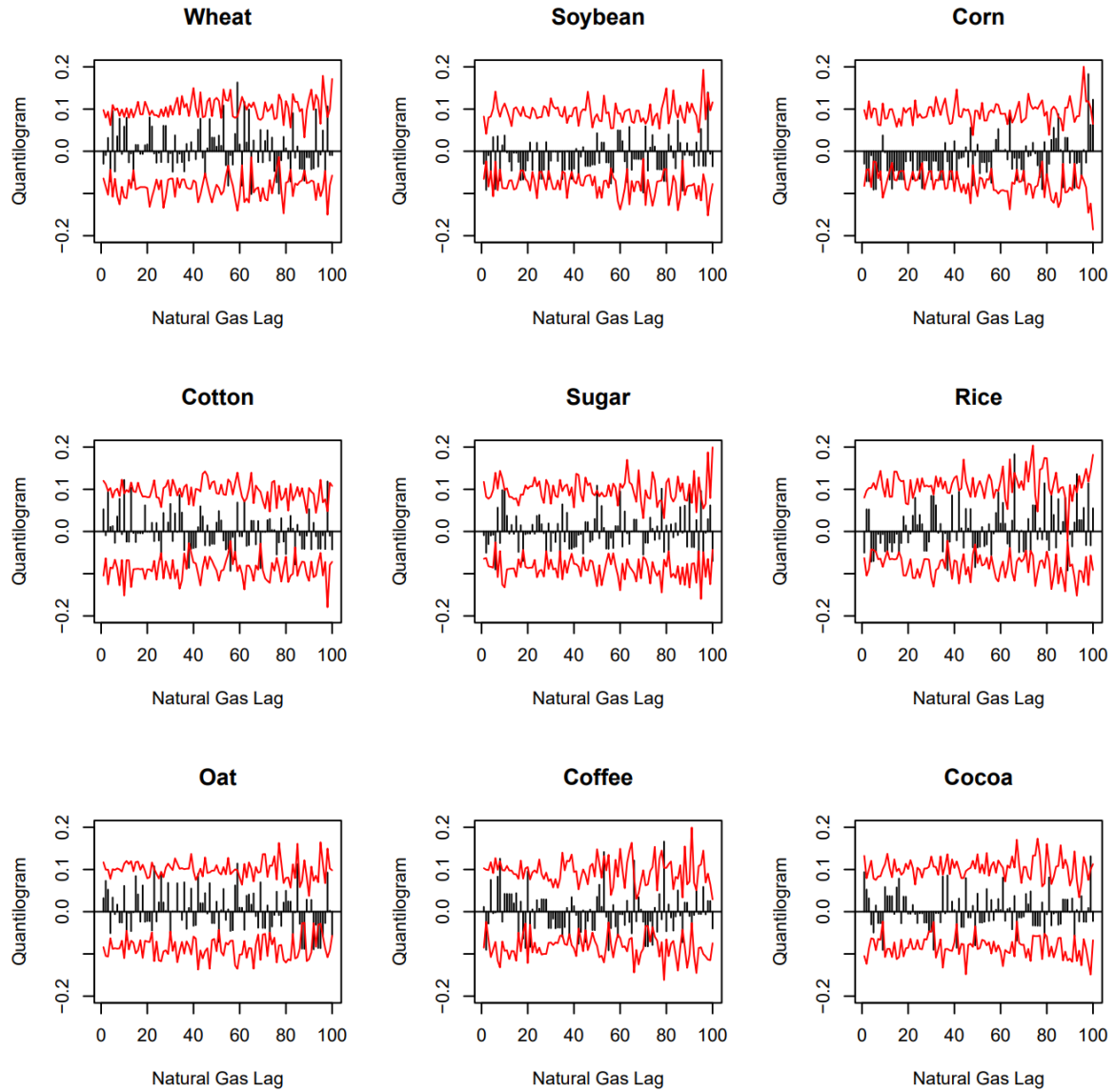


Figure A.26 : The cross-quantilogram results for Natural gas at lags 1-100 Covid-19 Era $\tau=[0-0.10]$

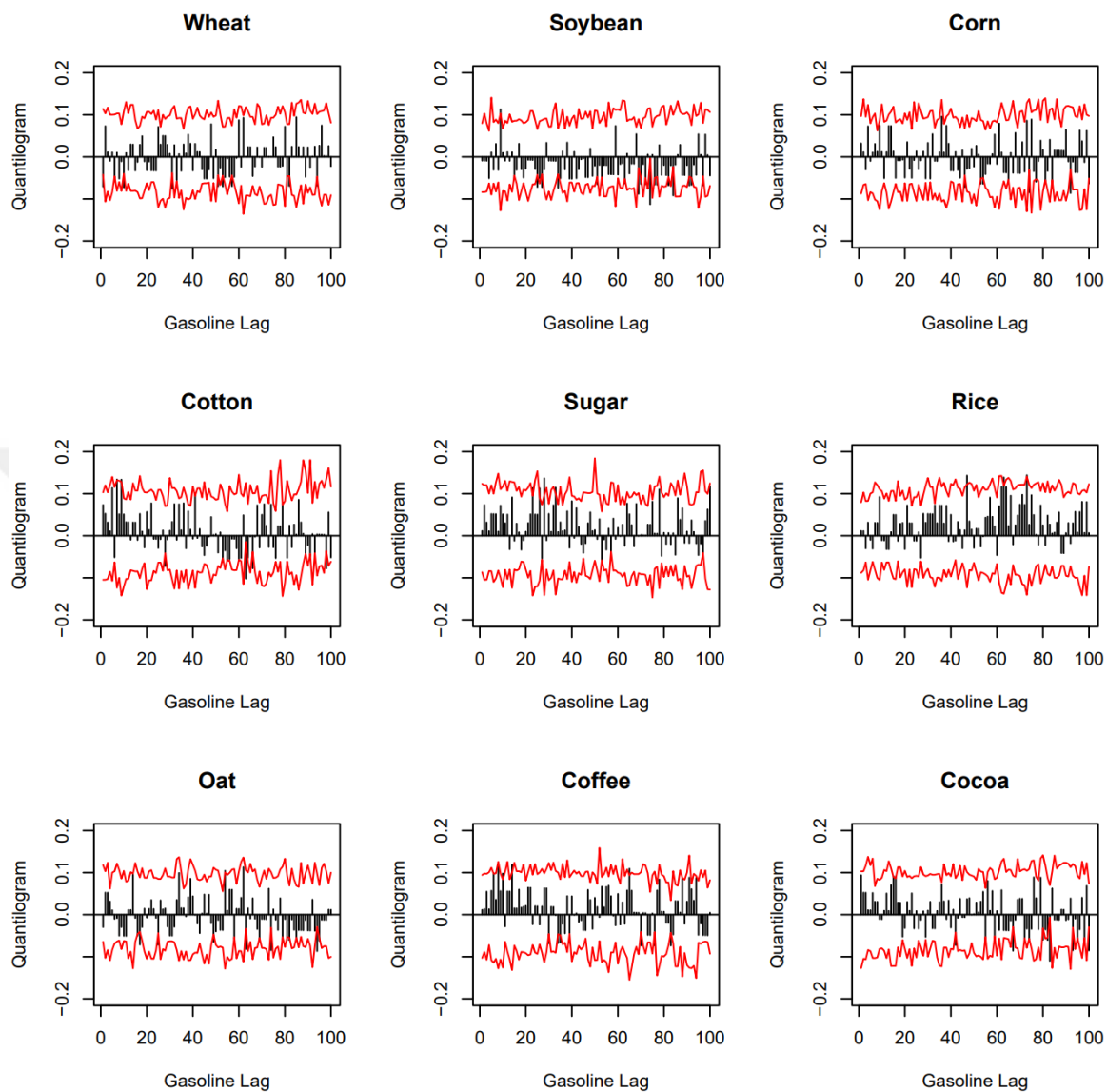


Figure A.27 : The cross-quantilogram results for Gasoline at lags 1-100 Covid-19 Era $\tau=[0-0.10]$

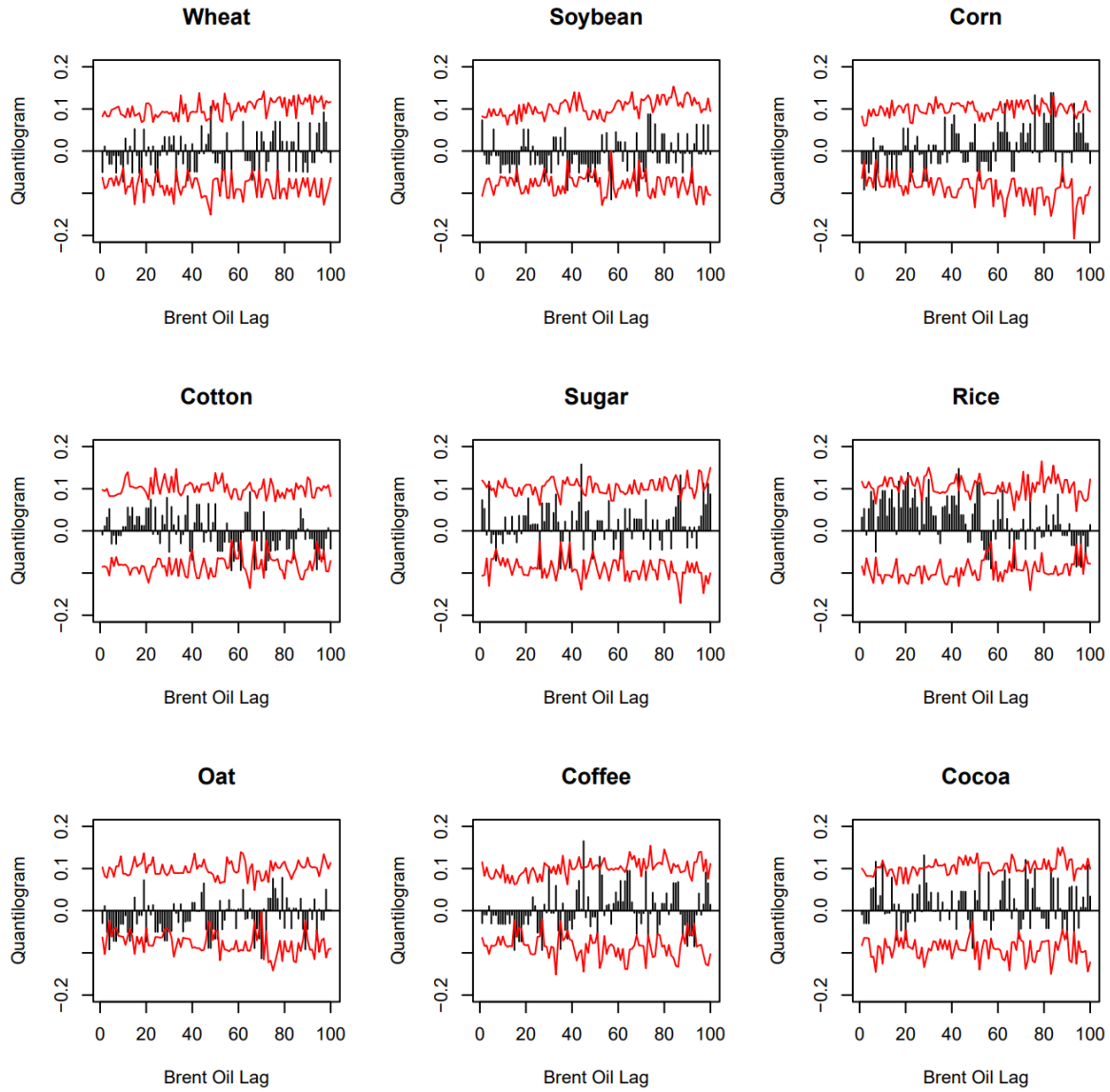


Figure A.28 : The cross-quantilogram results for Brent oil at lags 1-100 Covid-19 Era $\tau=[0.90-1]$

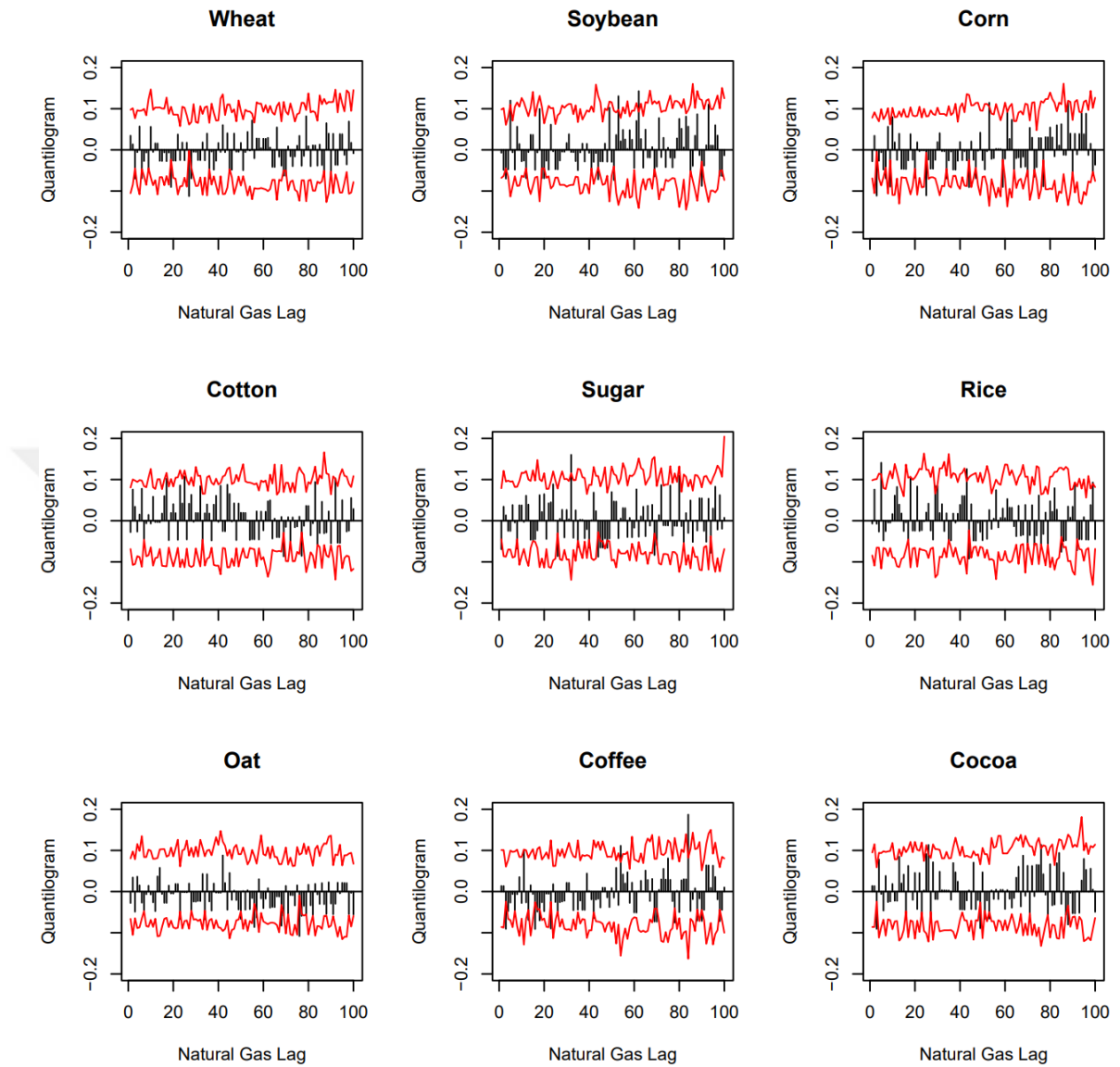


Figure A.29 : The cross-quantilogram results for Natural gas at lags 1-100 Covid-19 Era $\tau=[0.90-1]$

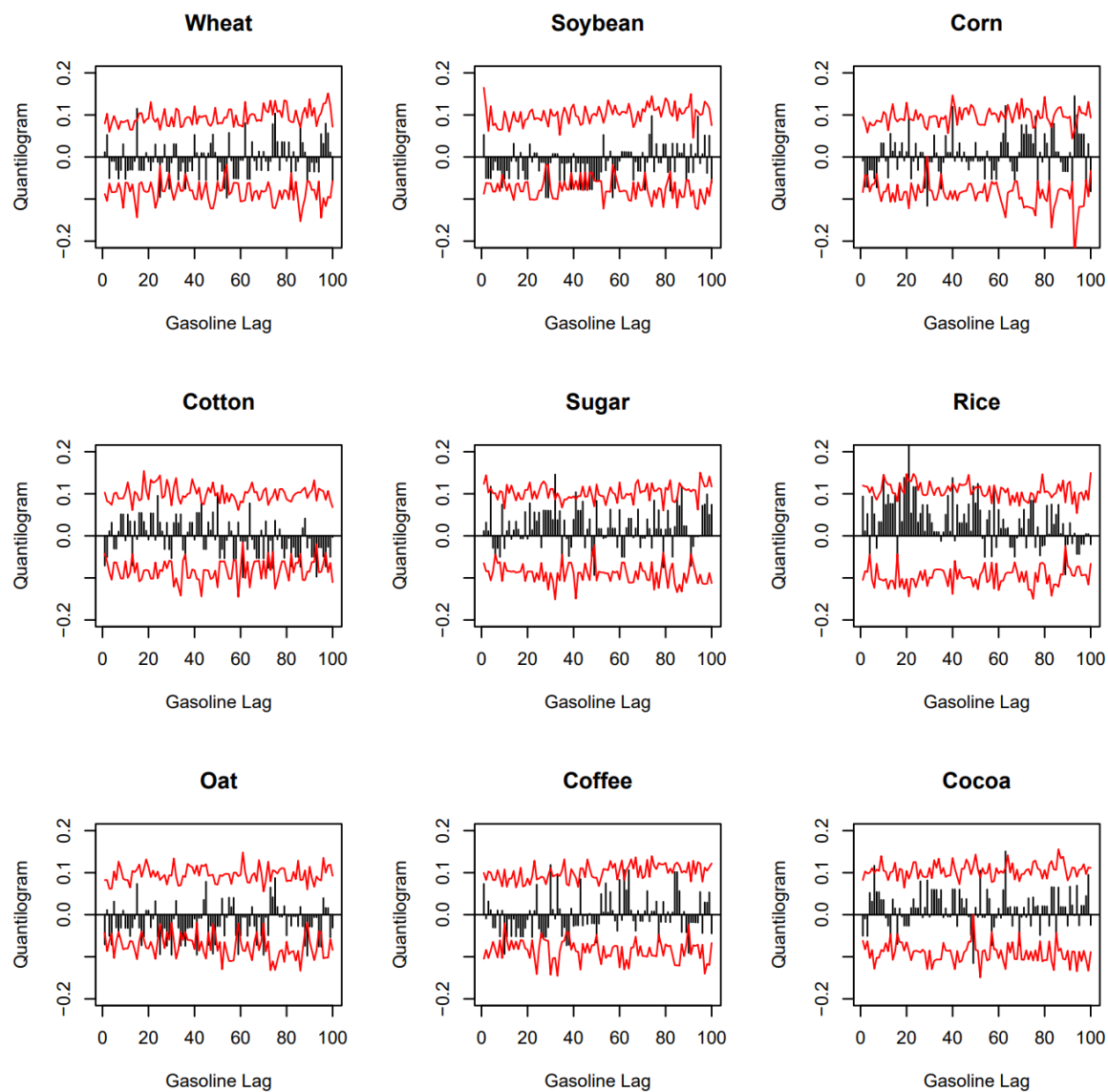


Figure A.30 : The cross-quantilogram results for Gasoline at lags 1-100 Covid-19 Era $\tau=[0.90-1]$

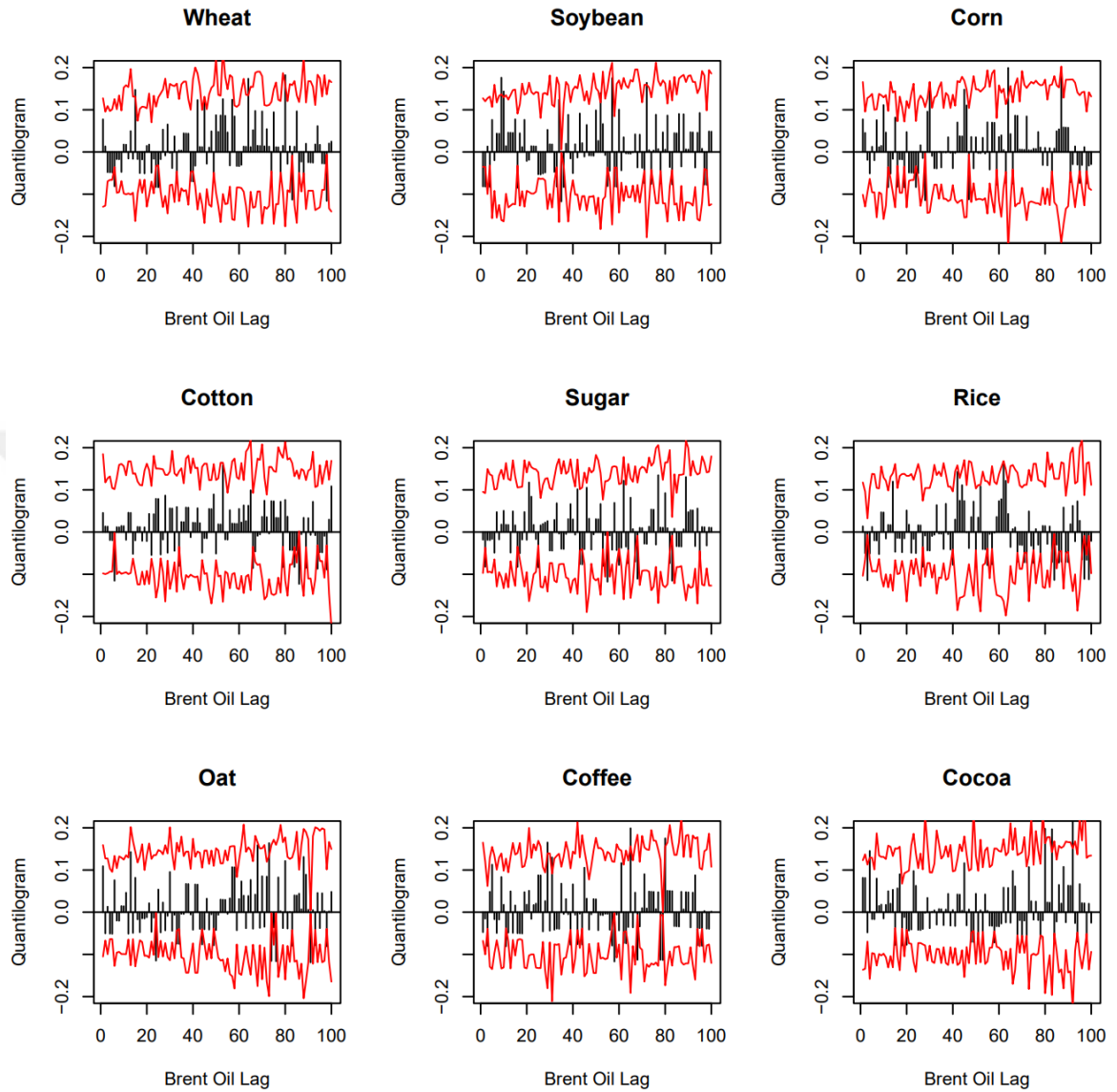


Figure A.31 : The cross-quantilogram results for Brent oil at lags 1-100 Post-Covid-19 Era $\tau=[0-0.10]$

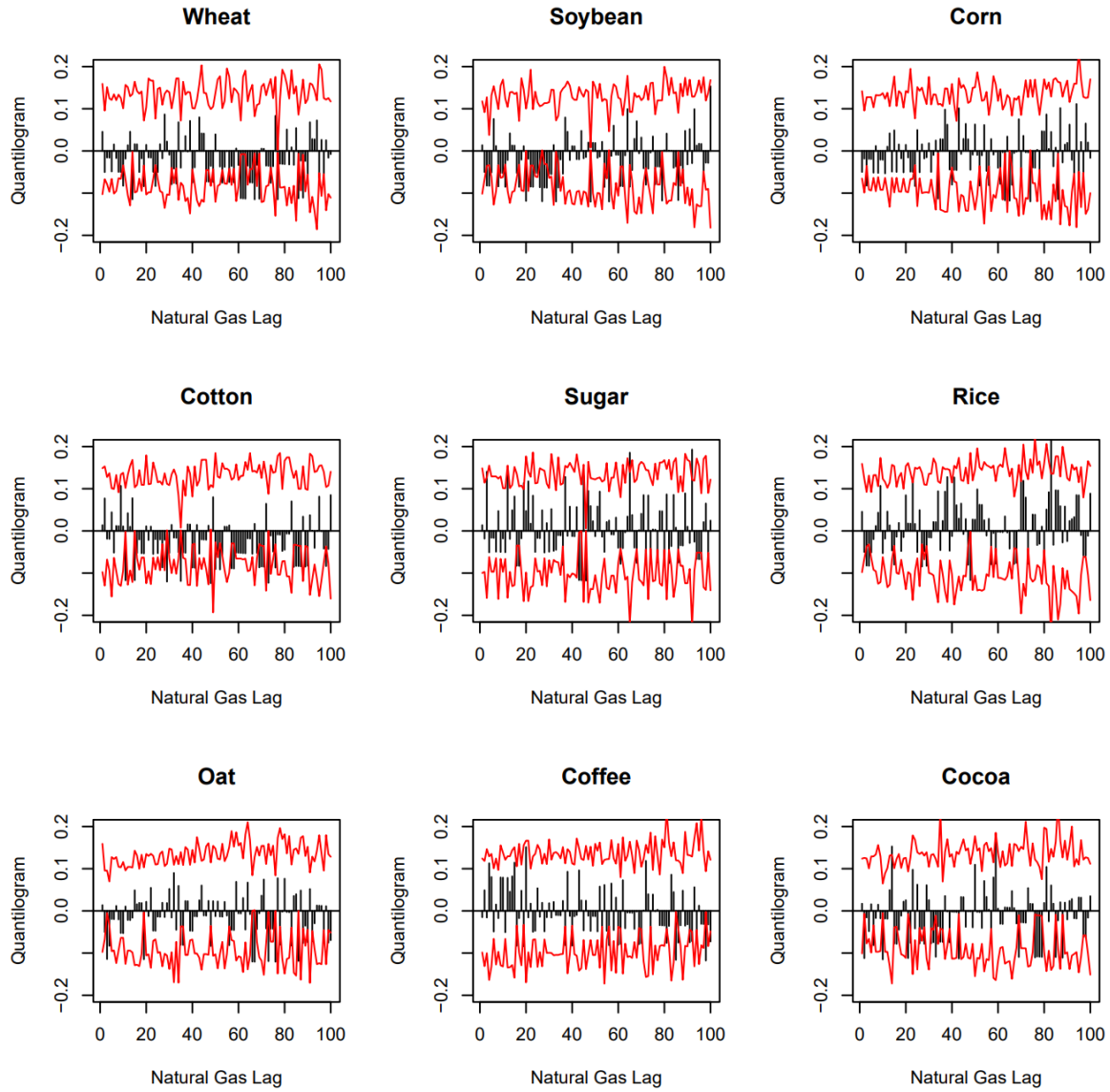


Figure A.32 : The cross-quantilogram results for Natural gas at lags 1-100 Post-Covid-19 Era $\tau=[0-0.10]$

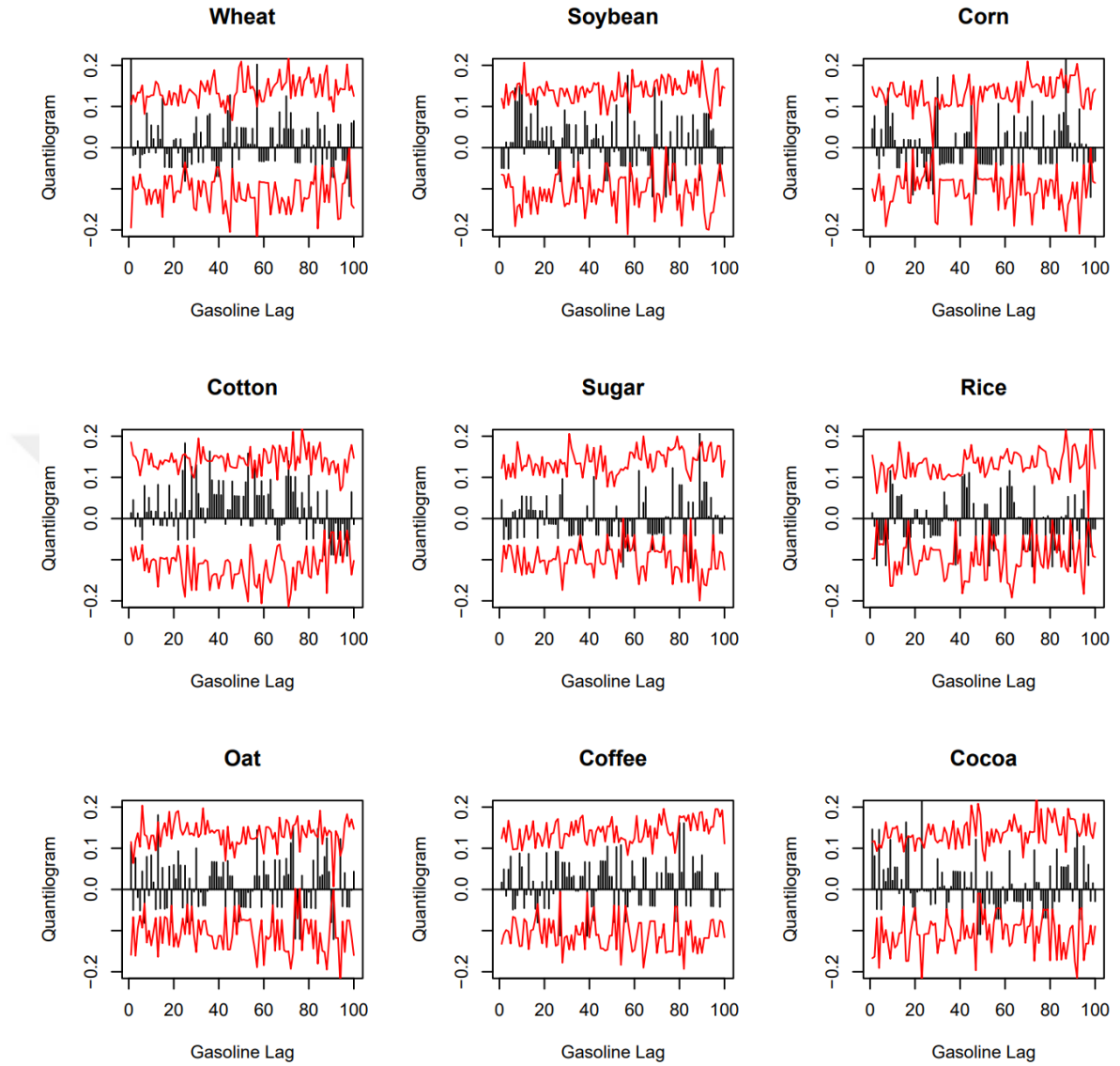


Figure A.33 : The cross-quantilogram results for Gasoline at lags 1-100 Post-Covid-19 Era $\tau=[0-0.10]$

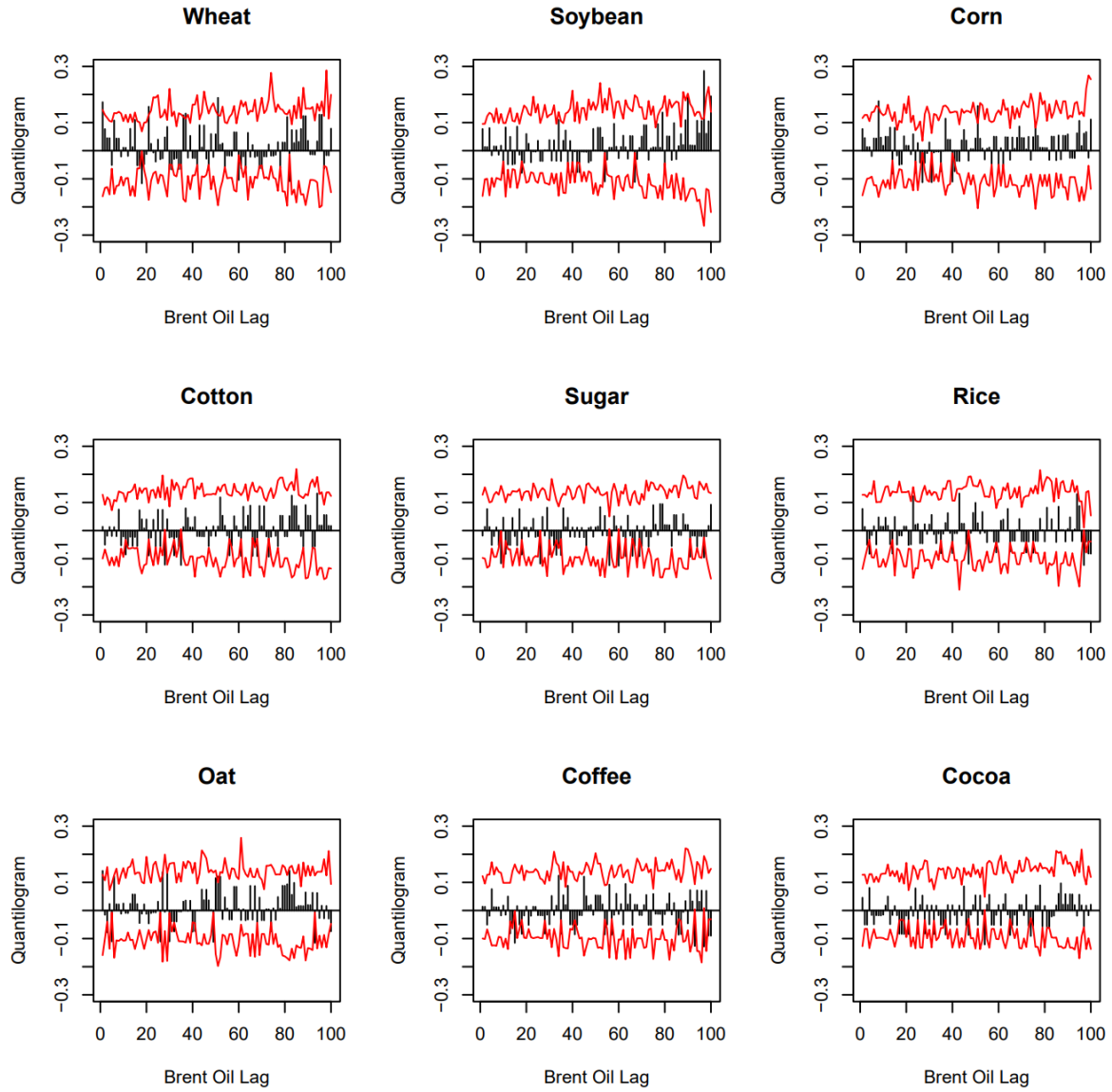


Figure A.34 : The cross-quantilogram results for Brent oil at lags 1-100 Post-Covid-19 Era $\tau=[0.90-1]$

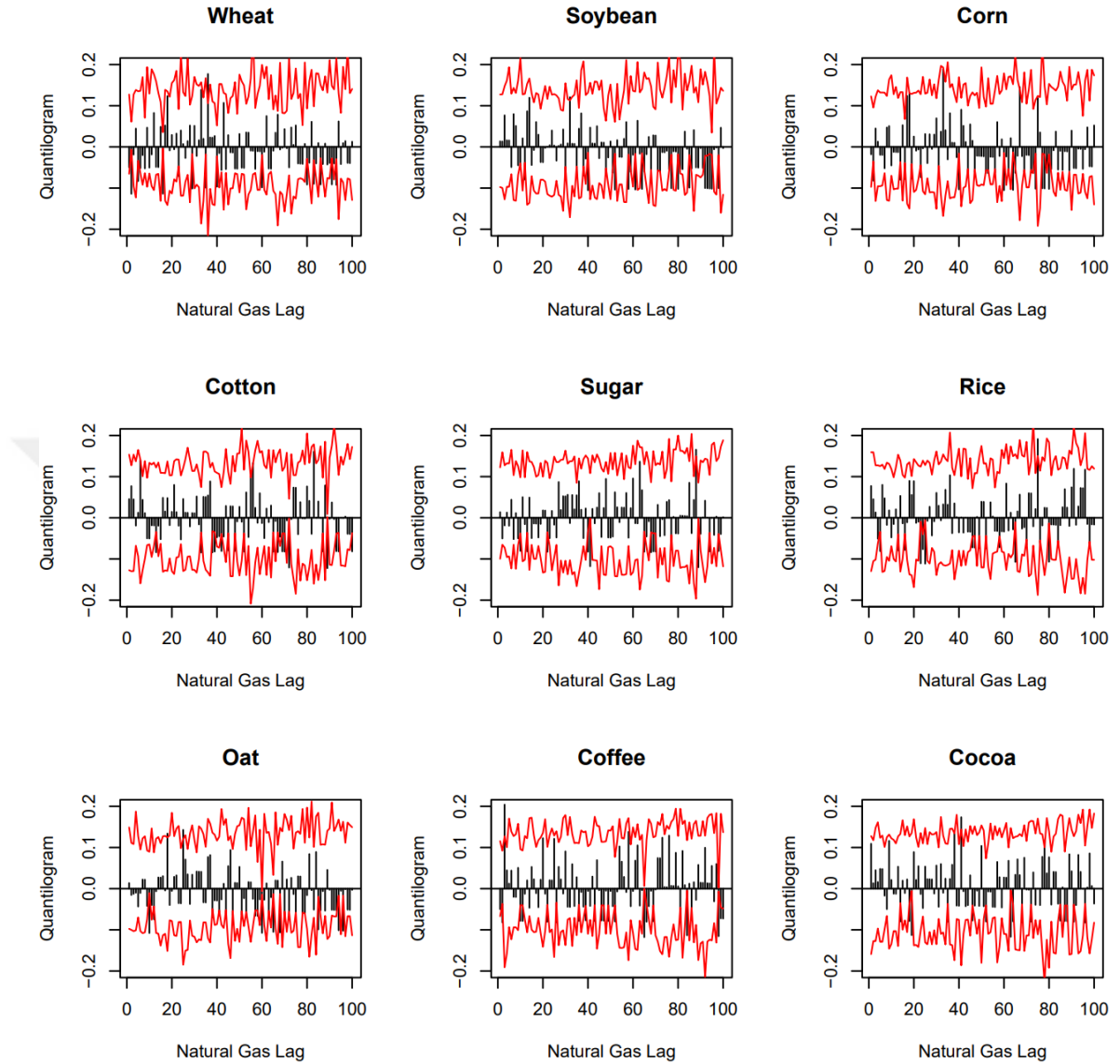


Figure A.35 : The cross-quantilogram results for Natural gas at lags 1-100 Post-Covid-19 Era $\tau=[0.90-1]$

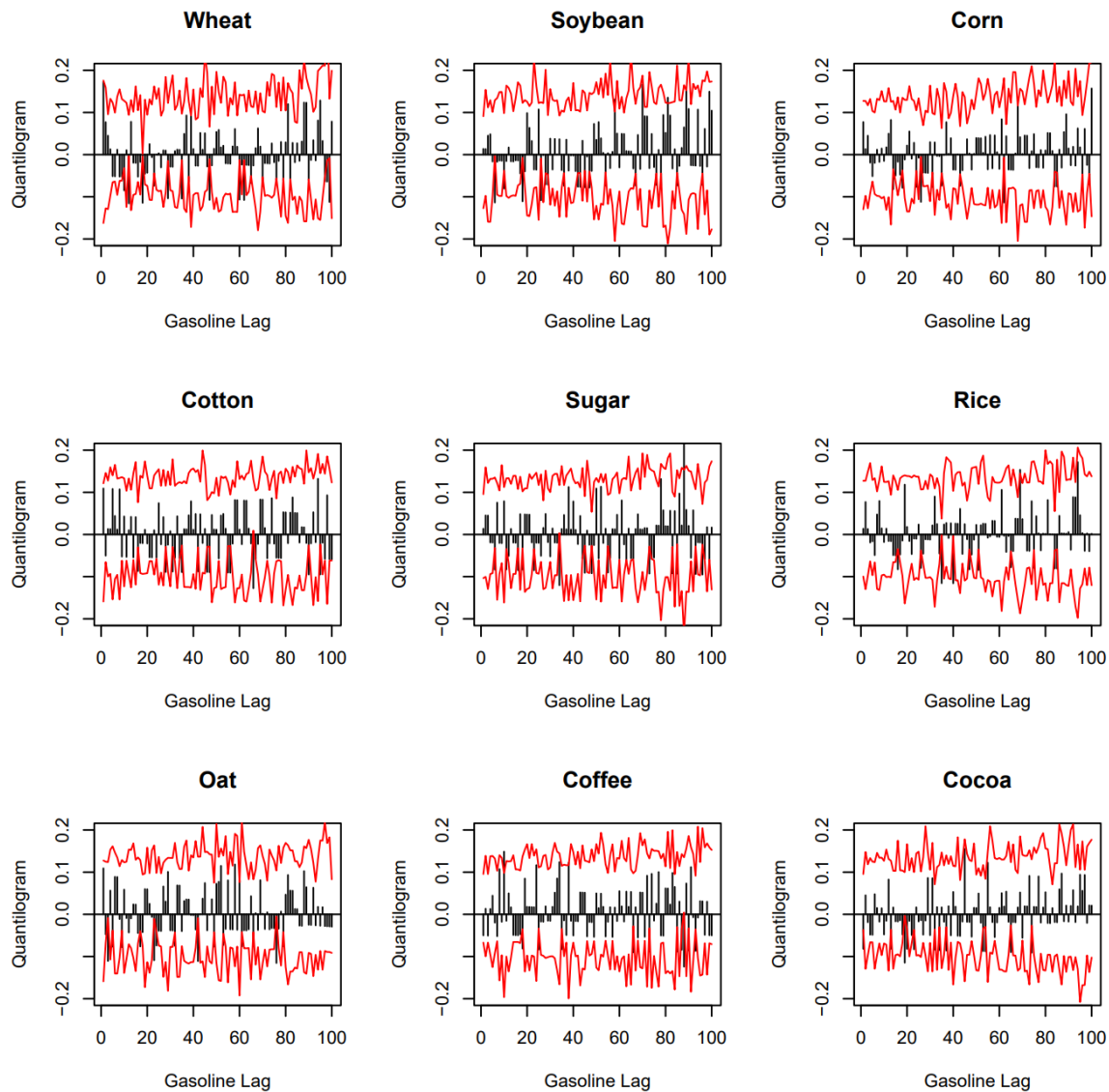


Figure A.36 : The cross-quantilogram results for Gasoline at lags 1-100 Post-Covid-19 Era $\tau=[0.90-1]$

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