Hacettepe University Graduate School of Social Sciences

Department of Economics

EMPIRICAL ESSAYS ON ENERGY ECONOMICS

Begüm AKÇORA

Ph. D. Dissertation

Ankara, 2024

EMPIRICAL ESSAYS ON ENERGY ECONOMICS

Begüm AKÇORA

Hacettepe University Graduate School of Social Sciences

Department of Economics

Ph. D. Dissertation

Ankara, 2024

ACCEPTENCE AND APPROVAL

The Jury finds that Begüm AKÇORA has on date of 24/01/2024successfully passed the defense examination and approves her PhD thesis titled "Empirical Essays on Energy Economics".

Prof. Dr. Tolga OMAY (Jury President)

Prof. Dr. Özge KANDEMİR KOCAASLAN (Main Adviser)

Prof. Dr. Ayşe Yasemin YALTA

Prof. Dr. Pelin ÖGE GÜNEY

Assoc. Prof. Dr. Doğuş EMİN

I agree that the signature above belong to the faculty members listed.

Prof. Dr. Uğur ÖMÜRGÖNÜLŞEN

Enstitü Müdürü

YAYIMLAMA VE FİKRİ MÜLKİYET HAKLARI BEYANI

Enstitü tarafından onaylanan lisansüstü tezimin tamamını veya herhangi bir kısmını, basılı (kağıt) ve elektronik formatta arşivleme ve aşağıda verilen koşullarla kullanıma açma iznini Hacettepe Üniversitesine verdiğimi bildiririm. Bu izinle Üniversiteye verilen kullanım hakları dışındaki tüm fikri mülkiyet haklarım bende kalacak, tezimin tamamının ya da bir bölümünün gelecekteki çalışmalarda (makale, kitap, lisans ve patent vb.) kullanım hakları bana ait olacaktır.

Tezin kendi orijinal çalışmam olduğunu, başkalarının haklarını ihlal etmediğimi ve tezimin tek yetkili sahibi olduğumu beyan ve taahhüt ederim. Tezimde yer alan telif hakkı bulunan ve sahiplerinden yazılı izin alınarak kullanılması zorunlu metinleri yazılı izin alınarak kullandığımı ve istenildiğinde suretlerini Üniversiteye teslim etmeyi taahhüt ederim.

Yükseköğretim Kurulu tarafından yayınlanan ***"Lisansüstü Tezlerin Elektronik Ortamda Toplanması, Düzenlenmesi ve Erişime Açılmasına İlişkin Yönerge"*** kapsamında tezim aşağıda belirtilen koşullar haricince YÖK Ulusal Tez Merkezi / H.Ü. Kütüphaneleri Açık Erişim Sisteminde erişime açılır.

- o Enstitü / Fakülte yönetim kurulu kararı ile tezimin erişime açılması mezuniyet tarihimden itibaren 2 yıl ertelenmiştir. (1)
- o Enstitü / Fakülte yönetim kurulunun gerekçeli kararı ile tezimin erişime açılması mezuniyet tarihimden itibaren ….. ay ertelenmiştir. (2)
- o Tezimle ilgili gizlilik kararı verilmiştir. (3)

24/02/2024

Begüm AKÇORA

[1] *"Lisansüstü Tezlerin Elektronik Ortamda Toplanması, Düzenlenmesi ve Erişime Açılmasına İlişkin Yönerge"*

*(1) Madde 6. 1. Lisansüstü tezle ilgili patent başvurusu yapılması veya patent alma sürecinin devam etmesi durumunda, tez **danışmanının** önerisi ve **enstitü anabilim dalının** uygun görüşü üzerine **enstitü** veya **fakülte yönetim kurulu** iki yıl süre ile tezin erişime açılmasının ertelenmesine karar verebilir.*

*(2) Madde 6. 2. Yeni teknik, materyal ve metotların kullanıldığı, henüz makaleye dönüşmemiş veya patent gibi yöntemlerle korunmamış ve internetten paylaşılması durumunda 3. şahıslara veya kurumlara haksız kazanç imkanı oluşturabilecek bilgi ve bulguları içeren tezler hakkında tez **danışmanının** önerisi ve **enstitü anabilim dalının** uygun görüşü üzerine **enstitü** veya **fakülte yönetim kurulunun** gerekçeli kararı ile altı ayı aşmamak üzere tezin erişime açılması engellenebilir.*

*(3) Madde 7. 1. Ulusal çıkarları veya güvenliği ilgilendiren, emniyet, istihbarat, savunma ve güvenlik, sağlık vb. konulara ilişkin lisansüstü tezlerle ilgili gizlilik kararı, **tezin yapıldığı kurum** tarafından verilir *. Kurum ve kuruluşlarla yapılan işbirliği protokolü çerçevesinde hazırlanan lisansüstü tezlere ilişkin gizlilik kararı ise, **ilgili kurum ve kuruluşun önerisi** ile **enstitü** veya **fakültenin** uygun görüşü üzerine **üniversite yönetim kurulu** tarafından verilir. Gizlilik kararı verilen tezler Yükseköğretim Kuruluna bildirilir.*
Madde 7.2. Gizlilik kararı verilen tezler gizlilik süresince enstitü veya fakülte tarafından gizlilik kuralları çerçevesinde muhafaza edilir, gizlilik kararının kaldırılması halinde Tez Otomasyon Sistemine yüklenir.

** Tez **danışmanının** önerisi ve **enstitü anabilim dalının** uygun görüşü üzerine **enstitü** veya **fakülte yönetim kurulu tarafından karar verilir.***

ETİK BEYAN

Bu çalışmadaki bütün bilgi ve belgeleri akademik kurallar çerçevesinde elde ettiğimi, görsel, işitsel ve yazılı tüm bilgi ve sonuçları bilimsel ahlak kurallarına uygun olarak sunduğumu, kullandığım verilerde herhangi bir tahrifat yapmadığımı, yararlandığım kaynaklara bilimsel normlara uygun olarak atıfta bulunduğumu, tezimin kaynak gösterilen durumlar dışında özgün olduğunu, **Prof. Dr. Özge KANDEMİR KOCAASLAN** danışmanlığında tarafımdan üretildiğini ve Hacettepe Üniversitesi Sosyal Bilimler Enstitüsü Tez Yazım Yönergesine göre yazıldığını beyan ederim.

Begüm AKÇORA

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to my supervisor Prof. Dr Özge KANDEMİR KOCAASLAN, not only for her invaluable guidance and contributions of this thesis, but also for her constant support, mentoring, patience, encouragement and kindness.

I would like to express my deepest gratitude to the members of my thesis committee, Prof. Dr. Tolga OMAY and Prof. Dr. Ayşe Yasemin YALTA, for their time to monitor my progress and provide valuable comments, contributions and suggestions on my thesis. I am also grateful to Prof. Dr. Pelin ÖGE GÜNEY and Assoc. Prof. Dr. Doğuş EMİN who honored me as a part of my thesis review committee, providing valuable contributions to this thesis.

I am grateful to my friends Ayşegül, Ezel, Gamze and Kübra their continous support, motivation and encouragement during this thesis.

I wish to express my deepest gratitude and appreciation to my family for their unconditional support, encouragement and patience throughout my life. This thesis is dedicated to my father who always be with me.

ABSTRACT

AKÇORA, Begüm. *Empirical Essays on Energy Economics,* Ph.D Dissertation, Ankara, 2024.

This thesis comprises three essays on energy economics. In the first chapter, we focus on detecting gas price bubbles by employing the generalized sup ADF (GSADF) test by Phillips et al. (2015). We utilize the Log-Periodic Power Law Singularity (LPPLS) method established by Filimonov and Sornette (2013) as a robustness check in the European gas markets. The findings from the GSADF test indicate that TTF exhibits the fewest number of price bubbles, followed by NBP. LPPLS test reveal that both TTF and NBP exhibit the fewest numbers of price bubbles. We underscore a significant level of gas market integration, notably evident in the similarity of dates of the bubble period in the Europe. The second chapter determines the causal link among EU ETS carbon prices as well as energy prices by employing a time-varying causality test (TVGC) by Shi et al. (2020, 2018). The robustness of the results is checked including stock market data and the Geopolitical Risk Index. Our study reveals a more evident causal relation between fossil energy and carbon emissions, particularly after 2016. The results indicate variations in energy prices are triggered by factors like surplus LNG, sanctions affecting oil prices, the COVID-19 pandemic, political announcements, spike natural gas prices due to stock levels, and similar factors affect carbon prices. The final chapter, the outcomes of oil price shocks on sectoral unemployment are considered by applying a Structural Vector Autoregression (SVAR) technique in the U.S.. The findings note evident heterogeneity in the response of sectoral unemployment to the oil-related shocks.

Keywords: Price Bubbles, Causality, Oil Price Shocks, Carbon Market, Energy Market, Sectoral Unemployment

ÖZET

AKÇORA, Begüm. *Enerji Ekonomisi Üzerine Ampirik Makaleler,* Doktora Tezi, Ankara, 2024.

Bu tez enerji ekonomisi üzerine üç makaleden oluşmaktadır. Birinci bölümde, 2015 yılında Phillips ve arkadaşları tarafından geliştirilen GSADF testini kullanarak Avrupa'daki belirli hublarda gaz fiyat balonları tespit edilmektedir. Daha sonra, Filimonov ve Sornette (2013) tarafından geliştirilen LPPLS yöntemi ile Avrupa doğal gaz fiyat balonları karşılaştırılmaktadır. GSADF testinden elde edilen bulgular, en az sayıda fiyat balonunun TTF'te sonra da NBP'de oluştuğunu göstermektedir. LPPLS testi, hem TTF'nin hem de NBP'nin en az sayıda fiyat balonu sergilediğini ortaya çıkarmaktadır. Sonuçlarımıza göre doğal gaz fiyat balon dönemi tarihlerinin benzerliğinden dolayı Avrupa'da önemli derecede entegre bir doğal gaz piyasası olduğu tespit edilmektedir. İkinci bölümde, Shi ve diğerleri tarafından geliştirilen TVGC testini kullanarak AB ETS karbon fiyatları ve enerji fiyatları arasındaki nedensellik bağlantısı araştırılmaktadır. Ayrıca daha sonra nedensellik ilişkisine borsa fiyat verileri ve Jeopolitik Risk Endeksi dahil edilerek sonuçların değişip değişmediği tekrar incelenmiştir. Çalışmamız, fosil enerji fiyatları ile karbon fiyatları arasında özellikle 2016 sonrasında daha belirgin bir nedensellik ilişkisinin var olduğunu tespit etmektedir. Enerji fiyatlarındaki dalgalanmaların karbon fiyatları üzerindeki etkisinin nedensellik ilişkisini arttırdığı ve dalgalanmalarında LNG miktar fazlası, petrol fiyatlarını etkileyen yaptırımlar, Kovid-19 salgını, Rusya-Ukrayna savaşı gibi faktörlerden kaynaklandığını göstermektedir. Son bölümde ise petrol fiyatı şoklarının Amerika Birleşik Devletleri sektörel işsizlik üzerindeki sonuçları, SVAR tekniği uygulanarak araştırılmaktadır. Bulgular, sektörel işsizliğin petrole bağlı şoklara verdiği yanıtta belirgin bir heterojenlik bulunduğuna dikkat çekmektedir. Talep kaynaklı petrol fiyat şokunun sektörel işsizlik üzerinde belirgin bir etkisinin olduğu gözlemlenmektedir.

Keywords: Fiyat Balonu, Nedensellik, Petrol Fiyat Şoku, Karbon Piyasası, Enerji Piyasası, Sektörel İşsizlik

TABLE OF CONTENTS

INDEX OF TABLES

INDEX OF FIGURES

INDEX OF ABBREVIATIONS

ACER	: European Union Agency for the Cooperation of Energy Regulators
AGTM	: ACER Gas Target Model
BIC	: Bayesian Information Criteria
CEGH	: Central European Gas Hub AG
CPI	: Consumer Price Index
EEX	: European Energy Exchange
ETS	: Emission Trading Scheme
FRED	: Federal Reserve Bank
GECON	: Global Economic Conditions
GOG	: Gas-on-Gas Pricing Mechanism
GPR	: Geopolitical Risk Index
GSADF	: Generalized Sup ADF Test
HHI	: Herfindahl-Hirschmann Index
LPPLS	: Log-Periodic Power Law Singularity
MSR	: Market Stability Reserve
NBP	: National Balancing Point
NCG	: NetConnect Germany
PSV	: Punto di Scambio Virtuale
RAC	: Refiner Acquisition Cost
RSI	: Residual Supply Index
SVAR	: Structural Var Model
TTF	: Title Transfer Facility
TVGC	: Time Varying Granger Causality Test
U.S..	: United States
VTP	: Virtual Trading Point

INTRODUCTION

The global energy market has encountered noteworthy transformations, and one of the critical components is energy financialization. In recent decades, energy prices have performed very much like financial commodities which have gone through exuberance volatility, uncertainty, speculative bubbles, ambiguity, shocks, etc. As a result of financialization, there is an urgent need to measure risk or predict energy prices more efficiently because of the advancement of interconnectedness among various energy sources and integration across regions.

Starting from 2018, the world energy market has undergone extraodinary shifts due to a diverse array of economic, political, and climate-related factors such as COVID-19 pandemic demand tightness, Ukraine–Russia conflict, European energy crisis, climate goals etc. In this context, energy prices have a crucial impact on macroeconomic and microeconomic dynamics which can cause either economic loss or welfare. It is crucial to understand the fundamental characteristics of energy commodities to better grasp the causes and results of economic impacts for economists and policymakers. Contributing to the energy economics and finance era, the present thesis is organized as three specific essays, which delve into energy commodities from various perspectives. First, as an energy commodity, natural gas prices are similar to financial assets that experience volatility, speculation, and price bubbles. Caspi (2016) states that price bubbles form when commodity price substantially strays from its fundamental value. When asset price bubbles persist, and the duration is long, the probability of a less efficient market can emerge. Natural gas price bubbles are disadvantageous for firms, energy sectors, and economies since natural gas is a crucial input for production processes and household needs. When markets experience price bubbles, misleading price signals can misdirect market participants, resulting in economic losses. Therefore, detecting bubbles within natural gas markets is crucial to manage risks and ensure market participants are not exposed to misaligned prices. Thus, we investigate price bubbles in the European gas hubs. The world gas market is marked into three predominant regions regarding geography and pricing methods (IEA, 2013). In the U.S., prices are determined by the gas-on-gas pricing mechanism (GOG), while in Europe, prices are formed by oil-indexed contracts with the hub price mechanism since the early 2000s. In Asia, prices are established through oil-indexed contracts. Therefore, by detecting gas price bubbles in Europe, we investigate that gas markets within the same geographic region employing a similar pricing methodology, such as the hub-based approach, might encounter varying occurrences of price bubbles owing to their distinctive characteristics. We contribute to the literature, examining price bubbles for the first time in the European hubs by employing two distinct methodologies. We present compelling evidence that not only does the price mechanism utilized in hubs play a role, but the unique characteristics of these hubs also decisively affect the occurrence of price bubbles. This research will empower market participants, economists, and policymakers to understand the distinct traits inherent to gas price bubble behavior in Europe.

Cope with climate change, the Emission Trading Scheme (ETS) was initiated in 2005. ETS is the first and still the most extensive cap-and-trade mechanism as a cost-effective instrument for mitigating emissions in the European Union. ETS retrains the amount of CO_2 allowances put into circulation from companies and can be subject to trade with each other. The objective of carbon pricing is diminishing greenhouse gases like carbon dioxide, thereby reducing the impacts of climate change. The primary carbon pricing systems are ETS as well as carbon taxes. The ETS operates through a cap-and-trade system, obligating actors possessing allowances equal to their emissions. The entire quantity of allowances diminishes, allowing companies to trade these allowances and consequently establish the carbon price. Climate change is a paramount driving force in the international energy market. A carbon tax directly sets a carbon price, aiming to incentivize companies to decrease their emissions. In this context, the ETS was operated marking the inception along with continued operation of the most comprehensive cap-and-trade mechanism within the European Union. It stands as a cost-effective instrument aimed at curbing greenhouse gas emissions. The EU ETS is currently in Phase 4 (2021 to 2030), which has progressively evolved into a more stringent mechanism. This study contributes by analyzing the causality link among the ETS carbon prices as well as energy prices. It employs a time-varying causality test (TVGC) developed by Shi et al. (2020, 2018). The rationale for investigating this issue lies in the strong equivalence among carbon and fossil energy. Fossil energy, primarily propelled by economic growth and industrial production, is the essential cause of emissions, establishing a profound connection among prices of carbon and energy. Furthermore, a cyclical interdependence exists among prices carbon allowance and energy despite the stability of the allowance supply, which originates externally. When carbon prices are low, there tends to be a surge for energy usage for affordability of carbon. Consequently, this surge causes a hike in the expenses of allowances. Alterations in the cost of fossil energy lead to substitution and income effects that influence carbon prices. This chapter emphasizes the causal relation among carbon and energy prices in the European Union that has become more evident since 2016, taking precautions to diminish emissions starting from the declaration of the Paris Agreement. Further, this study provides deep understanding between carbon and energy market, detecting causality periods and determines the reasons behind casual relations. Moreover, it is crucial for policymakers to attentively monitor and comprehend the dynamics of carbon in addition to traditional energy resources, in order to enhance carbon market effectiveness.

Since the beginning of the oil crisis in the 1970s, a noteworthy correlation has been established between significant surges in oil prices along with recessions in the United States. This correlation has boosted the interest of economists and policymakers, prompting extensive investigation into how shocks in oil prices influence various economic indicators. The final chapter scrutinize how oil price shocks influence sectoral unemployment in the United States. Our goal in studying to find out whether oil price shocks affect on unemployment in different sectors. This research significantly provides to the current knowledge of oil price shocks as well as how they relating various unemployment sectors, offering valuable insights into the labor market. There are limited numbers of study investigated deeply oil price shocks and labor market. This chapter contributes examining the conclusion of structural oil shocks on sectoral unemployment. The outcomes show that there is indeed heterogeneity in the reacts of sector-specific unemployment levels to various oil-related shocks in the U.S.. In particular, various unemployment sectors display significant responses to oil supply shocks at different magnitude levels. For all sectors of unemployment are significantly affected by aggregate demand shock. For this reason, policy makers should not make a uniform policy to apply to all unemployment, each sector should be examined specifically.

CHAPTER 1

DETECTION PRICE BUBBLES IN THE EUROPEAN NATURAL GAS MARKET: 2011-2020

1.1 INTRODUCTION

Hub trading allows market actors to exchange gas as a financial commodity with standardized contracts and rules (Shi and Variam, 2018). Standardization is the first condition for attracting traders to operate in the market since standardization engages with liquidity along with volume. Thus, all of these requirements facilitate market price transition (Heather, 2015). With the aim of establishing a reference price for natural gas, gas on gas price mechanisms through hub trading have emerged in the UK at National Balancing Point (NBP) (Grandi, 2014). Following the success of NBP, numerous individual hubs have emerged in Europe. However, each hub has different efficiency levels and specific conditions (Miriello and Polo, 2015). Shi and Variam (2018) clarify the framework of the elements to constitute gas hubs and evaluate them into two groups. The first group contains core elements of balancing hubs such as a trading point, hub operator, exchange, standard rules, spot products, and market actors. In the second group, it is stated that future products, financial actors, data transparency, and price reporting agencies index are required for an operational benchmark hub. Shi and Variam (2018) also argue that establishing a hub is not a sufficient condition to facilitate gas on gas price mechanism, and there is a strong need for both balancing and benchmarking hub elements.

To eliminate the differences across the countries, the European Commission (EC) presents "Energy Packages" to regulate the rules for building a harmonized, liberal natural gas market. Although there is a common political willingness by the EU, the development levels of particular hubs are different. In this context, there is a wide range of researches that regularly monitor and rank European hubs. For instance, the Oxford Institute for Energy Studies (OIES) conducts several reports on the development processes of

European hubs and evaluates them based on trading activity. Heather (2015) determines five trading measurements such as the product range, volume, churn rate, market participants, and tradability index and scores EU hubs according to those trading data measurements. In his recent study, Heather (2020) indicates that the Dutch Title Transfer Facility (TTF) is the supreme all hub in the EU according to the trading measurements. In this report, NBP gets the second highest score, which lost the dominant position to TTF, but it is still a mature and liquid hub. Although other hubs such as NetConnect Germany (NCG), Italian Punto di Scambio Virtuale (PSV), and Austrian Virtual Trading Point (VTP) score similarly among themselves, there is a clear difference between TTF and NBP. In addition to all these, the European Union Agency for the Cooperation of Energy Regulators (ACER) has prepared a guideline defined as the ACER Gas Target Model (AGTM) to evaluate the performance of European hubs. In AGTM, hubs are analyzed based on two primary metrics: market health metrics and market participants' needs metrics. Market health metrics display whether a gas wholesale market is competitive, resilient, and it signifies an adequate level of supply diversification. Market participants' needs metrics examine the products and the degree of liquidity of the market for the well-functioning of gas hubs. In accordance with the results of market participants' needs metrics, hubs are categorized into four groups: Established hubs are used as a benchmark for long-term agreements and other hubs. Advanced hubs have a high level of liquidity. Emerging hubs enhance liquidity starting from a lower baseline, capitalizing on improved interconnectivity. Finally, illiquid-incipient hubs mostly rely on long-term contracts.

Market fundamentals, with the prices of other competing energy sources such as oil, electricity, and coal have also substantial effects on hub prices (Stern, 2014). Due to the reflection of supply/demand conditions and unexpected events, gas prices are more volatile (Heather, 2010). Since 2008, energy commodities, including gas, exhibit similar characteristics with financial products. Therefore, volatility, speculation, and price bubbles in these commodities tend to be the consequences of financialization (Zhang et al., 2017). As it is known, when the asset price deviates excessively from the fundamental value, price bubbles occur (Caspi, 2016). Fama et al. (1991) argue that in an efficient market, prices occur according to the relevant information and respond immediately, and thereby; assets cannot be determined as undervalued or overvalued. When bubbles emerge in asset prices and they last longer, the likelihood of a less efficient market increases. As a result, economies are affected both at macro and micro levels by the natural gas price bubbles (Li et al., 2020). If markets are exposed to price bubbles, there will be false price signals for market actors that lead to an economic loss (Lammerding et al., 2013). Price bubbles are undesirable for both companies and energy sectors as energy is a vital input for production as well as for business operations. Thus, it is essential to identify bubbles in natural gas markets to mitigate risks and misaligned prices for market participants.

Honore (2019) consider that the European Commission aims to decarbonize of energy sources diminishing greenhouse gas (GHG) emissions as well as inhibit the influence on global climate change. In this regard, facilitating carbon reduction natural gas is the primary instrument transitting low carbon energy sources (Mac Kinnon et al., 2018). Hence, it is essential to schedule.

Therefore, the EU prioritizes diversifying gas supply and trading activities of gaseous renewables and executes extensive investments in renewable gas (e.g., blue hydrogen, biogas, and biomethane) to boost trading activities. Decarbonized natural gas goal gets more attention to natural gas infrastructure role to guarantee transportation and distribution of renewable gases and trading at natural gas hubs in the recent years (Khan et al., 2022). Hence, the in-depth assessments of the gas market and price bubbles will contribute to the transition of the decarbonized gas market along with drive the trading of low-carbon gas at the hubs that promote clean energy transition also energy and environmental sustainability.[1]

The global gas market is divided into three primary regions on the basis of both geography and pricing regimes (IEA, 2013). Prices are determined in the US by the gas on gas pricing mechanism (GOG), whereas in Europe, mainly by the oil-indexed contracts since

[1] Parallel to the trend of transition from fossil fuels to green energy alternatives to achieve decarbonization target, more studies focus on the investigation of clean energy transition and enviromental sustainability. See Irfan et al., (2022); Tang et al., (2022); Xie et al., (2022); Khan et al., (2022b); Zhang et al., (2022); Khan et al., (2022a); Shahzad et al., (2022).

the beginning of the 2000s with the hub price mechanism, and in Asia by the oil-indexed contracts. Zhang et al., (2018) investigate the price bubbles across those regions and examine which price mechanisms are subject to fewer price bubbles. In the US, which is found as the most efficient market by Zhang et al. (2018), owing to the gas on gas price mechanism (GOG), the least number of price bubbles (only five bubbles) is seen. With GOG, gas prices compete with each other, and market fundamentals are the leading sources of price bubbles. The highest number of price bubbles is observed in Japan and the price bubbles (eight bubbles found in total) mostly occurred on the dates with high oil price explosiveness due to the oil-indexed gas contracts. In a nutshell, Zhang et al. (2018) conclude that the GOG pricing mechanism in the US is the most effective price regime for gas compared to oil-indexation. Li et al., (2020) examine the price bubbles in Europe, the US, and Asia and they specify the reasons for the bubbles in these regions. The main reasons behind the two price bubbles in Europe are stated as geopolitical factors. Also, it is indicated that financialization causes five price bubbles in the US, and oil price volatility in Asia caused six price bubbles.

However, in our study, we argue that the countries which are in the same geographical region and using the same price methodology -hub-based- may experience different numbers of price bubbles due to their unique characteristics. The main reason behind this conviction is that, as we have already covered, in Europe, the degree of the development level of each hub differs substantially. That is, while some hubs are accepted as mature, others are considered as advanced hubs (see Heather (2020) and ACER (2020)). Mostly, the Dutch TTF is seen as the benchmark hub, followed by the British NBP and the German NCG, the Italian PSV, and the Austrian VTP are all classified as advanced hubs (see Heather, 2020; Shi, 2016; IEA, 2020a; ACER, 2020). In this respect, to test our main hypothesis and to understand the bubble behavior in natural gas markets with the same pricing methodology, we examine the natural gas markets in the Netherlands, the United Kingdom, Italy, Germany, and Austria by applying generalized sup ADF test by Phillips et al., (2015).As a robustness check, we also employ the Log-Periodic Power Law Singularity (LPPLS) method by Filimonov and Sornette (2013). Using these two methodologies, we examine the price bubbles in the European gas markets, which are applying the same pricing methodology but differ in market structure.

Overall, based on both two methodologies, we observe that more efficient markets are less exposed to price bubbles. More specifically, GSADF test results show TTF has the least number of price bubbles while NBP has the second least number of price bubbles. Meanwhile, according to the LPPLS test results, both TTF and NBP generate the least number of price bubbles. To underline, the results show that both TTF and NBP are the most established hubs. Moreover, in both approaches, the number of price bubbles seen in PSV, NCG, and VTP, respectively, follows TTF and NBP. Austrian VTP is found to have the highest number of price bubbles based on both methodologies. Moreover, we observe that the timing of the bubble periods is quite similar in each hub due to the high level of interconnections.

This paper makes several noteworthy contributions. This is the first research which identifies the gas price bubbles across European hubs. Besides, it is a contribution to the debate on whether the functionality of hubs, which use the same price methodology, affects the numbers of bubbles and the duration of the bubbles. Adopting two different well-suited approaches, we provide convincing evidence that not only the price mechanism used in hubs but also the characteristics of the hubs are decisive for the number of price bubbles. Understanding the bubble behavior in European natural gas hubs will enable market actors to better grasp the characteristics of these hubs.

This paper has been structured as follows: Section 2 reviews the empirical literature; Section 3 presents the empirical methodology. Data are explained in Section 4, and the empirical results are discussed in Section 5. Finally, section 6 covers the conclusion, discussion, and policy recommendations.

1.2 LITERATURE REVIEW

Natural gas is a substitute fossil fuel for oil in the global energy sector, and the prices of these two commodities are related. The most crucial reason behind this link is that natural gas producers determine the gas price, especially for long-term contracts, based on a formula that includes weighted averages of oil price (Asche et al., 2002; Stern, 2014). However, this situation has changed through shale gas production, which initiated to trade at Henry Hub in 2007. However, the abundant supply also global financial crisis in 2008 altered the dynamics of the global natural gas market (Caporin and Fontini, 2017). According to Zhang et al. (2018), the hub-based pricing mechanism reflects the supply and demand factors in the market. Besides, in a mature hub, prices adjust quickly when recent information comes into the market. A significant number of empirical works have scrutinized other energy commodity prices and various supply/demand-side factors to grasp a better understanding of natural gas hub-based pricing mechanism. Moreover, Brown and Yucel (2008) show that oil and gas prices behave similarly for a long period, while they differentiate from each other in the short run in the US for the period between January 7, 1994 and June 8, 2007. Brigida (2014) uses the same variables as Brown and Yucel (2008) and applies the Markov switching cointegrating method for the period between June 1997 and September 2012. They demonstrate a strong relation among oil and gas prices in the US. However, Wang et al., (2019) demonstrate the impact of oil prices on the Henry Hub prices decreases while the effect of supply/demand factors, stock market volatility, and speculative behavior have become more prominent for the period between 2001 and 2018.

The studies on European gas markets mainly concentrate on the link between natural gas prices and market fundamentals also other energy commodity prices. For instance, applying the structural VAR model, Nick and Thoenes (2014) find that extraordinary deviations from temperatures and supply shortages affect the NetConnect gas price in Germany in the short period, while oil along with coal prices affect in the long period. For Belgium's gas market, Regnard and Zakoïan (2011) demonstrate prices of Brent oil along with gas are integrated, and the temperature changes affect the volatility of Zeebrugge spot prices. Hulshof et al. (2016) show that market fundamentals impact the Dutch TTF hub price over the period 2011-2014 and they find that after establishing gas on gas competition, oil prices influence on gas prices.

Many other studies focus on the interactions between hub prices across Europe and their level of integration. For instance, Neumann and Cullmann (2012) apply the Kalman Filter method to show the degree of price cointegration for eight hubs in six European countries. Their study reveals that although TTF is the benchmark hub in Europe, not every hub in the sample is cointegrated with the TTF price. Gianfreda et al. (2012) investigate whether Europe has a unique natural gas market area using VECM for five main energy markets. They find that each hub interacts with at least one other hub; yet none of them are interrelated. The findings of Asche et al. (2013) confirm the level of market interconnection among the British NBP, The Dutch TTF, and Belgian Zeebrugge hubs are very high. Miriello and Polo (2015) examine the advancement level of European natural gas hubs using a simple analytical framework and consider that the wholesale markets in the UK and the Netherlands are more advanced than those in Germany and Italy due to their dependencies on long-term import sources. Also, they emphasize that the convergence of prices in each hub depends on the level of interconnection. Schultz and Swieringa (2013) focus on the price formation process of the North-West European natural gas market. They find that NBP's future contract leads to price discovery using the sample period between 2008 and 2011. Broadstock et al. (2020) investigate the level of interconnection of the North-West European gas market also find that the highest interconnectivity rate is around 65%, using Diebold and Yilmaz (2009) index for the period between 2005 and 2018.

Recently, researchers have given substantial attention to the financialization of energy commodities following the growing volume of trading activities, the appearance of speculation, and the volatility of futures contracts (see, Broadstock et al., 2012; Ji et al., 2018; Zhang, 2017). Implementing futures contracts for the commodity market entails the counterparties speculating and hedging on price movements in future due dates, leading to a commodity bubble (Creti and Nguyen, 2015). In their study, Cheng and Xiong (2014) mentioned the "Bubble view" of politicians, which is based on the opinion that futures contracts' speculative movements caused the oil price bubble in 2007-2008. This "Bubble view" caused a rise studies on extraordinary price oscillation. Sornette et al. (2009) diagnose that oil price fluctuations occurred faster than exponential growth between 2006 and 2008 by applying the log-periodic power law (LPPL) model. Wątorek and Stawiarski (2016) adopting the same approach, find a negative oil price bubble between 2014 and 2016.

The most common method to detect multiple bubbles is the generalized sup ADF test (GSADF), proposed by Phillips et al. (2015). This methodology depends on multiple regressions using various sizes of time windows detecting along with date-stamping bubbles. Gronwald (2016) shows the presence of oil bubbles using the GSADF method in 1990-1991, 2005-2006, and 2007-2008. Fantazzini (2016) applies both GSADF and LPPL methods. His results show that both tests confirm that the fundamental value of spot oil price declined between 2014 and 2015. Caspi et al. (2018) apply the GSADF test to determine the WTI bubbles between 1876 and 2014 and identify several bubble periods. Su et al. (2017) find deviations from WTI oil price's fundamental value in 1990, 2005, 2006, 2008, and 2015. Liu and Lee (2018) examine the explosive movements of oil, gasoline, and coal prices from 1970 through 2014 and show that oil and gasoline price bubbles affect each other. Sharma and Escobari (2018) observe price bubbles for oil, heating oil, natural gas. Figuerola-Ferretti et al. (2020) identify an explosive bubble before the global financial crisis, along with a negative bubble for 2014 and 2016 due to the OPEC's supply decision. Khan et al. (2021b) examine the bubbles in crude oil price employing GSADF test and determine the factors behind the price explosivitiy as imbalance among demand and supply of oil, supply surplus by OPEC, shale oil production in the U.S.. Recently, Yang et al. (2021) find price bubbles in the shale gas industry using GSADF test. Pastor and Ewing (2022) find the Alaska North Slope (ANS) West Coast oil price bubbles in North Slope throughout the period of 2007–2009 recession. Ajmi et al. (2021) find two episodes of mutual bubbles examining Brent oil, Dubai, and WTI (July 1986 and March–July 2008). Khan et al. (2022) observe price bubbles in various energy prices from January 2000 and September 2021 and they reveal that mildly explosive behavior is seen mostly in LNG prices.

Only Zhang et al. (2018) and Li et al. (2020) have investigated the natural gas price bubbles. Both studies compare the natural gas prices in three distinctive regions (the US, Europe, and Asia) by applying the GSADF method. Those regions have different price mechanisms, namely gas on gas (GOG) competing for price in the US, oil indexation in Japan, and mix price series of oil indexation and GOG in Europe. Zhang et al. (2018) emphasize that GOG is the most efficient price mechanism; therefore, it should be subject to fewer bubbles than oil indexation. They provide empirical evidence confirming their hypothesis showing that the number of bubbles seen in the US is lower compared to Europe, whereas the highest number of price bubbles is seen in Japan for the period between 1982 and 2017. Consequently, they suggest that policymakers should encourage transformation from oil indexation to a hub-based pricing mechanism for a more efficient natural gas market. Li et al. (2020) apply the same methodology to the same regions as Zhang et al. (2018) with a shorter sample period. The results of their study show that there are two bubble periods in Europe, five in the US and six in Asia. The main reasons for these bubbles are stated as political factors for Europe, oil price fluctuations for Asia, and price volatility and speculation for the US.

The key research question of this study is whether the number of gas price bubbles varies in countries that use the same price method -hub-based but have different market conditions. We search the bubble behavior in different European natural gas hubs, which apply the hub-based price methodology. This study fills the gap in literature scrutinizing the natural gas price bubbles and their possible reasons in Europe and reveals that benchmark hubs are exposed to less price bubbles. The results of this study are also important as understanding the European natural gas market dynamics more comprehensively is crucial in building and transitioning decarbonized internal gas market in the future.

In the rest of the paper, using the gas prices for TTF, NBP, NCG, PSV, and VTP between 03.01.2011 and 30.06.2020, we examine the price bubbles at the natural gas hubs in Europe. To this end, we apply both GSADF and LPPLS to understand whether that the countries in the same geographical region and those using the same price methodology may experience different numbers of price bubbles due to their specific characteristics.

1.3 EMPIRICAL METHODOLOGY

1.3.1 Generalized sup ADF Test

Phillips et al. (2011) (hereafter PSY), developed and extended the primary method, which uses the augmented Dickey-Fuller (ADF) model specification with a recursive evolving algorithm for multiple bubble identification. The algorithm depends on historical information and a time-varying model structure. By means of a flexible moving sample test procedure, the GSADF model can discover and date-stamp multiple bubbles despite the small size of data. In the ordinary market conditions, asset prices show a martingale characteristic, however in the expansion stage of the bubble they follow an explosive behavior (Phillips and Shi, 2018). If we consider y_t is a time series data with the total number of T observations and the rolling windows consist of r_1 and r_2 are the starting point and ending point respectively, the length of the window calculated as $r_w = r_1 - r_2$.

The classic ADF regression is:

$$y_t = \mu + \delta . y_{t-1} + \sum_{i=1}^{p} \phi_{r_w}^{i} \; \delta . y_{t-i} + \varepsilon_t \qquad (1)$$

where y_t is the price of an asset, μ, δ and ϕ are parameters measured applying OLS. The null hypothesis of the typical ADF test is H_0: $\delta = 1$ and alternative hypothesis is $H_1 : \delta > 1$. The number of observations taken into the consideration in the classic ADF is $T_w = [\,r_w T]$ where $[.]$ demonstrates the integer section. The ADF statistic denominated by $ADF_{r_1}^{r_2}$.

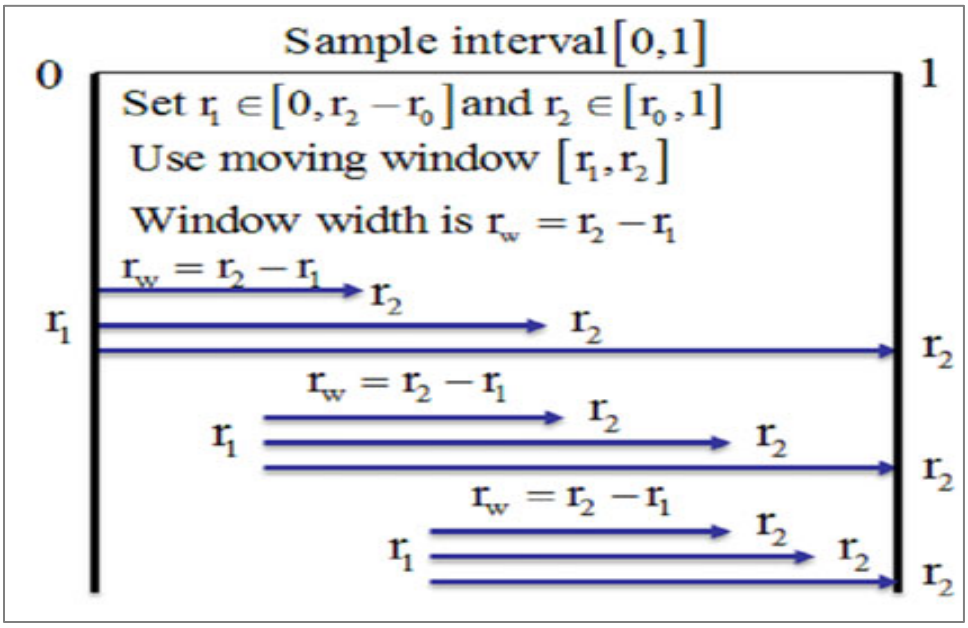
A backward sup ADF test codified by Phillips et al. (2014). Specific fraction r_2 is an endpoint of the entire sample, and the window size is widened from a beginning fraction r_0 to r_2. The backward sup ADF statistic can be represented as follows:

$$SADF_{r_2}(r_0) = sup_{r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2} \qquad (2)$$

The generalized sup ADF (GSADF) is converted by continuously applying the SADF test process for each $r_2 \in [r_0, 1]$. Then, the GSADF defined as:

$$GSADF\ (r_0) = \ sup_{r_2 \in [r_0,1]} SADF_{r_2}(r_0) \qquad (3)$$

The procedure is a recursive regression technique determined by equation (1), starting with the initial fraction $r_w = r_0$ and after extending the sample window advances up to $r_w = r_1 = 1$ which equals to the entire sample. The initial minimum fraction is chosen randomly, following that this procedure is applied continuously for any potential fraction. ADF statistics are estimated as ADF_{r_k} for all values of $\in (r_0, r_1)$. Results of this procedure are a sequence of ADF statistics. Figure 1.1 shows the comparative sample sequences used in the recursive GSADF.



Source: Phillips et al. (2015, p.1049).

Figure 1. *The Sample Sequences and Window Widths of the GSADF Test*

If the comparison between the supremum value of this sequence (SADF) to its corresponding critical values are significant which is indicated by $\delta_{r_1,r_2} > 1$, we could denote it as a bubble period. To detect multiple bubble periods in the sample, the GSADF test employs a variable window width approach which changes both starting and ending points within a specified range $[r_0, 1]$. The GSADF test, following the detection of bubble periods, determines the beginning and ending time of this (these) bubble(s) which is adhered as date-stamping. When the backward sup ADF sequence exceeds the respective critical value from below, it is determined as beginning time (T_{r_e}) . However, when the backward sup ADF sequence exceeds the respective critical value from above, it is defined as ending time (T_{r_f}).

GSADF test depends on the bubble periods shown as:

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \{ r_2 : \mathrm{BSADF}_{r_2} > \mathrm{cv}_{r_2}^{\beta_T} \tag{4}$$

$$\hat{r}_f = \inf_{r_2 \in [\hat{r}_e, 1]} \{ r_2 : \mathrm{BSADF}_{r_2} > \mathrm{cv}_{r_2}^{\beta_T}$$

In the model, the critical value of the sup ADF statistic shown as $\mathrm{cv}_{r_2}^{\beta_t}$ calculated $100\ (1 - \beta_t\ )$ % based on T_{r_2}observations. In this model, β_t is applied as 5%, which is a constant value, instead of appointing $\beta_T\ \to 0$ as $T \to 0$ due to eliminating asymptotically type 1 errors. Finally, the GSADF test statistic is denoted as follows:

$$\mathrm{GSADF}(r_0) = \sup_{r_2 \in [r_0, 1]} \{ \mathrm{BSADF}_{r_2}(r_0) \} \tag{5}$$

1.3.2 The Log Periodic Law Singularity Model

Johansen et al. (2000) established a method that defines the bubble regime as the faster-than-exponential price acceleration with a rising frequency of volatility movements. The original method (see, Johansen et al., 2000) has three linear parameters (A, B, C) and four nonlinear parameters $(\beta, \omega, t_c, \varphi)$. A, B, C are "slaved" in the fitting algorithm calculated from the derived values of the nonlinear parameters β, ω, t_c, and φ. The estimation technique for the model is the nonlinear multivariate least squares. To diminish the complication of the fitting process and to obtain more stable results, Filimonov and Sornette (2013) transformed three linear (A, B, C) and four nonlinear $(\beta, \omega, t_c, \varphi)$

parameters in the LPPLS model into four linear (A, B, C_1, C_2) and three nonlinear (m, ω, t_c) parameters. The main idea is to specify bubbles based on two common characteristics. The first one is the faster than exponential growth of the asset price throughout the bubble duration, which terminates when the bubble burst. The second one detects the critical time (t_c) which is the most possible time for end of bubble or regime changing.[2]

We use the LPPLS approach to determine both the development stage and the end time of bubbles in European gas prices. The method can be shown as follows:

$$\ln E\big(P(t)\big) = A + B(t_c - t)^m + C_1(t_c - t)^m cos(\omega \ln[t_c - t]) + C_2(t_c - t)^m sin(\omega \ln[t_c - t]) \qquad (6)$$

In the equation, lnE(P(t)) is the natural logarithm of the asset price at time *t*, t_c represents the critical time. *A,* which is the expected maximum logarithmic price, must be positive at the critical point of time t_c. Parameter *B* determines growth amplitude and $m \in [0,1]$ detects the level of the faster-than-exponential growth. To check for the amplitude of log-periodic oscillations and the log-periodic angular frequency, C_1 and C_2 are used as extra control variables (Geuder et al., 2019).

The positive bubbles are specified by $B < 0$, while negative bubbles are determined by $B > 0$. We apply the following restrictions proposed by Filimonov and Sornette (2013) to get more accurate results:

$0.1 \leq m \leq 0.9,\ 6 \leq \omega \leq 13,\ C_1^2 + C_2^2 < 1.$

[2] Regime changing refers as an alteration from exponential growth to a lower growth (Balcilar et. al, 2018).

1.4 DATA

There are several numbers of natural gas hubs in Europe. Due to structural differences and data availability considerations, we use natural logarithm of day ahead gas prices for TTF, NBP, PSV, NCG, and VTP for the period between 03.01.2011 and 30.06.2020. The day-ahead natural gas prices are the most commonly traded contracts, and they reflect the demand and supply changes in Europe the best (Petrovich, 2016; ACER, 2020). The NCG gas prices are collected from European Energy Exchange (EEX)[3] database. The NBP and TTF gas price series are gathered from Thomson Reuters database. PSV gas prices are obtained from S&P Global Platts[4]. VTP prices are retrieved from Central European Gas Hub AG (CEGH)[5]. All price series are Mwh/Euro except NBP, which is in pence/therm.

1.5 EMPIRICAL RESULTS

1.5.1 Identifying Explosive Price Movements

The GSADF test was employed using the R package PSYmonitor consisting of the bootstrap algorithm developed by Harvey et al. (2016) to overcome heteroskedasticity and multiplicity in recursive methods. The price movement is accepted as a bubble when the PSY test statistics surpass the 95% bootstrapped critical value. The bubble period is assumed to end when PSY statistics fall below 95% of the bootstrapped critical value. The lag order is chosen as six depend on the Bayesian information criteria (BIC). The initial window size is formulated depending on a calculation that considers total observations.[6]

[3] Source: European Energy Exchange https://www.eex.com/en/market-data/natural-gas
[4] Source: S&P Global Platts https://www.spglobal.com/commodityinsights/en/commodities/natural-gas
[5] Source: Central European Gas Hub AG https://www.cegh.at/en/exchange-market/market-data/
[6]Initial window size calculated as $r_0 = 0.01 + 1.8/\sqrt{T}$

Table 1. *Results of GSADF Tests for Natural Gas Prices in Europe*

	TTF	NBP	PSV	NCG	VTP
Statistical Value	2.04	2.45	3.64	1.89	1.50
Critical Value					
%90	0.60	0.43	0.27	0.24	0.24
%95	1.03	0.81	0.56	0.79	0.63
%99	1.81	1.36	2.06	1.33	1.80

Notes: TTF: Title Transfer Facility, NBP: National Balancing Point, NCG: NetConnect Germany, PSV: Punto di Scambio Virtuale, VTP: Virtual Trading Point

Table 1 presents the values of GSADF method statistics along with the critical values obtained by bootstrap replication by 199 times. For each hub, the values of GSADF test statistics exceed 95% of critical values, which shows that there are indeed some bubble periods in the European hubs.

The price bubbles found for each hub are illustrated with a yellow shaded area in Figures 1-5 and summarized in Table 2.

Table 2. *Bubble Periods: GSADF Test Results*

	TTF		NBP		PSV		NCG		VTP	
	Start	End	Start	End	Start	End	Start	End	Start	End
	6.06.2014	9.06.2014	12.03.2013	13.03.2013	8.02.2012	8.02.2012	13.03.2013	13.03.2013	8.02.2012	8.02.2012
	21.12.2015	24.12.2015	20.03.2013	27.03.2013	27.11.2013	29.11.2013	26.03.2013	26.03.2013	27.03.2013	27.03.2013
	27.02.2018	1.03.2018	2.04.2014	4.04.2014	30.05.2014	30.05.2014	6.06.2014	9.06.2014	6.02.2014	6.02.2014
	30.05.2019	3.06.2019	16.05.2014	16.05.2014	6.06.2014	6.06.2014	17.12.2015	28.12.2015	17.02.2014	17.02.2014
	5.06.2019	6.06.2019	30.05.2014	2.06.2014	4.07.2014	4.07.2014	15.01.2016	15.01.2016	24.02.2014	27.02.2014
	24.06.2019	28.06.2019	4.06.2014	12.06.2014	10.01.2017	10.01.2017	20.01.2016	21.01.2016	21.03.2014	21.03.2014
	3.09.2019	3.09.2019	19.06.2014	24.06.2014	24.11.2017	24.11.2017	25.01.2016	26.01.2016	25.03.2014	8.04.2014
	20.05.2020	21.05.2020	26.06.2014	26.06.2014	1.12.2017	6.12.2017	2.02.2016	2.02.2016	11.04.2014	11.04.2014
	28.05.2020	28.05.2020	30.06.2014	30.06.2014	12.12.2017	12.12.2017	4.02.2016	12.02.2016	24.04.2014	28.04.2014
			3.07.2014	11.07.2014	28.06.2019	28.06.2019	16.02.2016	17.02.2016	30.04.2014	2.05.2014
			15.06.2017	16.06.2017	16.07.2019	16.07.2019	19.02.2016	19.02.2016	8.05.2014	9.05.2014
			28.02.2018	1.03.2018	18.07.2019	18.07.2019	4.04.2016	14.04.2016	28.05.2014	29.05.2014
			25.03.2019	25.03.2019	22.07.2019	22.07.2019	12.12.2017	12.12.2017	2.06.2014	16.06.2014
			1.04.2019	3.04.2019	25.07.2019	25.07.2019	26.02.2018	1.03.2018	18.06.2014	18.07.2014
			23.04.2019	23.04.2019	29.07.2019	29.07.2019	31.05.2019	3.06.2019	22.07.2014	24.07.2014
			20.04.2020	21.04.2020	14.08.2019	19.08.2019	6.06.2019	6.06.2019	5.10.2015	5.10.2015
					21.05.2020	21.05.2020	20.06.2019	20.06.2019	15.10.2015	15.10.2015
					29.05.2020	1.06.2020	25.06.2019	25.06.2019	10.11.2015	10.11.2015
							28.06.2019	28.06.2019	12.11.2015	16.11.2015
							18.05.2020	22.05.2020	15.12.2015	21.04.2016
							27.05.2020	1.06.2020	27.11.2017	29.11.2017
									4.12.2017	11.12.2017
									13.12.2017	13.12.2017
									26.02.2018	26.02.2018
									28.02.2018	2.03.2018
									7.09.2018	13.09.2018
									21.09.2018	21.09.2018
									25.09.2018	26.09.2018
									14.03.2019	4.04.2019
									28.05.2019	28.05.2019
									30.05.2019	10.06.2019
									12.06.2019	15.07.2019
									17.07.2019	2.08.2019
									6.08.2019	30.08.2019
									3.09.2019	6.09.2019
									2.10.2019	2.10.2019
									10.10.2019	14.10.2019
									13.05.2020	14.05.2020
									18.05.2020	21.05.2020
									26.05.2020	1.06.2020
Number of Bubbles		9		16		18		21		40

Next, we look more closely at the bubble dates in Table 2. In February 2012, unpredictable cold snap increased the demand. Prices were relatively volatile as gas deliveries from Russia decreased around 30% created a bubble at PSV and VTP (European Commission, 2012). In March 2013, cold weather boosted gas demand, but the market could not meet increasing demand due to tight supply, low LNG import and storage level (European Commission, 2013). In the second quarter of 2014, the main factors behind the low prices were warm winter and spring climate across Europe. Consequently, there was less demand for storage injection. Moreover, weak demand and low gas prices in Asia caused LNG cargoes to divert into European hubs, leading to diversification of supply sources in Europe (European Commission, 2014a). Since mid-2014, oil prices were on a downward trend due to worldwide supply surplus. Also, in January 2016, Iranian sanctions led to a fall in Brent oil prices to its lowest level since 2003. Oil price variations reflect to the oil-indexed gas contracts formula after 6 to 9 months (European Commission, 2016). As a result, gas price bubbles occurred from the last quarter of 2015 to the first quarter of 2016 in Germany and Austria. On the 12th of December, the explosion of Baumgarten forced the system operator to halt the gas flow from Russia and led to the price bubble in Germany, Italy, and Austria (European Commission, 2017). In March 2018, hub prices peaked dramatically to their highest levels in our sample period due to the extremely cold weather (European Commission, 2018). Also, in the third quarter of 2018, European hub prices increased approximately by 50-60 % compared to the previous year. The upward trend in oil, coal along with carbon prices also supported the high prices in the European gas market (European Commission, 2018). In 2019, there was a high level of LNG flow to Europe. Thus, prices revealed a declining trend (European Commission, 2019). In the second quarter of 2020, gas prices dropped in every hub due to the Covid-19 pandemic lockdowns addressing mitigating demand. Besides, European gas consumption fell by 10% compared to the previous year due to the low demand in industry and electricity generation also high-level capacity of storage (European Commission, 2020). Thus, overall, it can be argued that the natural gas prices are reflections of the market fundamentals as also argued in Stern (2014) and Zhang et al. (2018). Next, we summarize our findings and discuss the main characteristics of each European hub.

1.6 THE NETHERLANDS – TTF

The Dutch TTF has the least number of price bubbles. As shown in Figure 1, most of these bubbles occurred in 2019 due to the excessive flow of LNG, which led to low prices and the highest traded volume (European Commission, 2020). TTF is a specific location for LNG market actors to hedge global LNG portfolios. LNG actors use new contracts formula changing from 'Henry Hub cost plus' to TTF as a netback price (ACER, 2020). Moreover, TTF is the dominant hub in Europe, surpassing the NBP since 2016 (European Commission, 2016). Thanks to its significant geographic position within other important natural gas markets, various interconnection capacities with its nearby countries, abundant LNG terminals, multiple storage facilities, Netherland is the third-largest gas producer on the continent (IEA, 2020a). As reported by the AGTM market health metrics, which shows the number and concentration of supplies and the potential of hubs to cover the demand, the Netherlands has nine supply sources. Besides, domestic production and the import from Norway covers 80% of supply (ACER, 2020). There are two other market health indicators. The first one is Herfindahl-Hirschmann Index (HHI) which measures the upstream companies' supply ratio at hubs. The second one is the residual supply index (RSI), and it assesses the dependency on the countries' largest gas suppliers. The RSI ratio for the Netherlands is approximately 200%, which is well above the required level (110%), and it is the highest ratio among the hubs. In addition, the market concentration index HHI is well below the benchmark level of 2000.

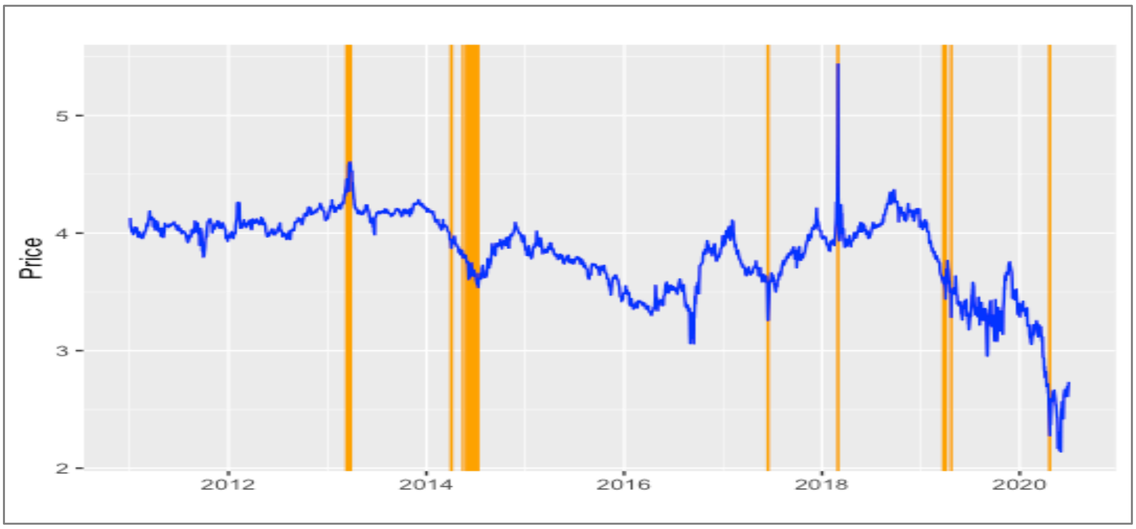
As stated before, to establish market-based price transition, political willingness, market liberalization, cultural effects, and regulations are the most significant factors (Shi, 2016). The Dutch market is fully liberalized, providing easy access to market participants to perform transactions (IEA, 2020a). Moreover, the leading companies in the Netherlands, such as GasTerra, Exxon, and Shell encourage gas trading at TTF (Franza, 2014). Also, Heather (2020) states that TTF is the leader, supreme hub of all European hubs, and ranked first according to the trading metrics. Based on these characteristics of the TFF, which position it differently among all other major hubs, it is not surprising to observe the lowest number of price bubbles out there.

Notes: The blue line represents the price series, and the yellow segments indicate the periods during which the PSY statistic surpasses its 95% bootstrapped critical value.

Figure 2. *Bubble Periods of the Netherlands – Title Transfer Facility (TTF)*

The United Kingdom – National Balancing Point (NBP)

In the British NBP, the number of explosive price movements is found as slightly higher than TTF. In Figure 2, the explosive price movements mainly occurred in the second quarter of 2014 and lasted longer because of the competitive advantage of coal over gas to produce electricity (European Commission, 2014a). Like the Netherlands, the UK has diversified its instruments to control the supply and demand balance. More specifically, domestic production has a significant share in both countries' gas supplies. In the ACER (2020) report, the number of supply sources states twelve for the UK. The gas supply mainly includes domestic production and the import from Norway. The UK RSI ratio is close to 150%, modestly above the required level (110%). The market upstream concentration index (HHI) has the lowest level among other hubs. Its supply sources are from Norway, the Netherlands, and Belgium. Although the British NBP had been the benchmark hub until 2016, it is currently the second most advanced hub in Europe (IEA, 2019). The reason behind the NBP's loss of leadership to TTF is that trading is carried out in pence/therm in NBP. Thus, it causes a currency risk for market actors. In 2009, Germany and Russia agreed on using TTF prices in contracts while negotiating the long-term contract prices. Although NBP had higher liquidity and was the most advanced hub in Europe, it conducted trade activities in pence/therm different from Germany. This situation would have caused German companies using the Euro/MWh to be exposed to currency risk. Due to its neutrality, the acceptability of TTF increased, and it was started to be used as a hedging tool in the European natural gas market (Shi, 2016).



Notes: The blue line represents the price series, and the yellow segments indicate the periods during which the PSY statistic surpasses its 95% bootstrapped critical value.

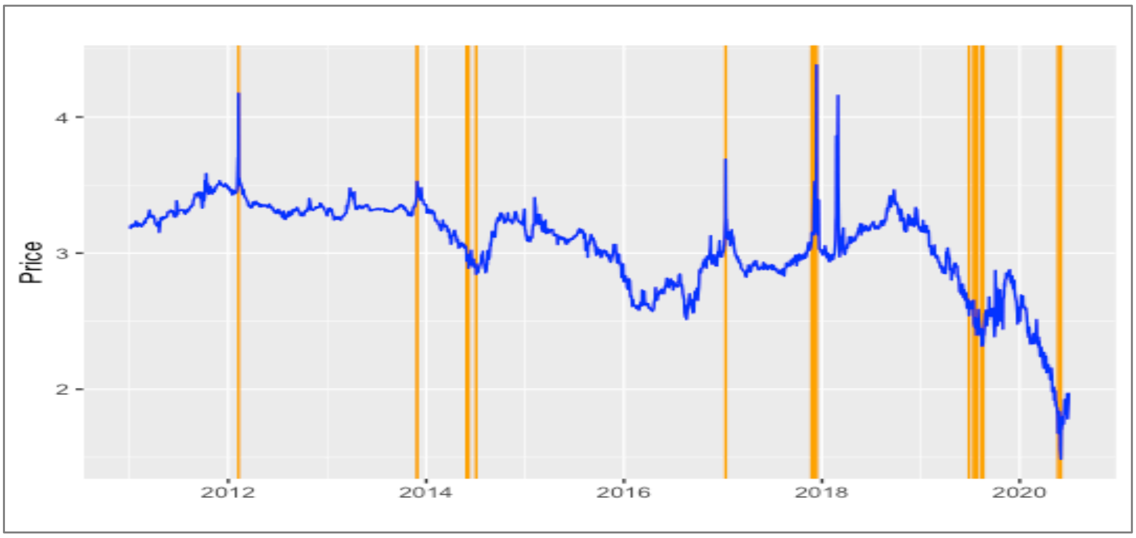
Figure 3. *Bubble Periods of United Kingdom - NBP*

Italy- Punto di Scambio Virtuale (PSV)

As shown in Table 2 and Figure 3, 18 price bubbles were observed in the Italian gas market. A closer look at the dates shows that the price bubbles occurred mostly at the end of 2017. More specifically, on 12th December 2017, Russian transit gas flows to Italy were interrupted due to an explosion at Baumgarten facility in Austria, and the day-ahead price reached 80 Euro/MWh. Due to the strong demand and the reduction in import capacity through Switzerland, the Italian gas supply-demand balance struggled at the beginning of the month. As a result, the Italian government announced an early warning (European Commission, 2017). However, later in 2019, the EU benefited from a large LNG influx due to the low spot prices, leading to the highest number of price bubbles in Italy (European Commission, 2019).

In Italy, there are multiple gas supply sources compared to other EU countries. Natural gas is imported from Russia, Algeria, Libya, Norway, Qatar, Azerbaijan, the Netherlands, and other countries. There are also LNG and storage facilities in Italy. Nevertheless, natural gas prices at PSV are high due to the structure of gas import contracts and the lack of liquidity in the wholesale market. The reasons for illiquidity at this hub can be the challenge of approaching the capacity of pipelines, the complication of system rules, and the existence of multiple long-term contracts.

Moreover, the Italian gas market is heavily concentrated. Therefore, market actors hesitate that dominant traders can manage the prices at the exchange, which creates a wrong price signal discouraging them from becoming a player at the hub (IEA, 2016). As stated in Heather (2020), the churn rate, which shows the ratio of how much physical volume of gas is traded at PSV before the actual delivery, is considerably low in Italy.



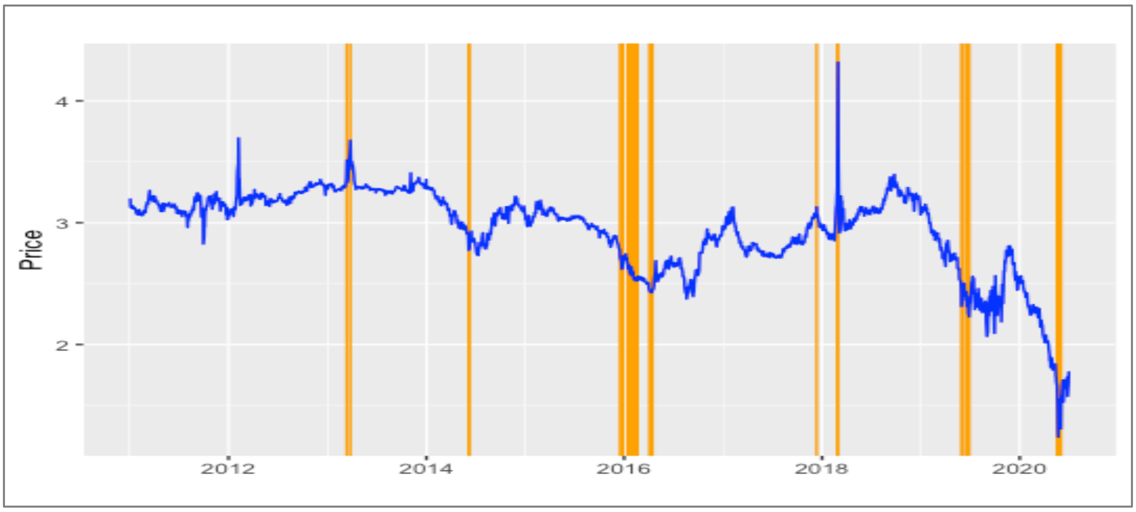
Notes: The blue line represents the price series, and the yellow segments indicate the periods during which the PSY statistic surpasses its 95% bootstrapped critical value.

Figure 4. *Bubble Periods of Italy - PSV*

Although Italy has the highest supply sources (13), it still depends mainly on Russian gas (ACER, 2020). Looking more closely at the results, price bubbles occurred immediately when a supply interruption from the Russian route (e.g., 08.02.2012 and 12.12.2017 bubbles). Besides, Italy complies with the criteria of 110% RSI benchmark level, while its upstream market competition index (HHI) is between 2000 and 3000 and higher than the criterion (ACER, 2019).

Germany- Netconnect Germany (NCG)

The results of the GSADF analysis show that in Germany, 21 price bubbles were experienced. Germany heavily relies on natural gas imports, accounting for 92% of its supply sources. The largest proportion of the import comes from Russia, which is around 57%, followed by the Netherlands with 35%, and Norway with 5% (IEA, 2020b). Two primary factors had a significant effect on price bubbles. Firstly, as presented in Figure 4, the bubbles occurred mainly in the last quarter of 2015 and in the first quarter of 2016. Because low oil prices in these periods affected both the domestic prices in Germany and the prices in the leading supplier Russia. Moreover, apart from the period affected by the low oil prices, the price bubbles in TTF and NCG appear to have occurred in the same period. It is clear that gas prices in these hubs interact with each other frequently as TTF is the second-largest supply source for Germany, and there is a high level of interconnection between them.



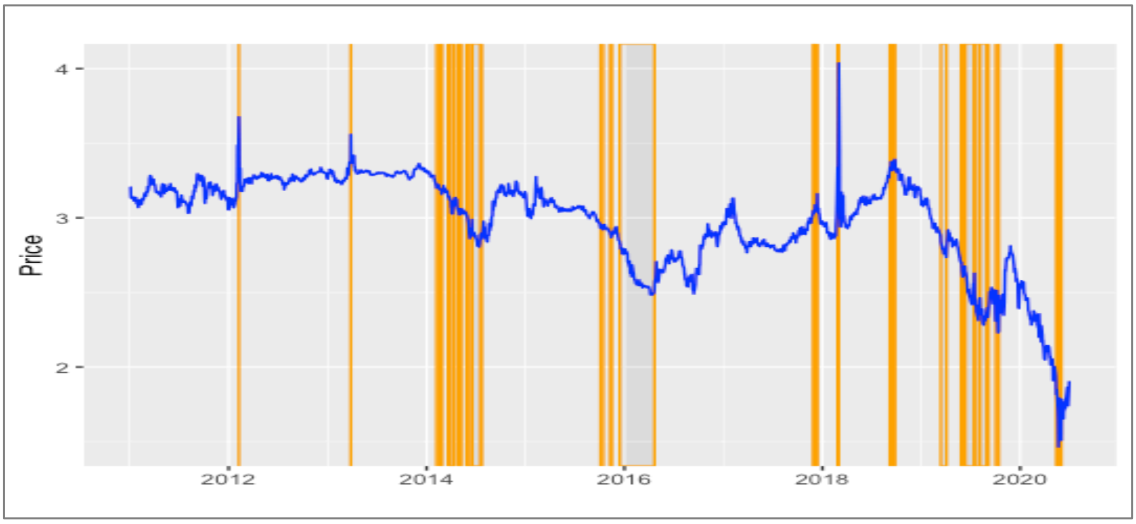
Notes: The blue line represents the price series, and the yellow segments indicate the periods during which the PSY statistic surpasses its 95% bootstrapped critical value.

Figure 5. *Bubble Periods of Germany - NCG*

Germany does not have an LNG terminal, and it benefits from global LNG prices through interconnection with the Netherlands, which explains the negative price bubbles caused by excess LNG supply in 2019. Also, Germany has 49 natural gas storage facilities, which are the largest storage capacities in the EU, and they fulfill the country's 47 days of peak demand. German gas market area is divided between NCG and Gaspool, which leads trade activities to share. Hereafter, Germany aims to merge these two market zones to create a single market in 2021 to increase liquidity (IEA, 2020b). For Germany, RSI is slightly below the benchmark level, while the HHI is between 3000 and 4000 (ACER, 2020).

Austria- Virtual Trading Point (VTP)

Austria distributes gas from Russia to Eastern and Southern European countries as a vital transition road, implying a high degree of interconnectedness. In 2018, Austria's domestic production accounted for 12% of the total gas supply and imported the remaining predominantly from Russia. While Austria has no LNG terminal, the gain from multiple gas storage facilities covers almost its yearly consumption. The challenges for further development of Austrian VTP are the two-tier balancing regime, dependency on a single country and single company, and the degree of market concentration level (IEA, 2020c). Austria has the lowest number of supply sources, and more than 60% of its supply depends on Russian imports. When we look at its market health metrics, its HHI is well above 6000, which is the highest level in our sample. However, its RSI meets the benchmark level of 110.



Notes: The blue line represents the price series, and the yellow segments indicate the periods during which the PSY statistic surpasses its 95% bootstrapped critical value.

Figure 6. *Bubble Periods of Austria - VTP*

The Austrian VTP has the highest number of price bubbles in our sample. Figure 6 shows that since 2012, in each year, gas price bubbles with different durations have emerged at VTP. The price bubble with the longest duration appeared in 2016 because of the plummeted oil price. Oil prices dramatically decreased from $112 in June 2014 to $31 in January 2016, and the total decline was more than 70% (Prest, 2018). The sharp increase in supply resulted mainly from shale oil production in the US, and the decline in demand, especially in China, led to the decline in the oil price (Su et al., 2017). Taken together, the decline in oil prices affected gas prices with a 6 to 9 months lag due to the contracts' structure and led to gas price bubbles (European Commission, 2016). The second most prolonged bubble period was observed in 2014 on account of extreme warm weather in both winter and spring. However, on 12th December 2017, an explosion at the Baumgarten facility led to a lack of Russian gas supply to the country. The prices increased to 33 Euro/MWh, although gas demand was covered by storage withdrawals and supply outages solved within a day (European Commission, 2017). In 2019, the second largest increase in the traded volume occurred in VTP, after TTF. As a consequence, the bubble with the third-longest duration burst in this period.

Austria has been exposed to a higher number of price bubbles. For a country to reduce price bubbles, it must have various supply and demand instruments. However, Austria is highly dependent on Russian gas imports; if there is a problem in supply flow from Russia, it directly affects the Austrian gas market and will reflect on to the price. Yet, when there are multiple gas supply sources and other instruments, it would be easier for the country to compensate supply disruption problems. Regarding the degree of market concentration, Austria’s HHI levels were always quite higher than the benchmark level and two times higher than the HHI levels of other advanced hubs during our sample period. In this respect, the challenges for further development of Austrian VTP are the two-tier balancing regime, dependency on a single country and a single company, and the degree of market concentration level (IEA, 2020c). Given Austria has the lowest number of supply sources and its high levels of HHI, it is not surprising that Austria has been subject to expose more price bubbles compared to the other hubs.

To summarize the results up to this point, the findings of the GSADF test help us to understand whether countries using the exact hub price mechanism differ significantly in the number and duration of price bubbles. The empirical evidence shows that explosive price changes, ranked from least to most, are seen in the Netherlands, the United Kingdom, Italy, Germany, and Austria, respectively. These substantial differences in the number of price bubbles across the European hubs support the fact that more efficient markets constitute fewer price bubbles. These empirical findings are also in line with ACER's (2020) market participants' needs metrics, which states that both the TTF and NBP are the established hubs due to the extreme level of liquidity, generating a benchmark price for other hubs as well as for long term contracts. TTF has the best results, followed by NBP (ACER, 2020). Besides, both TTF and NBP are the only hubs that confront all criteria of the AGTM market health metrics (ACER, 2020). TTF and NBP were also stated as benchmark hubs by Shi (2016) since they have significant elements of the hub price mechanism. The results for both TTF and NBP in our study support the findings of Shi (2016), which argue that domestic production is a crucial element in providing the gas on gas price transition. Shi (2016) lists the primary factors for enabling hub price mechanism as market liberalization and competition, price transition, political will and regulations, domestic production, and culture. The requirements for transition hub pricing are a large number of suppliers and customers, LNG terminal to benefit from global prices, storage facility to balance supply and demand, and interconnection with neighboring countries. Based on the results of the average bid-ask spread[7], trading frequency, and market concentration on both the buying and selling sides, PSV; NCG; and VTP are listed as advanced hubs in ACER (2020). While the related scores of these three hubs are relatively close to each other, those of Austria are the lowest. However, as discussed before, there are distinct differences among them according to the AGTM market health metrics. The empirical results of our analysis support the market health metrics. Although Italy has the highest number of supply sources, which is a crucial element for price transition, its upstream market competition index is higher than those of TTF and NBP. This might be the reason why PSV is not effective as much as TTF and NBP. Even though Germany is in better condition than Italy in terms of market

[7] Average bid-ask spread is defined as measuring the average delta among the lowest ask price and the highest bid price that is explained as a percentage term of the highest bid-price throughout the day (ACER, 2017).

participants' needs metrics and HHI, its number of supply sources is lower than Italy. Furthermore, there are no LNG facilities in Germany, and it benefits from global LNG prices via interconnections. This situation limits the flexibility of divergence of supply (IEA, 2020b). Well-functioning hubs with low HHI values can be achieved by virtue of flexible sources such as domestic production and LNG (ACER, 2020). In the case of Austria, there is a strong willingness to trade at the hub by market actors. Still, due to the dependence on a single country and single company, Austria suffers the most explosive price changes experience. According to AGTM health market results, Austria shows the lowest performance in terms of supply divergence, HHI ratio, which measures the concentration of upstream companies and dependency level on the largest supplier.

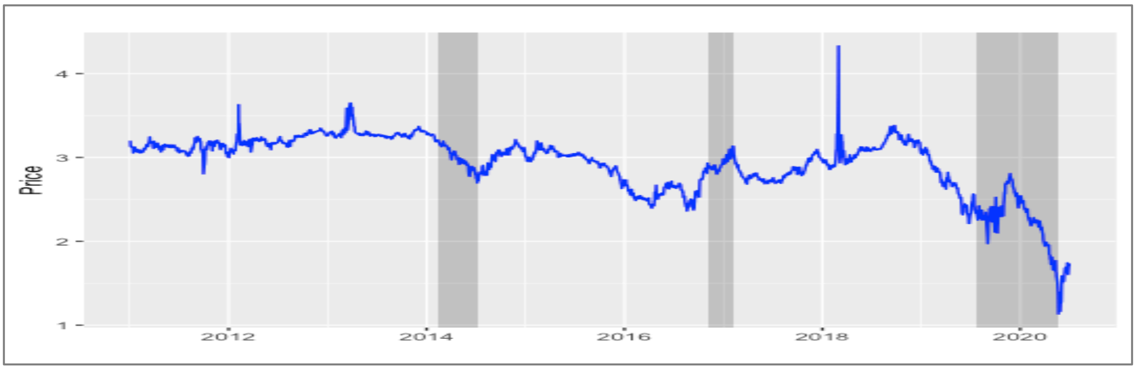
1.6.1 The Log Periodic Power Law Singularity (LPPLS) Model

As a robustness check, we employ the LPPLS methodology. Here, we apply the Epsilon Drawdown Method proposed by Johansen and Sornette (2001) to identify the peak dates of each price series and set the end time of the bubble as the peak time (t_2). Using the shrinking window approach with fixed t_2, we also determine the beginning time of the bubble (t_1) by going from t_2-29 to t_2-719 trading days, with windows abbreviated for iteration of five trading days. We employ the LPPLS method by applying a Covariance Matrix Adaption Evolution Strategy (CMAES) for optimizing the variables. The results of the analysis for each hub are summarized in Table 3 and shown in Figure 6. The LPPLS approach detects the least number of price bubbles in TTF and NBP, followed by PSV, NCG and VTP with the highest number of explosive price movements. Since the LLPLS test counts the duration of bubbles as at least 30 trading days, the number of explosive attitudes can differ between GSADF and LPPLS. However, the timing of intense price movement periods found in the GSADF test is similar to that diagnosed by the LPPLS test as a price bubble. In TTF and NBP, several price bubbles detected in 2014, 2019 and 2020 with the GSADF test were also determined by the LPPLS method. Both tests show that TTF and NBP are efficient markets, which produce the least number of price bubbles. NCG and PSV come after TTF and NBP in LPPLS test, and the highest number of price bubbles is observed in VTP in both tests. Thus, we conclude that Austria is the most inefficient market across the countries in our sample.

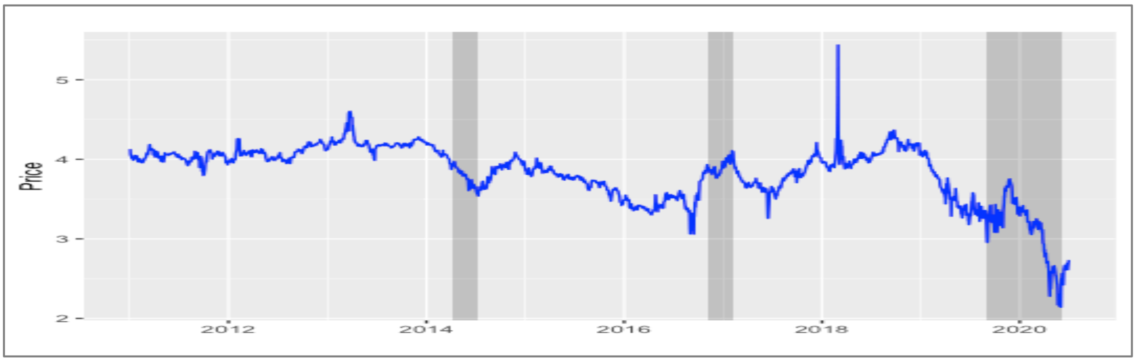
Table 3. *Bubble Periods: LPPLS Test Results*

	TTF Bubble Period	**NBP** Bubble Period	**NCG** Bubble Period	**PSV** Bubble Period	**VTP** Bubble Period
	10/02/2014-07/07/2014	05/04/2014-11/07/2014	24/01/2014-11/07/2014	24/10/2013-03/12/2013	30/01/2014-14/07/2014
	03/11/2016-03/02/2017	05/11/2016-03/02/2017	15/12/2015-14/04/2016	05/04/2014-04/07/2014	19/09/2015-16/11/2015
	20/07/2019-21/05/2020	01/09/2019-01/06/2020	01/11/2016-06/02/2017	05/01/2019-16/08/2019	02/02/2016-12/04/2016
			26/07/2019-22/05/2020	25/09/2019-01/06/2020	28/10/2016-06/02/2017
					07/11/2017-31/01/2018
					01/03/2019-21/05/2020
Number of Bubbles	3	3	4	5	6

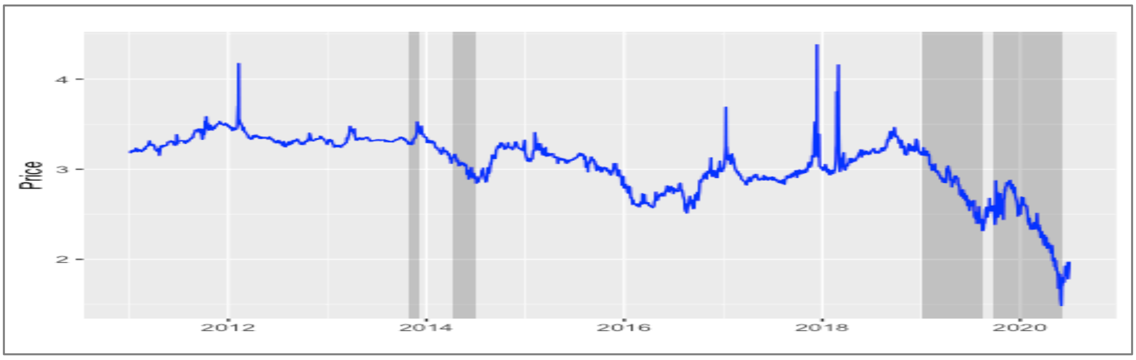
The LPPLS test discovers bubble periods between early November 2016 and early February 2017 in each country except for Italy. However, this price bubble period is not identified by the GSADF test for any country in our sample. Some possible reasons which might lead the bubbles in that period are strong gas demand in power generation, abnormally cold weather, diminishing storage levels, weak LNG delivery, and ambiguity about the UK's Rough storage site. In that period, any price bubble was not found for Italy due to a revised long-term contract between Italy and Algeria, which enormously increased its import volume (European Commission, 2017). Despite the methodological differences among the LPPLS and the GSADF techniques, both approaches confirm that more efficient markets are subject to less extreme price behavior.



Netherlands- TTF

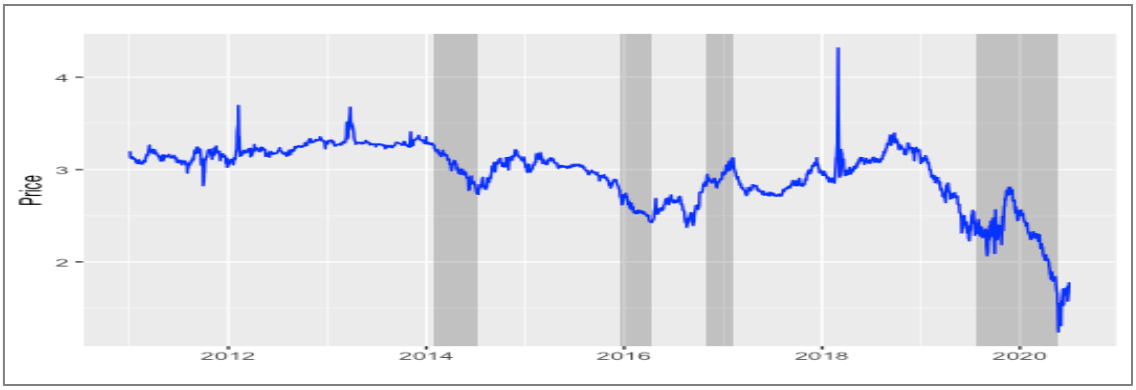


United Kingdom – NBP

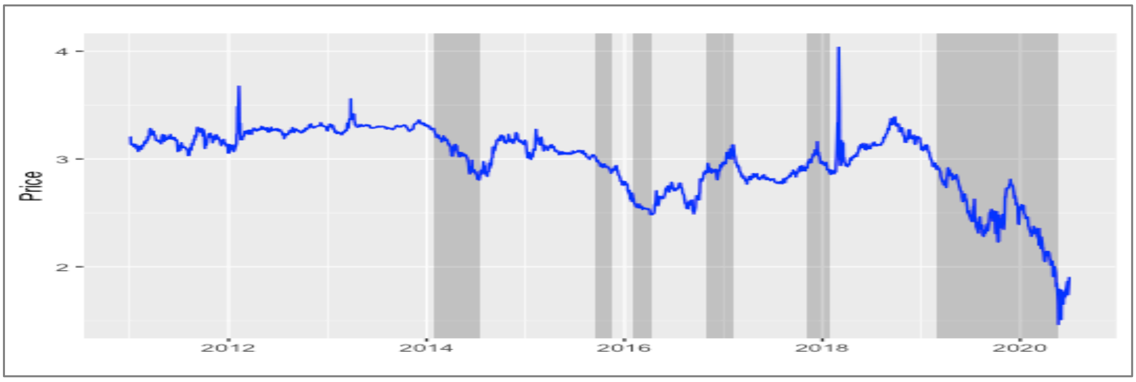


Italy – PSV

Figure 7. *LPPLS Test Results for European Natural Gas Price Series*



Germany - NCG



Austria – VTP

Figure 7. (continued) *LPPLS Test Results for European Natural Gas Price Series*

1.6.2 Discussion

The central question of our study is whether the number of price bubbles differs in countries using the same price methodology due to their specific conditions. We are also interested in examining the validity of the efficient market hypothesis in the European natural gas markets. To investigate these questions, we apply the GSADF test for 5 European natural gas hubs: TTF, NBP, PSV, NCG, and VTP. To summarize the results up to this point, the findings of the GSADF test help us to understand whether countries using the exact hub price mechanism differ in the number and duration of price bubbles. The empirical evidence shows that explosive price changes, ranked from least to most, are seen in the Netherlands, the United Kingdom, Italy, Germany, and Austria, respectively. These substantial differences in the number of price bubbles across the European hubs support the fact that more established markets constitute fewer price bubbles. These empirical findings are also in line with ACER's (2020) market participants' needs metrics, which states that both the TTF and NBP are the established hubs due to the extreme level of liquidity, generating a benchmark price for other hubs as well as for long term contracts and in our sample TTF has the best results, followed by NBP. Besides, both TTF and NBP are the only hubs that confront all criteria of the AGTM market health metrics (ACER, 2020). TTF and NBP were also stated as benchmark hubs by Shi (2016) since they have significant elements of the hub price mechanism. The results we provided for both TTF and NBP support the findings of Shi (2016), which argue that domestic production is a crucial element in providing the gas on gas price transition. The requirements for a transition hub pricing are a large number of suppliers and customers, LNG terminal to benefit from global prices, storage facility to balance supply and demand, and interconnection with neighboring countries. In 2014, the TTF surpassed the UK NBP as the most liquid hub with traded volumes at the Dutch hub increasing by a robust 59% compared to 2013 (European Commission, 2014b). As in other markets, higher liquidity in a hub implies rise in price transparency and fall in transaction costs. Liquidity and market transparency in turn assure reliability of hubs for portfolio management and optimisation increases and lead to higher volumes at the hub European Commission (2014a) implying less bubbles in prices at hub. Not suprisingly, we observe TTF has experienced less price bubbles since 2014 compared to the other established hub, NBP.

Based on the results of the average bid-ask spread[8], trading frequency, and market concentration on both the buying and selling sides, PSV; NCG; and VTP are listed as advanced hubs in ACER (2020). While the related scores of these three hubs are relatively close to each other, those of Austria are the lowest. Among the advanced hubs, Austria has the highest number of price bubbles. Austria has no LNG terminal due to no access to the sea, has the lowest number of supply sources, and more than 60% of its supply depends on a single country- Russia. Regarding the degree of market concentration, its HHI levels were always quite higher than the benchmark level and two times higher than the HHI levels of other advanced hubs during our sample period. When we compare the other two advanced hubs, Italy has the highest number of supply sources while Germany

[8] Average bid-ask spread is defined as measuring the average delta among the lowest ask price and the highest bid price that is explained as a percentage term of the highest bid-price throughout the day (ACER, 2017).

is mainly dependent on gas supplies from Russia. Furthermore, there are no LNG facilities in Germany, and it benefits from global LNG prices via interconnections. This situation limits the flexibility of divergence of supply (IEA, 2020b).

When considering policy implications, the results suggest that policymakers should focus more on improving gas supply divergence, LNG facilities to connect to global markets, various interconnection points with different countries, and multiple supply/demand instruments as storage facilities. Additionally, policymakers should take several precautions as increasing political willingness to trade at hubs, providing a low level of market concentration, and supporting the high competition.

The results from our research make several contributions to the current literature. First, this is the first study examining explosive price behavior and its possible reasons in European hubs. Second, this study provides additional evidence of integration across the European gas market and supports the cointegration studies (see Neumann and Cullmann, 2012; Asche et al., 2013; Gianfreda et al., 2012; Broadstock et al., 2020). Third, in line with the efficient market hypothesis, the benchmark hubs TTF and NBP are found to be more resistant to price deviations from fundamental values and experience fewer bubbles compared to other hubs. Last, this study also lays the foundation for future studies that will focus on decarbonized gas market by enhancing the understanding of the European natural gas market dynamics more comprehensively.

1.7 CONCLUSIONS

This paper applies GSADF and LPPLS methods to examine the number and period of price bubble action in the gas markets in Europe (TTF, NBP, PSV, NCG, and VTP) between 03.01.2011 and 30.06.2020. We choose to investigate the price bubbles in these hubs because although they are using the same pricing methodology, they are quite different in terms of their market characteristics. Unlike Zhang et al. (2018) and Li et al. (2020) which study gas price bubbles in different geographic locations having different pricing methodologies, we analyze the spot contracts determined by the same pricing methodology at the countries located on the same continent. In this study, we examine whether having different development levels at these hubs affects the number of speculative bubbles. Indeed, our results provide a clear idea that benchmark hubs are more efficient, and they are subject to fewer price bubbles. Furthermore, our findings on bubble formation in European hubs are in line with the AGTM metrics.

The empirical evidence from both tests shows that benchmark hubs as TTF and NBP experienced less explosive price fluctuations during the sample period. According to ACER's (2020) market participants' needs metrics; TTF and NBP are referred to as established hubs as they generate a benchmark price for other hubs as well as for long-term contracts. TTF has the best scores, followed by NBP. Moreover, both TTF and NBP compromise all criteria of the AGTM market health metrics (ACER, 2020). Although PSV, NCG, and VTP are listed as advanced hubs in ACER (2020), there are significant differences between them based on market health metrics and these differences are reflected in our results. The highest number of price bubbles is observed in VTP due to its dependence mainly on one country (Russia), its oil-indexed contracts, and its high HHI. To sum up, our empirical evidence significantly supports the hypothesis that the more developed the hub, the less exposed it is to price bubbles.

Price bubbles are undesirable phenomena for both market actors and for industries, and they affect market risks, speculation, financialization, cash flows, and investment projects. The primary factors that lead to price bubbles in European hubs are unexpected weather conditions, level of economic development, supply disruptions, oversupply, oil indexation, cross commodity prices, and extraordinary occasions as Covid-19.[9] Moreover, we observe that the timings of the price bubbles are close to each other in these hubs. This result can be seen as an indicator of integration in the EU gas market also supports Broadstock et al. (2020), who argue the European gas market is not fully integrated, but the level of integration has been increasing as a result of the (European Parliament and Council of the European Union, 2009).

[9] Stern and Roger (2014) also show that European hub prices are determined by the supply-demand related issues like abnormal weather and supply disruptions and global market dynamics.

Given our empirical results, some policy implications can be drawn. First, establishing a hub is not enough to obtain an effective gas on gas price mechanism. Further conditions are essential for becoming a benchmarking hub. Zhang et al. (2018) claim that as information spreads very accurately in an effective market, as well as the market actors react to new information quickly. Hence, price bubbles are seen less frequently in effective markets. Our empirical findings reveal that the established hubs in Europe are TTF and NBP. Therefore, each country must comply with characteristic elements in NBP and TTF to be subject to less speculative price movements. Many of the elements required to become a benchmarking hub are listed in previous hub review techniques (e.g., in ACER, 2020; Shi, 2016). However, the criteria we focused on in our study are supply divergence, LNG facilities to connect to global markets, various interconnection points with different countries, and multiple supply/demand instruments as storage facilities, political willingness to trade at hubs, low level of market concentration and high competition. Second, when natural gas price is not determined by its own value but depends on oil price in the long-term contracts, natural gas price will inevitably display similar explosive movements whenever the oil price creates a bubble. For instance, Fantazzini (2016) states that plummeted oil prices of 2014/2015 led to a negative oil price bubble, affected gas prices by a 6 to 9-month lag, and thereby contributed to the natural gas price bubbles observed in Germany and Austria. This implies that the actors in both industrial and financial sectors should carefully watch the factors that constitute the value of gas and oil to reduce the risks and uncertainty in the natural gas market. It is essential to facilitate gas on gas price mechanism to increase the effectiveness in natural gas markets.

CHAPTER 2

TIME VARYING CAUSAL RELATIONSHIP BETWEEN CARBON PRICE AND ENERGY PRICES

2.1 INTRODUCTION

Coping with climate change, Emission Trading Scheme (ETS) initiated in 2005, the first also still the most extensive cap-and-trade mechanism as a cost practical instrument mitigating greenhouse gas emissions in European Union. EU ETS retrain the amount of CO_2 allowances put into circulation from companies and can be subject to trade with each other.

Cap-and-trade mechanism, aims to systematically decrease pollution by providing companies with motivation to allocate resources towards cleaner alternatives. The government allocates a specific number of allowances to companies, establishing a limit on permissible carbon dioxide emissions. Firms exceeding the emission cap face penalty, whereas those reducing their emissions have the option to sell or trade surplus credits in the ETS.

Carbon trade is formed by companies' decision about the expenses of descending emissions is less or equal to the carbon price, actors invest in mitigating carbon emissions; otherwise, they can buy additional emission allowances. The EU ETS is in Phase 4 (2021 to 2030) at present, which has gradually transformed into a more restrictive tool over the years. Since 2009, there are boost of emissions mainly because of immense volume of international credits and the economic crisis that caused lower carbon prices and weak motivation to decrease the amount of emissions in the ETS. The surplus risk weakens the proper operation in the short term while altering the strength of ETS's cost-effective emission decline target for long period. Therefore, the European Commission revised the ETS procedure in 2018 to facilitate the 2030 emission mitigation goal of 43% in contrast to 2005 standards. In Phase 4, the cap on emission allowances was determined to reduce accelerated annually according to a linear reduction factor of 2.2%, whereas 1.74% throughout Phase 3 (2013 – 2020) (Barnes, 2021). Uncertainty and volatility in prices of energy directly affect the request of fossil sources, consequently altering the emissions stemming from fossil fuel usage. These changes in emissions, alongside shifts in the demand for carbon emission permits, subsequently influence carbon prices. Thus, fluctuations in energy prices create an impact on carbon prices to arrange both the supply and demand drivers (Li et al., 2022). More specifically, implementing greenhouse gas policies and regulations aims to mitigate carbon footprints, which leads to manufacturing firms heavily performing curtailing their reliance on fossil energy sources (Jiang et al., 2023).

We aim to contribute literature analysing the connection among EU ETS prices of carbon and energy by employing a time-varying Granger causality test (TVGC) developed by Shi et al., (2020, 2018). It is worthwhile to examine this issue for many reasons: first, there is a powerful connection among carbon and energy due to fossil energy is driven mainly by economic enhancement, industrial production, etc.. Fossil energy is one of the fundamental cause of emissions. Next, carbon allowance prices and energy prices are in a reciprocal cyclical relation. Although, the amount of allowance supply is stable and determine externally by European Commission. Initially, when carbon prices are low, the demand for energy use will increase due to the amount of carbon, as a consequence, the cost of allowances will rise (Zhang and Sun, 2016). This is because changing the cost of nonrenewable energy has substitution and income effects on carbon prices. From the point of income effects, there is a negative reciprocal connection among energy consumption and allowances demand. If the prices of energy increase, actors mitigate their energy consumption, as follows carbon allowance demand (Lovcha et al., 2022). In the sense of substitution effects, market actors desire to minimize their cost of production for power generation; therefore, they can switch among fossil fuel sources according to alternative expenses (Tan and Wang, 2017). Finally, energy and carbon commodities are in a tight connection in the financial markets, especially when there is fluctuation and policy uncertainty (Fan et al., 2013).

We fulfill the gap in the carbon researces by applying the novel Granger causality technique of Shi et al. (2020, 2018) and analyze the outcomes with the technique of Swanson (1998) and Thoma (1994) covering the period 15 March 2010 to 29 September 2023. TVGC (Time-Varying Granger causality test) method has several benefits that motivate us to use this method, determining how the causal linkages emerge over the specified time window. First of all, this method examines whether the causal relationship occurs or not between variables. After that, it is more accurate in identifying the timing of the specific starting point and collapse of Granger causality. In addition, this method shows the timing of inconsistency relations among variables, economic instability, and, more precisely, a casual route of change.

Detrending and differencing of the data are unnecessary for this method to maintain robust econometric tests for integration. To control as well as compare of our outcomes, we add additional data, such as stock market price and geographic political risk index (GPR) and compare the outcome of the multivariate Granger causality framework. The fossil energy and carbon causality examined bivariate in the carbon literature. At the same time, in this research, we also expand the literature by reviewing time-varying links and checking the robustness of the outcomes by multivariate structure. We also change the window size to control the Granger causality outcomes of carbon and fossil energy sources. Our hypothesis is whether oil, coal, natural gas Granger cause or not plus vice versa. Further, this hypothesis repeat again with by multivariate analysis, including stock market and GPR index variables.

The findings of our study show that the causal association from the energy to the carbon has been more evident since 2016, taking precautions with the objective of diminishing emissions starting from the declaration of the Paris Agreement. It is seen in the results that fluctuations in energy prices based on LNG surplus, oil price sanctions, the COVID-19 crisis, the Russian-Ukranian war, political declarations, high natural gas prices because of stocks, etc., reflect directly on carbon prices. In the context of causality, the casual relation carbon prices as well as oil and coal prices, is more specific after 2020. In line with Gong et al. (2021), Lovcha et al. (2022) along with Qiao et al. (2023) our outcomes indicate that the transformative pattern of the carbon market affects the increase in fossil energy prices when the ETS demonstrates the characteristic of the mature commodity. However, we could not find any causal association among the carbon and gas prices. Qiao et al. (2023) state gas is a cleaner along with more reliable source compare to the other fossil fuels. Natural gas is more abundant, and the investment decisions such as pipelines or terminals are operated for the long term.

In this study, we scrutinize the Literature Review in Section 2.2 and introduce the data along with the methodology in Section 2.3. We provide the empirical outcomes in Section 2.4 also conclusion part of the study In Section 2.5.

2.2 LITERATURE REVIEW

Like any other financial commodity, carbon allowance prices are determined by its supply/demand components. The amount carbon allowances is determined by the EU Parliament to affect the attitude of market actors that are informed before the announcement. Depending on the cost of the carbon price market, actors change their behavior. Zhang and Sun (2016) state when the expenses of mitigating emissions is less compare to the carbon price, then they reduce the amount of emissions; conversely, they can purchase extra emission allowances (Barnes, 2021). Allowances supply is more stable compared to the demand side. Many studies specifically focus on determining the carbon market fundamentals. Lovcha et al. (2022) consider that the major determinants of carbon allowances price comprise the price of energy commodities, economic movements, institutional choice, and weather circumstances. Gong et al. (2021) state that early studies primarily concentrate on carbon price determinants. Mansanet Bataller et al. (2006) searched the link of prices among carbon as well as fossil sources and electricity by applying a multiple regression model the begining part of EU ETS. The model shows strong link carbon with fossil energy. Hintermann (2010) explains carbon allowance price fluctuations by examining the price of nonrenewable energy, temperatures, stock prices as finds the most significant carbon price determinant is fuel prices. Gronwald et al. (2011) use different copula models to understand the relation among European carbon plus finance sector to and obtain an essential positive dependence among EUA futures as well as coal, gas, along with electricity prices. The link amid carbon and fossil sources has received enormous consideration from academic scholars since the initiation of EU ETS. Certain studies (Mansanet Bataller et al., 2006; Hammoudeh et al., 2015; Chen et al., 2022; Jiang et al., 2023) search the relation among prices of carbon energy, discovering that energy prices, encompassing fossil fuels effect on carbon. However, when authors examine the relation among prices of carbon along with energy, they acquire different results (Gong et al., 2021).

For instance Zhang and Wei (2010) show market of energy and carbon have a vital cointegration relation and long-term equilibrium link according to VAR model. Specifically, the oil price is the most vital energy sources affect carbon price, along with the impact of natural gas. Chevallier (2009) states that the Brent price affects carbon price the most, according to the result of the Markov-switching technique. Byun and Cho (2013) predict the next day's carbon price volatility by using fossil fuels and electricity by applying GARCH models. Liu and Chen (2013) show there is a dynamic interrelation and also has long memory impact between the future returns of carbon and energy. The findings of the DDC-GARCH and BEKK GARCH tests show that European carbon as well as non renewable energy prices affect positively as well as there is powerful volatility coal price to carbon price along with carbon price to gas price, while no crucial volatility relation among price of carbon along with oil in EU ETS phase II. Reboredo and Ugando (2015) observed the dynamic effect and leverage effect among EUA and oil in Phase II, whereas they could not observe any significant volatility spillover effect among these markets. Furthermore, Balcilar et al. (2016) scrutinize the risk spillover impact among contracts of energy and carbon according to MS-DCC-GARCH model. The reason why energy prices affect carbon is the the heavy usage of fossil fuels. These fuels are enormously consumed in different kinds of human activities like transportation, energy generation, and industrial manufacturing, as things stand the primary subscribers to the carbon market (Chen et al., 2022). Furthermore, many scholars (see, among others, Dowds et al., 2013 and Duan et al., 2021) search for the influence on converting prices of conventional energy into carbon within power enterprises, examining both the effect of fuel switch.

Gong et al. (2021) state that the ETS's objective is to diminish emissions by virtue of affecting the conventional energy market. Lin and Li (2015) examine that the production of fossil energy market is much more sensitive to carbon prices compared to other markets. The interlinkage connection among carbon and energy prices may offer a comprehensive understanding of carbon market dynamics.

Various GARCH methods were applied in the literature to examine volatility relations between carbon and energy prices (Byun and Cho, 2013; Hammoudeh et al., 2015; Ji et al., 2018; An et al., 2020). Byun and Cho (2013) apply three methods for forecasting volatility. When comparing the findings of the methods, the GARCH-type method outperforms the others for estimating carbon volatility. Moreover, according to the outcome of the methods, Brent oil, coal as well as electricity serve as signals for predicting carbon price. Balcilar et al. (2016) search risk transmission among the energy align with carbon market by employing the Markov regime-switching dynamic correlation method, aiming to determine time periods and structural breaks in these risk transmissions. The outcomes of their study demonstrate there is a critical volatility from energy contracts to carbon contracts.

Yu et al. (2015) investigate the volatility mechanism among the carbon price along with the oil price and find that there is a noteworthy connection among the EUA along with oilmarkets and this connection is affected from crucial economic situations such as financial crises etc. Duan et al. (2021) investigate how fluctuations affect price of energy along with carbon within ETS Phase III whom find asymmetric and adverse effects of energy contracts on carbon contracts. Further, their findings support the studies in the literature, which show energy prices influence carbon prices through the effect of the fuel conversion. Li et al. (2022) determine link among clean energy, carbon together with green bonds and indicate that these three commodities have strong connections, specifically during the COVID-19 period. Tan and Wang (2017) search the connectivity among the EUA and its determining factors, such as energy contracts plus macroeconomic uncertainty determinants of the EU ETS and finding of carbon sector risk applying by Value at Risk is primarily affecting by energy contracts. Chen et al. (2022) investigate the interconnections among energy, metal, and carbon commodities by using a quantile-based connectedness model and reveal that the dynamic connectedness in these commodities differs between severe ascending as well as descending movements, which means there are disparate spillover dynamics during upward and downward market periods. Zhang and Sun (2016) examine the dependence of European allowances align with fossil fuels which exist a crucial spillover both from coal to carbon. This relation could not be observed amid the price of carbon and oil. Notably, coal contracts have enourmous effect on carbon, pursuid by gas together with Brent oil contracts, over the sample period. Hammoudeh et al. (2015) investigate how asymmetry affected by the alteration of fossil contracts plus electricity on carbon prices by employing the NARDL technique and display essential findings. First, Brent oil prices have an asymmetrical along with long-term negative impact on carbon futures. Even though, gas prices also electricity prices affect carbon prices symmetrically, their impacts are different in that natural gas prices influence negatively, while electricity prices have a positive one. Jiang et al. (2023) address the interaction of fossil energy besides the carbon futures under diverse circumstances by employing the Granger causality method at quartiles, understanding the causality relation at median and tail levels in the period between June 1, 2015, and October 31, 2022.

We address the carbon research gap by employing the innovative Granger causality technique developed by Shi et al. (2020, 2018) and examining the outcomes using Swanson's (1998) and Thoma's (1994) analytical techniques. Our analysis spans the period from March 15, 2010, to September 29, 2023. The utilization of the TVGC method is motivated by its distinct advantages. This approach allows us to explore how causal connections evolve over a specified time frame. We examine casual relation between carbon and energy contracts and how it evolves with time, and precautions taken by European Commission.

2.3 DATA AND EMPIRICAL METHODOLOGY

2.3.1 Data

In line with the literature, we apply our test to fossil energy sources, which consist of ICE Brent crude oil futures prices, ICE the Title Transfer Facility (TTF) natural gas futures prices, ICE Rotterdam Coal futures prices are collected from the website investing.com[10]. Spot EU ETS allowances data is from European Energy Exchange (EEX)[11]. The time period for the analysis is between March 15, 2010 and September 29, 2023. To eliminate the currency fluctuations we deflate to the currencies[12]. Phase I, there was a surplus of allowances because of this carbon prices traded close to zero. In addition, because of the data avaliability of TTF prices, we conduct our analysis starting from March 15, 2010.

Moreover to investigate the multivariate causality we use the stock market of the EU which is Stoxx 600[13] with daily global Geopolitical Risk Index (GPR)[14] proposed by Caldara and Iacoviello, (2018). We choose GPR as the prices of energy are very sensitive to the geopolitical risks and affect investment desicions (Su et al., 2019).

Table 4. *Descriptive Statistics*

	CARBON	BRENT	COAL	TTF	STOXX	GPR
Mean	24.29455	64.66291	86.17114	31.23738	356.6990	108.2113
Median	13.02000	62.89522	68.93788	21.60100	364.0700	99.56850
Maximum	97.58000	117.4769	402.7892	339.1960	494.3500	542.6571
Minimum	2.680000	17.80582	34.69094	3.509000	214.8900	9.491598
Std. Dev.	26.59052	18.42692	63.26074	35.38030	65.82579	48.24478
Skewness	1.480231	0.073114	3.000983	3.652919	-0.089135	2.292607
Kurtosis	3.752677	2.342904	12.04593	18.61132	2.161102	14.54937
Jarque-Bera	1285.715	62.44141	16239.09	40936.34	101.3501	21276.71
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	80342.09	213840.3	284968.0	103302.0	1179603.	357854.7

[10] Source: investing.com
[11] Source: https://icapcarbonaction.com/en/ets-prices
[12] Source: https://www.investing.com/currencies/eur-usd-historical-data
[13] Source: https://finance.yahoo.com/quote/%5ESTOXX/
[14] Source: https://www.matteoiacoviello.com/gpr.htm

In above the descriptive statistics of data are shown. Table 4 reports the main descriptive statistics for the time series of interest. The standard deviations of the coal price are greater than carbon, oil and gas prices. Data demonstrates positive kurtosis as well as a removal from normality corresponded to the Jarque-Bera method.

2.3.2 Empirical Methodology

It is important to determine the interactivity among financial variables. The approach of Granger causality reveals the casual impact between time series (Wang and Fu, 2022). In this study, the causality link among coal, Brent oil, naural gas, carbon prices are examined by applying the TVGC technique introduced by Shi et al. (2020, 2018) identifying to possibility of causality in various time frequency.

When we compare the TVGC approach to earlier approaches, it is superior to earlier causality estimation techniques in many aspects Primarily, the results of earlier studies are very vulnerable to the history of time series. Additionally, TVGC approach determine specifically the begining and ending point of casual relation between variables. Therefore this model contribute to well understanding of causality link among variables. Furthermore, the lag-augmented VAR (LA-VAR) technique proposed by Toda and Yamamoto is employed in TVGC to guarantee the predominance of control range and accurate the capability of conventional asymptotic tests also prevent the question of hypothesis examination failing in the existence of unit roots (Jiang et al., 2023).

The causality link among coal, Brent oil, natural gas along with carbon prices are analyzed by implementing the TVGC technique introduced by Shi et al. (2020, 2018). For the comparison, purpose, we apply forward expanding technique by Thoma (1994) and rolling window approach introduced by Swanson (1998). Dolado and Lütkepohl (1996) offer the lag augmented VAR approach conducting for a Granger causality method to apply e_t as potential integrated variable is shown as in the method:

We employ the theoratical approach of the LA-VAR technique established by Dolado and Lütkepohl (1996) besides Toda and Yamamoto (1995) shown as in the model:

$$Y = \tau\Gamma' + X\Theta' + B\Phi' + \varepsilon \quad (1)$$

where $Y = (y_1, \dots\dots\dots, y_T)_{Txn'}$, $\tau = (\tau_1, \dots\dots\dots, \tau_T)_{Tx2'}$, $X = (x_1, \dots\dots\dots, x_T)_{Txnp'}$, $x_t = (y_{t-1}{}', \dots\dots\dots, y_{t-p}{}')_{npx1'}$, $\Theta = (c_1, \dots\dots\dots, c_p)_{nxnp'}$, $B = (b_1, \dots\dots\dots, b_p)_{Txnd'}$, $b_t = (y_{t-p-1}{}', \dots\dots\dots, y_{t-p} - d')_{ndx1'}$, $\Phi = (c_{p+1}, \dots\dots\dots, c_{+dp})_{nxnd'}$, $\varepsilon = (\varepsilon_1, \dots\dots\dots, \varepsilon_T)_{Txn'}$ (2)

and d is the extreme degree of integration for y_t

The Wald method establish on constraints by $H_0: R\theta = 0$ represents as:

$$w = [R\hat{\theta}]'[R(\hat{\Omega} \otimes (X'QX)^{-1}))\ R']^{-1}[R\hat{\theta}]$$

Where $\hat{\theta} = vec\ (\widehat{\Theta})$ represents the row vectorization with $\widehat{\Theta}$ demonstrate a least-squares estimator of type $\widehat{\Theta}$=$Y'QX\ (X'QX)^{-1}\widehat{\Omega} = T^{-1}\hat{\varepsilon}'\hat{\varepsilon}$ and R is a m × n^2p matrix where m shows the constraint' unit.

TVGC method apply supremum (sup) Wald statistic sequences denoted as $W_{f_2}(f_1)$ the Wald statistic over $[f_1, f_2]$ that the model's sample size fraction is demonstrated by $f_w = f_2 - f_1 \geq f_0$. The sup Wald statistic is illustrated as:

$$SW_f(f_0) = \frac{sup}{(f_1, f_2) \in \lambda_0, f_2 = f} \{W_{f_2}(f_1)\}$$

where, for abbreviated sample magnitude $f_0 \epsilon, \lambda_0 = \{(f_1, f_2) : 0 < f_0 + f_1 \leq f_2 \leq 1, and\ 0 \leq f_1 \leq 1 - f_0\}$ and shown the minimum data range $f0 \in (0,1)$ in the model. In this approach flexible of f_1, provides the adjustable implication of reinitialisation for individual piece of data.

Recursive evolving: $\hat{f}_e = \frac{inf}{f\in[f_0,1]} \{f: SW_f(f_0) > scv\}, and\ \hat{f}_f = \frac{inf}{f\in[\hat{f}_e,1]} \{f: SW_f(f_0) < scv\}$

Rolling window:

$$\hat{f}_e = \frac{inf}{f \in [f_0, 1]} \{f: W_f(f - f_0) > cv\}, and\ \hat{f}_f = \frac{inf}{f \in [\hat{f}_e, 1]} \{f: W_f(f - f_0) < cv\}$$

forward expanding:

$$\hat{f}_e = \frac{inf}{f \in [f_0, 1]} \{f: W_f(0) > cv\}, and\ \hat{f}_f = \frac{inf}{f \in [\hat{f}_e, 1]} \{f: W_f(0) < cv\}$$

2.4 EMPIRICAL RESULTS

We first demonstrate the casual relation among carbon emission prices with fossil energy prices. In addition we present the factors that affect the causality relation across the entire time frame. After we regress multivariate TVGC integrating two additional data: stock market price and geopolitical risk index. We would like to compare bivariate TVGC findings with multivariate findings. Moreover, as a robustness check, we change the window size to understand whether it has a significant effect on findings or not.

2.4.1 Unit Root Test

As a first step in our analysis, we begin by analyzing the stationarity and nonlinearity characteristics of the data by applying Dickey and Fuller (1979) and Perron and Phillips (1988) techniques. Table 5 displays that coal, carbon and Brent oil prices exhibit stationarity when considering their first-order differences whereas natural gas, geopolitical risk index (GPR) and stock market prices demonstrate stationarity at their levels. This technique allows to conduct under the assumption that the order of integration lies between one and two, denoted as d = 1, 2 , (Baum et al., 2021). These findings directly guide the specification of TVGC, we set d = 1.

Table 5. *Findings of Unit Root Test*

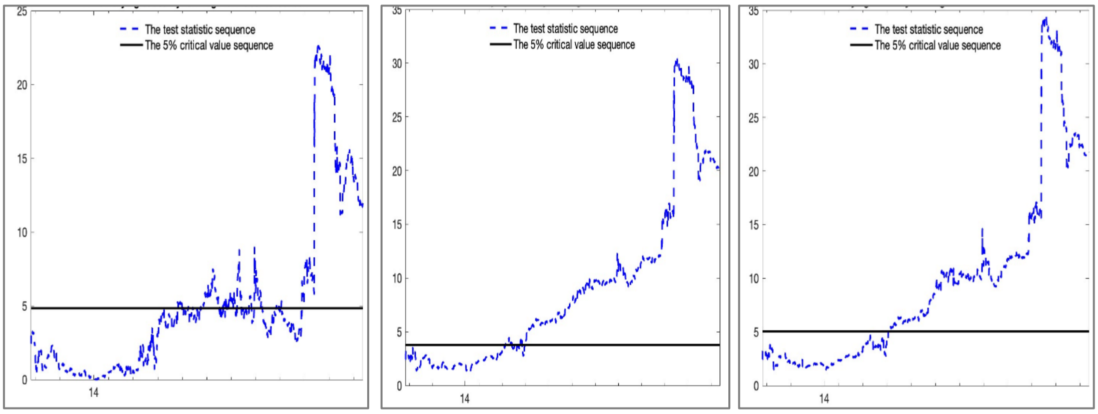
Variables	Levels		1st Difference		Outcome
	ADF	PP	ADF	PP	
Crude Oil	-1,724599	-1,795247	-24,75661	-57,23423	I(1)
Coal	-2,138314	-2,480329	-12,79854	-58,80607	I(1)
Natural Gas	-3,168502	-3,492768	-11,44307	-51,35633	I(0)
Carbon	-1,226366	-1,43052	-14,03831	-60,67323	I(1)
Stoxx 600	-3,954023	-3,918437	-21,47124	-56,45474	I(0)
GPR	-6,539784	-49,11187	-15,51014	-490,2569	I(0)

2.4.2 Findings of Carbon and Coal Causal Relation

In this section, we start with the brief history of the EU ETS scheme, which consists of four different phases; phase I was an experimental stage aimed at determining a price for carbon to institutions that were mainly allocated their allowances without charge. Further, in Phase II, the auctioning of EU Allowances (EUAs) was announced which initiated in 2008. In addition, considerable allowances in this period led to highly volatile carbon prices. Since 2009, an excess of emission allowances has accumulated within the ETS. The European Commission (EC) has taken steps to solve this surplus through both immediate and enduring measures. Allowances surplus primarily stems from the economic crisis, which resulted in mitigating emissions beyond initial expectations.

Consequently, this surplus has contributed to the decreased carbon prices, thereby, institutions were unwilling to curb emissions. This surplus poses a risk to the effectiveness of the carbon market, potentially disrupting its stability. The possibility of this surplus might affect ETS's capability to meet more stringent emission reduction goals efficiently in the long run. Phase III covers the years between 2013 and 2020 that witnessed a surge in carbon prices, reaching to dramatic high levels by the period's end in 2019. The reason behind that is that EU members decided to change the unbalanced market fluctuations with comprehensive market reforms, primarily the implementation of the Market Stability Reserve (MSR).

The creation of the MSR initiated as a lasting solution to address the accumulation of excess allowances that was explained to the public in 2015, underwent amendments and ratification in June 2018, and became operational in 2019. The MSR was planned with the intention to diminish the surplus of allowances in the short period slightly along with dynamically regulate the amount of carbon in reaction to possible shocks of the future and was initiated in January 2019 (Barnes, 2021).



*The horizontal axis represents years.
i)Recursive Evolving ii)Rolling Window iii)Forward Expanding

Figure 8. *TVGC Results of Coal to Carbon*

Further, based on outcomes depicted in Figure 8, it becomes evident there is a strong casual link amongcoal and carbon prices. The Granger causality test results can be examined in detail in Table 6.

In Figure 8 (column 1), one distinct period (01.03.2017-29.09.2023) exhibits notable instances of Granger causal association from coal to carbon, evidenced by the test statistic surpassing the 5% critical level. Notably, both the rolling and forward techniques yield consistent outcomes that causality relation emerges from 2017 to 2023. Several vital circumstances in the coal market can affect the causality relation in this period. In 2017, the European coal market experienced a resurgence, benefiting both lignite producers and hard coal importers, primarily supported by a strong beginning to the year. Since 2012, coal prices had a downward trend in Europe. Unfavorable weather conditions, reduced electricity generation from renewable sources, and substantial system outages collectively contributed to heightened coal usage and production. This positive upturn was attributed to decreased output from renewable energy sources, reaffirming coal's significance in maintaining the balance of the electricity grid (EURACOAL, 2017). In 2018, coal prices surged due to low cost of gas due to liquefied natural gas (LNG) being at times lower than coal prices when evaluated on an energy basis, leading to a massive volume of LNG imports. This situation prompted many countries to engage in coal-to-gas switching (EURACOAL, 2019). Carbon emission prices rose in 2018 and continued to increase in 2019 due to the amendments to the EU ETS Directive that concluded earlier of 2018. Power entities, these high levels of carbon prices equal the expense of mining a tonne of lignite to the carbon expense of using a tonne of lignite to produce electricity, causing financial challenges for entities due to the significant increase in input expenses (EURACOAL, 2019). Coal prices declined and fell below the marginal supply costs to produce coal because of the Covid-19 pandemic which led to lower demand for power and industrial producers in Europe. Another reason for high carbon emission prices is the political decision of the EC, which will to mitigate emissions by 55% by 2030 (EURACOAL, 2022).The COVID-19 crisis in 2020 has additionally driven down coal prices, dipping below the marginal supply costs for numerous producers (EURACOAL, 2019). The sky gas prices across Europe valued coal's significance in the energy mix, particularly in power generation. Market dynamics have witnessed a shift from gas to coal due to favorable clean-dark spreads since June (EURACOAL, 2023).

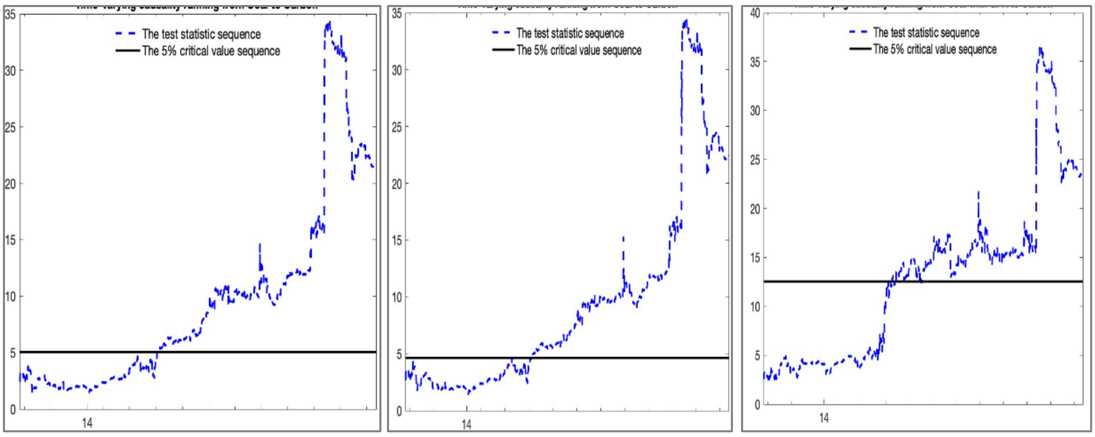
Further, in 2021, initiating the Emission Trading System phase 4 regulated new rules with stricter caps and revised allocations of free quantities, triggering steeper carbon prices. Investors exhibit strong confidence for phase 4, fostering the aim of the ongoing energy transformation to clean energy. This mechanism compels a carbon price as an evolving investment commodity, increasing liquidity thanks to market actors for hedging purposes and contributing to the steep carbon price. The coal industry was affected by Russia-Ukraine war in 2022. This sustained conflict has drastically disrupted energy markets, notably within the EU, where bans on Russian coal imports and promptly evolving energy policies have enormously affected all energy commodities. Coal prices have reached dramatic peaks, and it is possible to take a couple of months before the coal price stabilizes (EURACOAL, 2022).

Table 6. *TVGC Results of Coal to Carbon*

TVGC from Coal to Carbon		
Recursive Evolving	**Rolling Window**	**Forward Expanding**
17Mar01-23Sep29'	'17Sep12-17Nov07'	'16May09-16Aug02'
	'17Nov24'	'16Nov10'
	'18Jan17'	'16Nov14-16Dec06'
	'18Jan19-18Jan22'	'17Jan12-23Sep29'
	'18Jan24'	
	'18Mar05-18Mar07'	
	'18Mar14'	
	'18Mar20'	
	'18Jun01'	
	'18Jun15-18Jun19'	
	'18Jul03-19Jan22'	
	'19Feb04'	
	'19Mar06-19Mar07'	
	'19Mar13-19Apr01'	
	'19Apr04-19Apr08'	
	'19Apr11-19Apr18'	
	'19Apr25-19May02'	
	'19May06-19May09'	
	'19May13'	
	'19May15-19Jul05'	
	'19Jul09-19Aug05'	
	'19Aug23-19Oct14'	
	'19Oct28-19Oct29'	
	'19Dec09'	
	'19Dec13-19Dec16'	
	'20Jan13-20Feb12'	
	'20Mar16-20Jun15'	
	'20Dec02-20Dec04'	
	'20Dec08-20Dec10'	
	'21Jan06-21Jan12'	
	'20Dec16-20Dec17'	
	'20Dec21'	
	'20Dec29'	
	'21Jan22'	
	'21Jan27'	
	'21Feb02-21Feb05'	
	'21Sep30'	

These conclusions align with Tan and Wang (2017), Duan et al. (2021), Gong et al. (2021), Lovcha et al. (2022) and Jiang et al. (2023) which show that coal contracts crucially affect carbon contracts. Gong et al. (2021) highlighted that coal price shocks contribute notably to the frequent fluctuations in carbon pricing, particularly from 2017 onward. During this period, alongside escalating carbon prices, other climate policies further motivate the shift away from coal.

Moreover, as coal prices increase, there's a stronger motivation to replace coal with natural gas or vice versa low gas prices also led to use of more gas in the energy mix. Because of aforemention situation in high gas prices from 2021, support the usage of coal in the energy mix, and led to high coal prices and therefore high carbon prices. Chevallier (2009) consider as coal contracts volatility may affects substantially carbon contracts. The carbon futures and the coal futures news spillover is powerful in comparison with the oil align with gas contracts (Wu et al., 2018).



*The horizontal axis represents years.

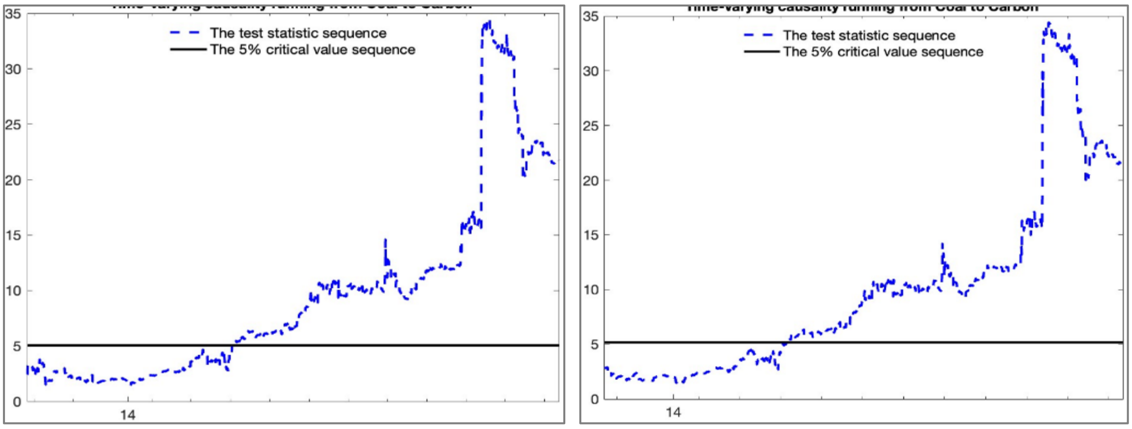
i)Bivariate ii)Multivariate Stoxx iii)Multivariate GPR

Figure 9. *Comparison of Bivariate and Multivariate Results*

Figure 9 illustrate that the outcome of the bivariate test and the multivariate consisting two additional variables as stock market prices and GPR are consisted. When look into detail in the Table 7 it can be seen that the periods of causality relations are similar to bivariate calculations.

Table 7. *TVGC Results of Coal to Carbon*

TVGC from Coal to Carbon		
Bivariate	**Multivariate Stoxx**	**Multivariate GPR**
17Mar01-23Sep29'	'16Jun29-16Jun30'	'17Feb27'
	'17Feb01-17Feb10'	'17Apr05-17May02'
	'17Feb28-23Sep29'	'17May31-17Sep05'
		'17Sep07-18Mar20'
		'18Mar27-18Apr04'
		'18Apr19-23Sep29'



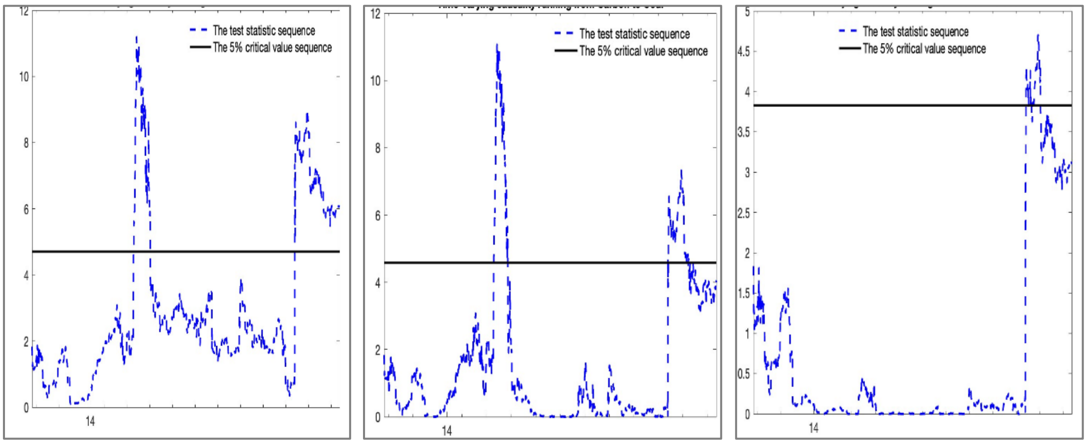
*The horizontal axis represents years.
i)Windows 0.2 ii)Windows 0.25

Figure 10. *Comparison of Window Size*

Table 8. *Comparison of Window Size*

TVGC from Coal to Carbon	
Windows 0.2	**Windows 0.25**
'17Mar01-23Sep29'	'17Mar01-23Sep29'

In Table 8, it is clearly obvious that changing window size has not any affect on casual relation from coal prices to carbon allowances prices.



*The horizontal axis represents years.
i) Recursive Evolving ii)Rolling Window iii)Forward Expanding

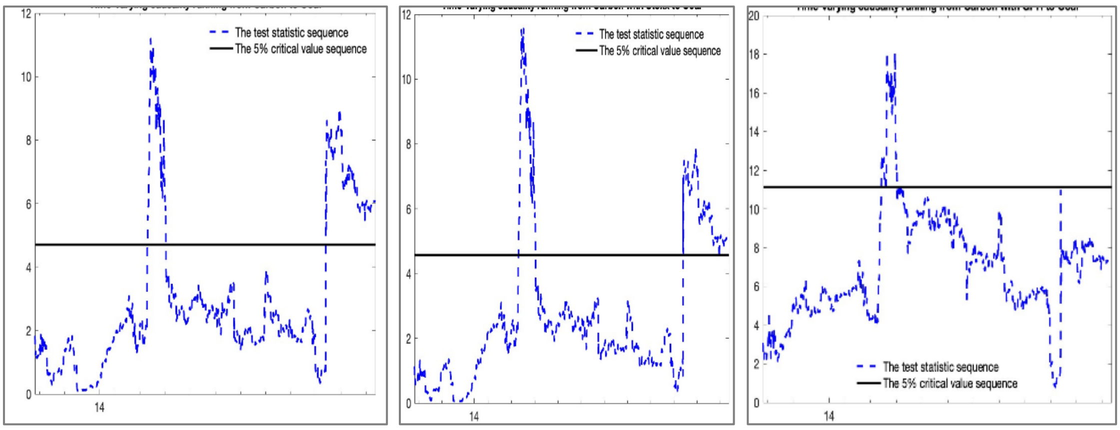
Figure 11. *TVGC Tests Between Carbon to Coal*

Figure 11 present the outcome of the recursive evolving test, rolling window test and forward expanding test illustrate that coal prices significantly affect from carbon prices. Recursive evolving test covered the most wide period (27 June 2016 to -27 January 2017 and 02 March 2022- 29 September 2023) compare to the rolling window test and forward expanding test. Besides, both rolling window and forward estimation techniques display the causality relation form carbon to coal in 2022. However both approaches could not identify any casual relation for 2023. The reason might be why carbon prices affected from coal prices in 27 June 2016 to - 27 January 2017, the regulation of The Paris Agreement which oblige to member states mitigate greenhouse gas emissions (EURACOAL, 2017). In EURACOAL (2022) stated that after the initation of the MSR, hedging operations have started in the carbon market.

Table 9. *TVGC Tests From Carbon to Coal*

TVGC Tests from Carbon to Coal		
Recursive Evolving	**Rolling Window**	**Forward Expanding**
'16Jun27-17Jan27'	'16Jun27-16Dec12'	'22Mar10-22Apr07'
'22Mar02-23Sep29'	'22Mar02'	'22Apr12-22May03'
	'22Mar09-22Oct05'	'22May05-22May18'
	'22Oct11-22Oct28'	'22May30-22Sep06'
	'22Nov02-22Nov04'	
	'22Dec27'	

When looking at the details, financial players hedge future operations by using the amount of allowances, which means hedgers withdraw allowances from the carbon market. This situation causes that there is an allowance surplus in the market; therefore, via the MSR, fewer allowances are permitted to circulate in the system through auctions to achieve present demand. Because of fewer allowances in the system, carbon prices increase, and emission demand can not be met. Hedgers uses the gap in the MSR system that a long period of hedging induces all the time in the future, showing there is an excess allowance in the market. As a result, coal industries are exposed to compensate for the high carbon fee (EURACOAL, 2022). Jiang et al. (2023) also find a Granger causality link from carbon emission contracts to coal contracts in quantiles. Gong et al. (2021) emphasize as coal is the primary supply of electricity production, carbon allowances are mainly specified by the charge of electricity production; therefore, carbon prices affect coal prices. In addition, if the carbon futures hike and the conversion price of producing electricity from gas is cheaper compare to coal, then the demand for coal diminishes. Carbon contracts' impact on the coal contracts hit record levels in 2020 because of the low amount of allowances due to "carbon neutrality." COVID-19's impact of contagion risk was brought to both markets after the covid increase demand as an accelerated demand for economic revival (Qiao et al., 2023).



*The horizontal axis represents years.

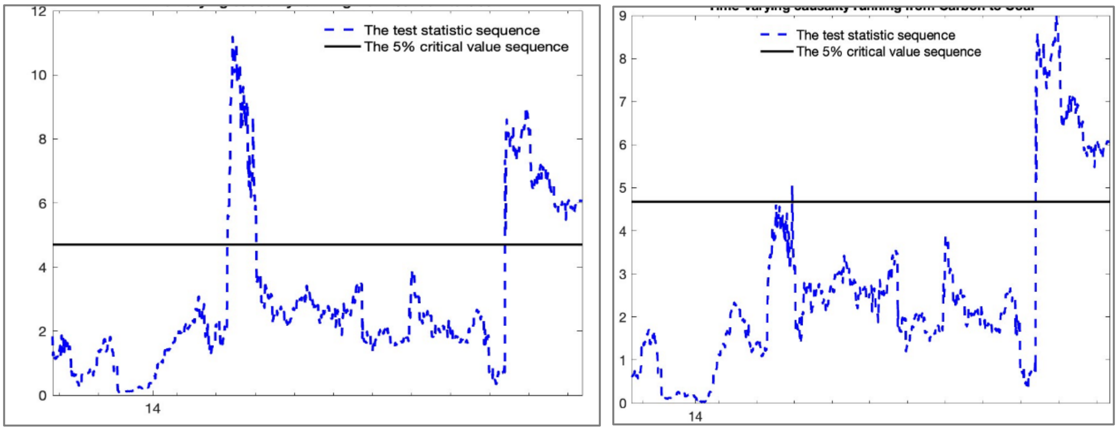
i)Bivariate ii)Multivariate Stoxx iii)Multivariate GPR

Figure 12. *Comparison of Bivariate and Multivariate Results*

Table 10. *TVGC Tests From Coal to Carbon*

TVGC Tests from Carbon to Coal		
Bivariate	**Multivariate Stoxx**	**Multivariate GPR**
'16Jun27-17Jan27'	'16Jun30-17Jan27'	'16Aug04-17Jan27'
'22Mar02-23Sep29'	'22Mar02-23May26'	'17Mar08'
	'23Jun02-23Sep29'	

In the Table 10 it is shown that the results of bivariate causality and multivariate causality are robust we when add a control variable, stock market. However, when add the control variable, GPR, the causality relation only exist the year between 2016 and 2017. This suggest that GPR may be a less crucial determinant factor for coal because it is more local compare to the oil plus gas.



*The horizontal axis represents years.

i)Windows 0.2 ii)Windows 0.25

Figure 13. *Comparison of Window Size*

Table 11. *Comparison of Window Size*

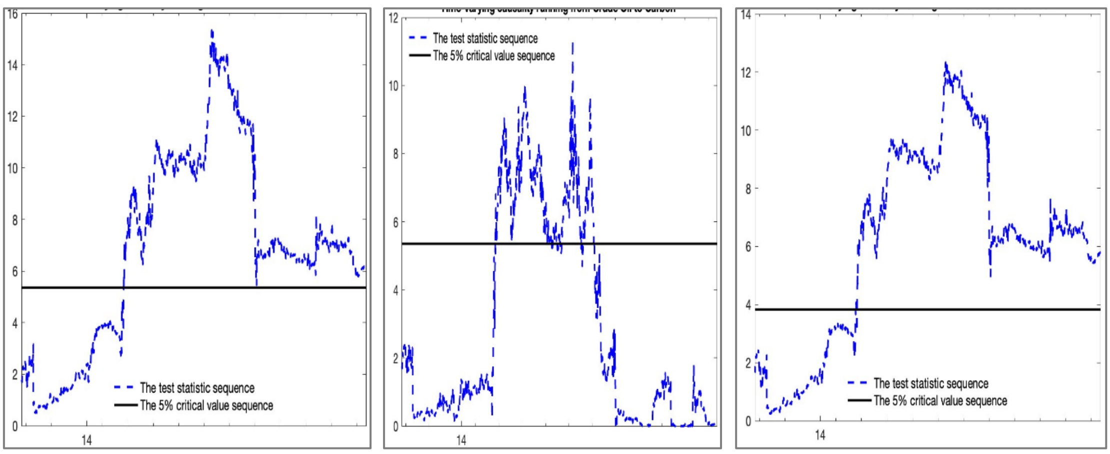
TVGC Tests from Carbon to Coal	
Windows 0.2	**Windows 0.25**
'17Jan04-17Jan06'	'16Jun27-17Jan27'
'22Mar02-23Sep29'	'22Mar02-23Sep29'

In Table 11, both window size detect the casual relation from carbon to coal the period between March 2022 and September 2023.

2.4.3 Findings of Carbon and Crude Oil Causal Relation

The causal link from oil price to carbon price is illustrated in Figure 14. Both recursive evolving methods and forward method determine the causality relationship from February 2016 till September 2023. However, the rolling window approach identifies causality relations in several dates covering February 2016 to July 2019. The oil price affected the carbon contracts, in 2016, because the oil price crashed as a result of Iranian sanctions (European Commission, 2016). Because of COVID-19, there was huge amount of oil in economy that hit the oil prices (EURACOAL, 2019). In 2021, it is the first time after 2014 oil contracts arrived the top level, and just as in 2022 since 2008, due to the economic rebound effect after the pandemic and the expectation of inflation, an increasing trend in oil prices was triggered (European Commission, 2022). If positive oil shock emerges, carbon price will increase.

Lovcha et al. (2022) also obtained similar results to ours: from 2015-2016, there was an increased association amid prices of oil and carbon. Additionally, the oil contracts affect carbon allowances in long period. Qiao et al. (2023) specify that the oil price has been positively and negatively affected the carbon market, and compared to the other fossil fuels, its impact has the most.



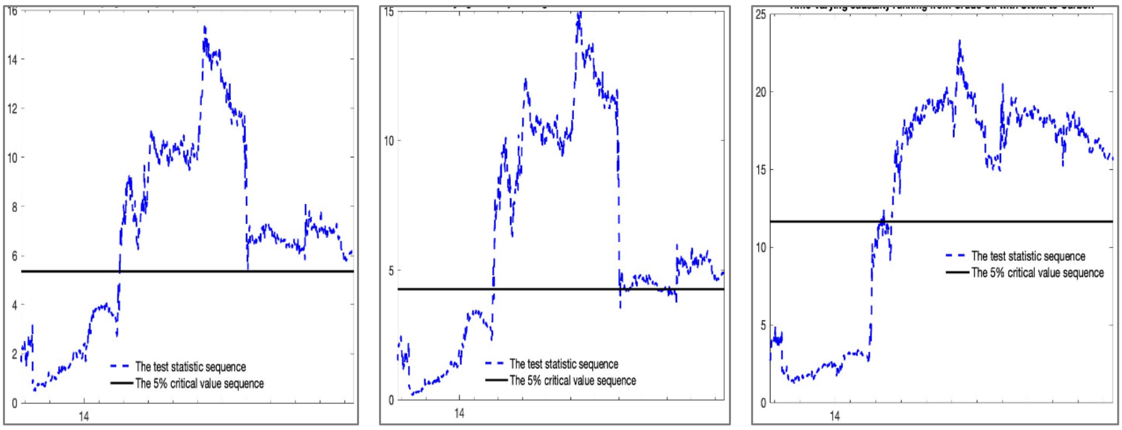
*The horizontal axis represents years.

i)Recursive Evolving ii)Rolling Window iii)Forward Expanding

Figure 14. *TVGC Tests Between Crude Oil to Carbon*

Table 12. *TVGC Tests From Crude Oil to Carbon*

TVGC Tests from Crude Oil to Carbon		
Recursive Evolving	**Rolling Window**	**Forward Expanding**
'16Feb16-23Sep29'	'16Feb16-16Feb17'	'16Feb16-23Sep29'
	'16Feb23-17Dec04'	'16Feb01-16Feb02'
	'17Dec07-18Jan23'	
	'18Feb08-18Apr03'	
	'18Apr19-18May09'	
	18May31-19Jan22'	
	'19Jan29-19Feb11'	
	'19Jan29-19Feb11'	
	'19Feb26-19Jul09'	



*The horizontal axis represents years.

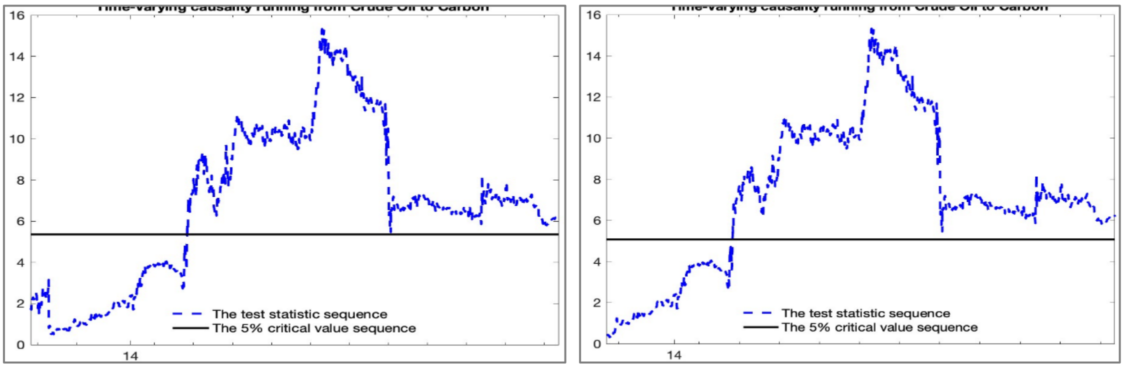
i)Bivariate ii)Multivariate Stoxx iii)Multivariate GPR

Figure 15. *Comparison of Bivariate and Multivariate Results*

Table 13. *TVGC Tests From Crude Oil to Carbon*

TVGC Tests from Crude Oil to Carbon		
Bivariate	**Multivariate Stoxx**	**Multivariate GPR**
'16Feb16-23Sep29'	'16Jan28-16Feb09'	'16May18'
	'16Feb16-20Apr09'	'16Jun06-16Jun15'
	'20Apr16-20Apr20'	'16Jun29-16Jul14'
	'20Apr22-20Jun15'	'16Oct03-23Sep29'
	'20Jun18-20Jun22'	
	'20Jul10'	
	'20Jul14-20Jul17'	
	'20Aug10-21Jul19'	
	'21Jul30'	
	'21Aug12-21Aug18'	
	'21Aug23'	
	'21Sep28-21Sep29'	
	'21Oct06-21Oct19'	
	'21Dec02-21Dec06'	
	'22Mar01-23Sep29'	

It is clearly seen both in above Figure 15 and Table 13, both bivariate and multivariate approaches detect casual link from crude oil to carbon in a similar dates.



*The horizontal axis represents years.

i)Windows 0.2 ii)Windows 0.25

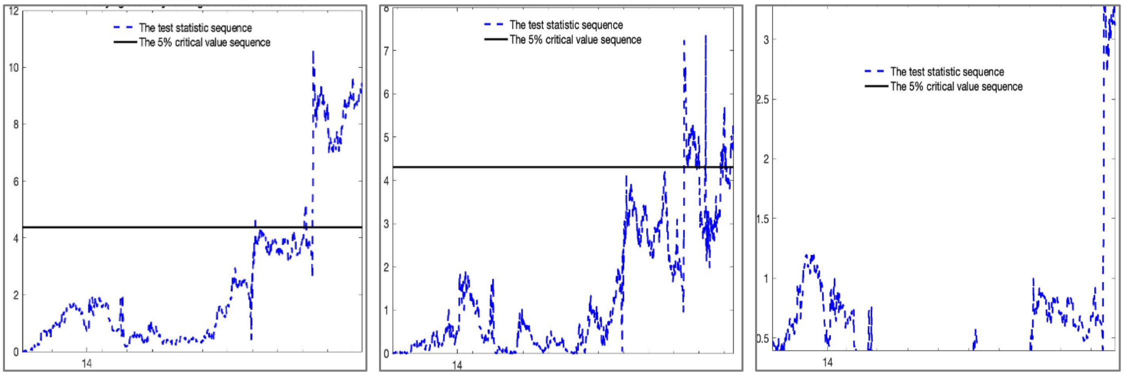
Figure 16. *Comparison of Window Size*

Table 14. *Comparison of Window Size*

TVGC Tests from Crude Oil to Carbon	
Windows 0.2	**Windows 0.25**
'16Feb16-23Sep29'	'16Feb16-23Sep29'

In Table 14, it is seen that TVGC from crude oil to carbon is not affected by changing the window size.

In Fig 17 display the casual spillover link from carbon futures to oil futures, recursive algorithm determined the causality link in more wide period May 2020, November-December 2021, March 2022-September 2023), while rolling approach just specify from 2022 to 2023.Although forward identify casual relation just for 10 March 2022. Känzig and Konradt (2023) point out that when carbon futures increase oil futures increase more significantly because carbon market includes oil entities.



*The horizontal axis represents years.

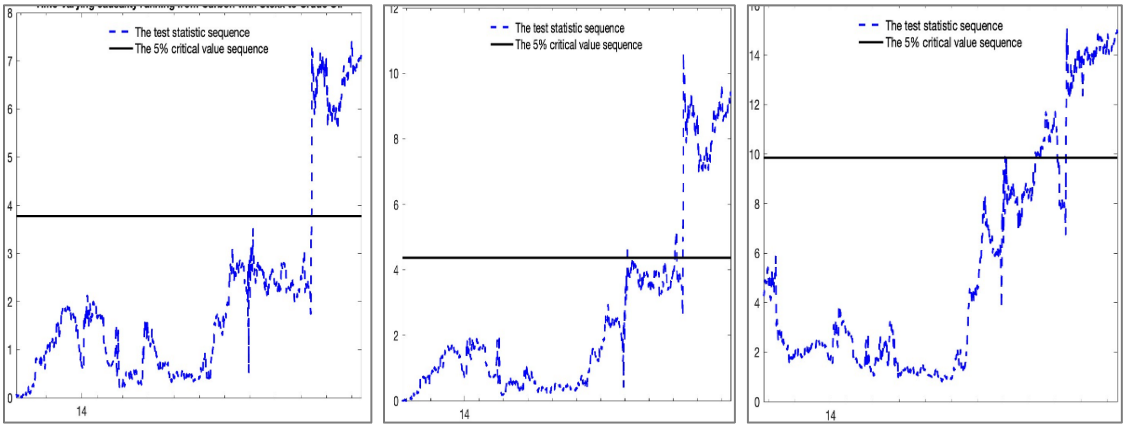
i)Recursive Evolving ii)Rolling Window iii)Forward Expanding

Figure 17. *TVGC Tests Between Carbon to Crude Oil*

Table 15. *TVGC Tests from Carbon to Crude Oil*

TVGC Tests from Carbon to Crude Oil		
Recursive Evolving	**Rolling Window**	**Forward Expanding**
'20May05'	'22Mar09-22Apr21'	'22Mar10'
'20May07'	'22Apr25-22Jul29'	
'21Nov26-21Dec17'	'22Aug03-22Aug30'	
'22Mar02-23Sep29'	'22Nov04'	
	'22Nov08'	
	'22Nov10-22Nov14'	
	'23May04-23May05'	
	'23May11-23May25'	

In addition, Lovcha et al. (2022) considers that oil contracts are crucial for determining carbon prices because of their tied link with natural gas and as a reference price on the worldwide energy system. Moreover, oil-related merchandise generally prefer transportation, which leads to emission and oil refinery entities. Jiang et al. (2023) found a Granger causality relation from carbon to oil at lower also upper quantiles while could not identify at the middle quantile. As can seen from Figure 17 and Table 15, the causality relationship has increased since 2020 from the carbon contracts to the oil contracts. A possible explanation for this relationship considered by Qiao et al. (2023) might be the restriction of carbon allowances as a phenomenon of "carbon neutrality" due to Market Stability Reserve. COVID-19's effect of possible contagion risk came into appear in both markets after the covid increase accelerated demand as a result of economic revival.



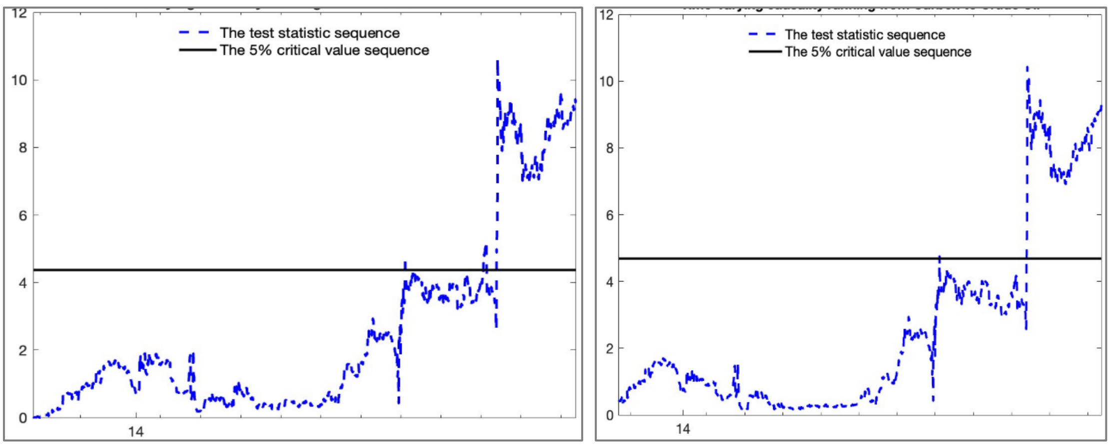
*The horizontal axis represents years.
i)Bivariate ii)Multivariate Stoxx iii)Multivariate GPR

Figure 18. *Comparison of Bivariate and Multivariate Results*

Table 16. *TVGC Tests from Carbon to Crude Oil*

	TVGC Tests from Carbon to Crude Oil	
Bivariate	**Multivariate Stoxx**	**Multivariate GPR**
'20May05'	'22Mar08-23Sep29'	'20Apr21'
'20May07'		'20May05'
'21Nov26-21Dec17'		'21Mar24-21Apr06'
'22Mar02-23Sep29'		'21Apr14-21May03'
		'21May06-21May20'
		'21May25-21Nov26'
		'22Mar04-23Sep29'

Both bivariate and multivariate test results from carbon allowances to crude oil prices are robust.



*The horizontal axis represents years.
i)Windows 0.2 ii)Windows 0.25

Figure 19. *Comparison of Window Size*

Table 17. *Comparison of Window Size*

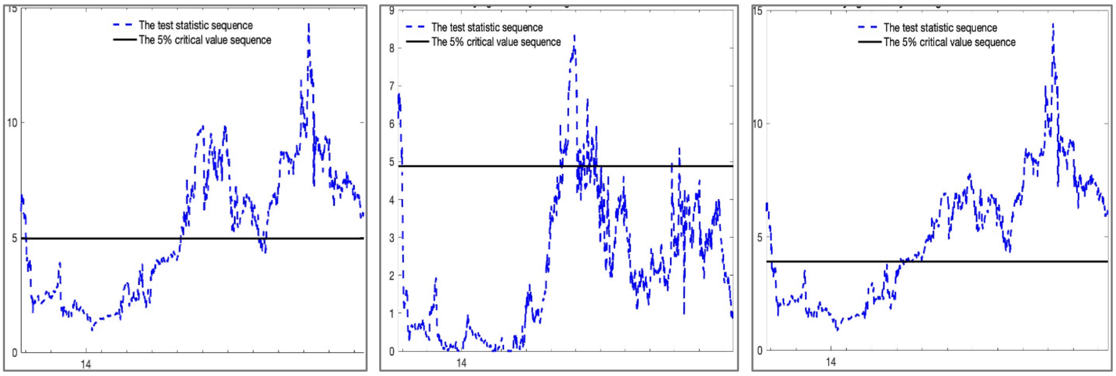
TVGC Tests from Carbon Crude Oil	
Windows 0.2	**Windows 0.25**
'20May05'	'20May05'
'20May07'	'22Mar02'
'21Nov26-21Dec17'	'22Mar04-23Sep29'
'22Mar02-23Sep29'	

In Table 17, both window size confirm the there is a crucial causal relation among carbon prices with oil prices especially the period between March 2022 and September 2023.

2.4.4 Findings of Carbon and Natural Gas Causal Relation

Figure 20 illustrates the causality link among the natural gas and carbon contracts. All approaches identify the causality from November 2012 to January 2013. Further, both recursive algorithms and forward-expanding approaches capture the causal link from natural gas to carbon from 2017 until 2023. Although the rolling window approach just recognizes the causality period between 2017 and 2022, however, it is not observed after 2022. Low gas prices in Europe occur because of the surplus of shale gas in the US, which creates an import flow via LNG to Europe. Because of the LNG glut in Europe, the power generation market, actors chose natural gas instead of coal, which led to a coal surplus as well, which is a commodity of choice for electricity production. Due to low coal prices also cause low carbon prices (European Commission, 2013). In 2019, there was a LNG wave from the US to Europe.

Similarly, in 2013, it led to low gas prices together with made gas favorable to coal; the demand for coal decreased crucially as the stock of coal boosted in Europe. Also, high carbon prices led to coal being unprefered for power generation (European Commission, 2019). In 2020, because of COVID-19, natural gas prices experienced the historical lowest price level. Nevertheless, in 2021, because of low stock levels in winter time and also high prices of oil, carbon, and coal prices, less Russian gas flow than in the past, harsh winter, outage of a nuclear plant in France, lower wind electricity generation, Nordstream declaration motivate the boost in gas prices. Because the high gas prices, market actors prefer coal-fired generation to produce electricity, which leads to gas-to-coal switches higher carbon emission amounts, and higher carbon prices. Even though much LNG is imported to Europe, the European gas market will still experience volatile gas prices and high prices in 2022 because the Russian-Ukraine war plus political declarations and sanctions until high gas prices (European Commission, 2022).



*The horizontal axis represents years.

i)Recursive Evolving ii)Rolling Window iii)Forward Expanding

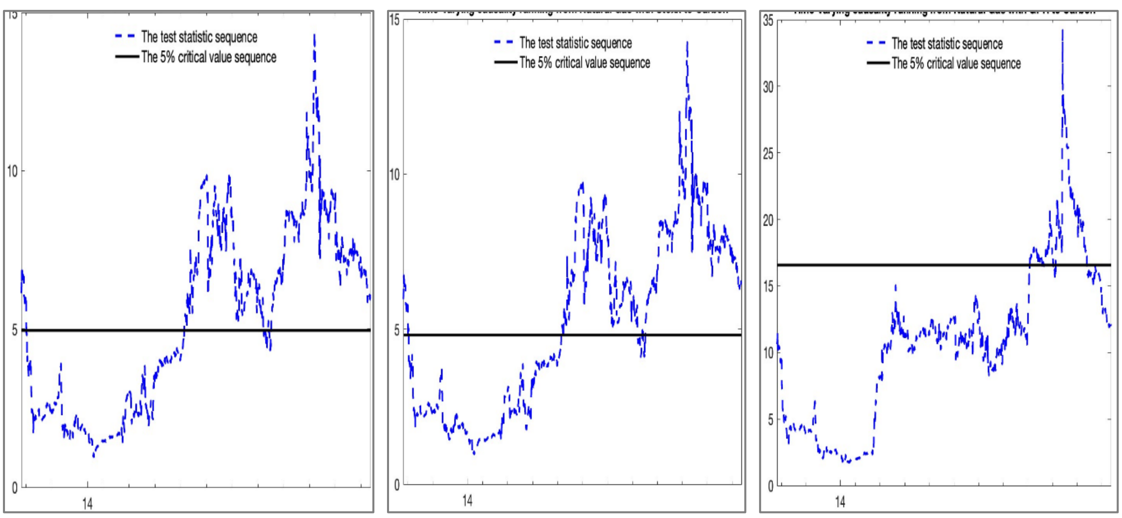
Figure 20. *TVGC Tests Between Natural Gas to Carbon*

Lovcha et al. (2022) consider gas together with coal as substitute fuels; therefore, market actors prefer to substitute coal for power generation when there is a price hike in natural gas. Compared to coal, natural gas is a more clean energy that emits less CO_2; therefore, high demand for coal leads to more emissions and higher carbon price. According to their result, natural gas prices interpreted carbon prices more in the period between 2011 and 2015, while oil prices disclosed more between 2015 and 2016.

Table 18. *TVGC Tests From Natural Gas to Carbon*

TVGC Tests from Natural Gas to Carbon		
Recursive Evolving	**Rolling Window**	**Forward Expanding**
'12Nov30-13Jan22'	'12Nov30-13Jan15'	'12Nov30-13Jan31'
'13Jan24-13Jan25'	'18Feb27-18Mar14'	'17Mar01-17Mar24'
'17Dec19-20May29'	'18Mar27-18Sep12'	'17Mar28-17Mar29'
'20Jun12'	'18Sep25-18Sep27'	'17Apr03-17Apr04'
'20Jul24-20Aug03'	'18Oct15-18Oct25'	'17May05-17May17'
'20Aug31-23Sep29'	'18Nov14'	'17May31-17Jun09'
	'18Nov20-18Dec04'	'17Jun13-17Jun15'
	'18Dec07-18Dec11'	'17Jul10'
	'19Jan08-19Jan30'	'17Jul12-17Jul17'
	'19Feb04-19Feb11'	'17Jul21-23Sep29'
	'19Feb21-19Mar28'	
	'19Apr03'	
	'19Apr09-19Apr15'	
	'19Apr18-19May02'	
	'19Jun26'	
	'21Oct06-21Oct07'	
	'22Jan03-22Jan07'	

Gong et al. (2021) clarify the importance of gas contracts in determining carbon contracts in the ETS phase III. They summarize the connection among fossil fuels and carbon. On the one hand, an escalation in carbon futures accelerates the future of conventional energy sources, primarily boosting the amount of emissions for producing electricity. On the other hand, an escalation in conventional energy sources causes a hike in electricity production costs and carbon futures.



*The horizontal axis represents years.

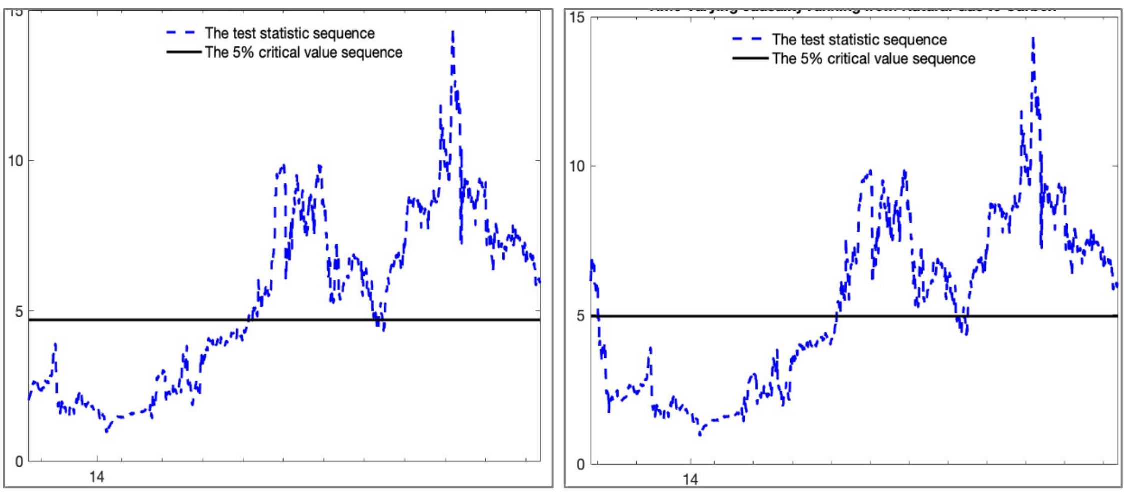
i)Bivariate ii)Multivariate Stoxx iii)Multivariate GPR

Figure 21. *TVGC Tests Between Natural Gas to Carbon*

Table 19. *TVGC Tests From Natural Gas to Carbon*

TVGC Tests from Natural Gas to Carbon		
Bivariate	**Multivariate Stoxx**	**Multivariate GPR**
'12Nov30-13Jan22'	'12Nov30-13Jan22'	'21Feb12-21May18'
'13Jan24-13Jan25'	'13Jan24-13Jan31'	'21May20-21May26'
'17Dec19-20May29'	'17Dec20-18Jan12'	'21May28-21Jul08'
'20Jun12'	'18Jan17-20May29'	'21Jul12-21Jul23'
'20Jul24-20Aug03'	'20Jul27-20Aug03'	'21Jul30'
'20Aug31-23Sep29'	'20Aug31-23Sep29'	'21Aug03-21Aug04'
		'21Aug10-21Nov15'
		'21Nov17'
		'21Dec14'
		'21Dec17-22Dec20'
		'23Mar24-23Mar27'

For bivariate analysis and multivariate analysis, including stock market prices, it is clear that casual links from natural gas prices to carbon prices occur; however, while we include GPR in the multivariate analysis, casual links from natural gas prices to carbon prices occur after 2021.



*The horizontal axis represents years.

i)Windows 0.2 ii)Windows 0.25

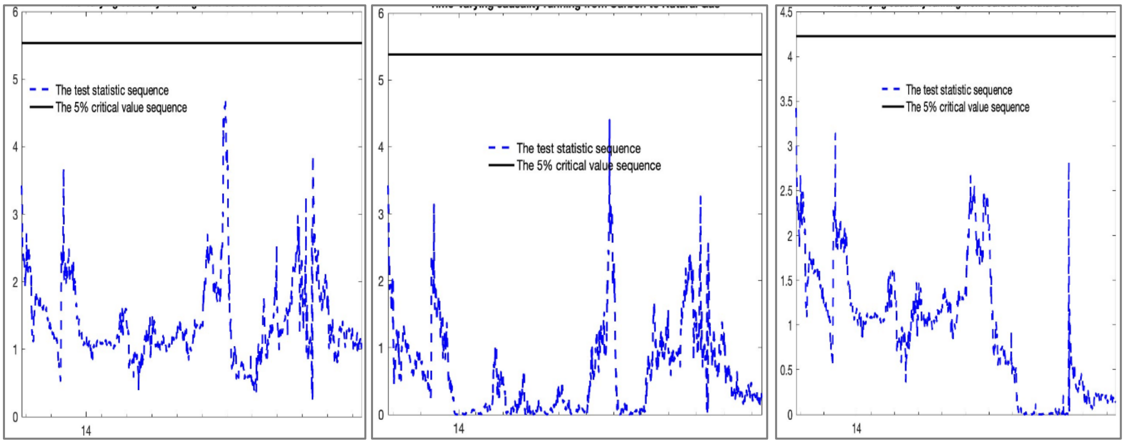
Figure 22. *Comparison of Window Size*

Table 20. *Comparison of Window Size*

TVGC Tests from Natural Gas to Carbon	
Windows 0.2	**Windows 0.25**
'12Nov30-13Jan22'	'17Dec19-18Jan12'
'13Jan24-13Jan25'	'18Jan17-20Jun30'
'17Dec19-20May29'	'20Jul17-20Aug12'
'20Jun12'	'20Aug24'
'20Jul24-20Aug03'	'20Aug31-23Sep29'
'20Aug31-23Sep29'	

In addition, it is seen in table 20, when we change the window size, it also shows that casual links are more powerful after 2020.

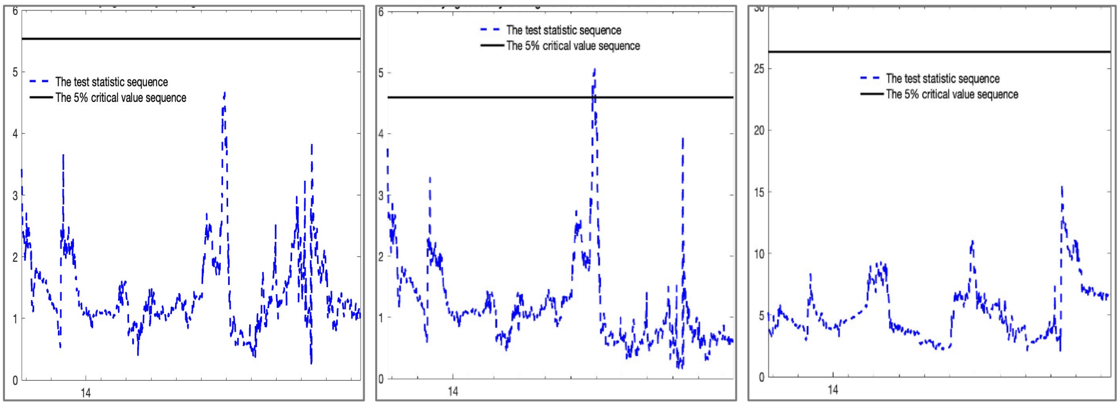
From the outcomes of Granger causality relations, regardless of the estimation methods, there is no evidence that a causality relation exists from the carbon contracts to the gas contracts as displayed in Figure 23. As explained by Qiao et al. (2023) due to natural gas being referred to as a clean source compared to other fossil fuels and also regulations that support the transition to low carbon and green and more environmentally friendly economy, manufacturing firms which omit high emissions prefer to consume more natural gas. Further, there is an ample amount of reserves, ongoing development studies in natural gas production, extended processes, and infrastructure to expedite the boost of gas consumption along with diminishing gas prices. Different from the natural gas contract response, both coal and crude oil contracts markets show an upward and affirmative reaction to shocks stemming from the carbon contract, reaching the highest point around the year 2020. Jiang et al. (2023) state that there is no confirmation of a causality relation among carbon futures and natural gas futures in the middle quantile; however, they identify casual link from carbon to natural gas at the lower and upper quantiles.



*The horizontal axis represents years.
i)Recursive Evolving ii)Rolling Window iii)Forward Expanding

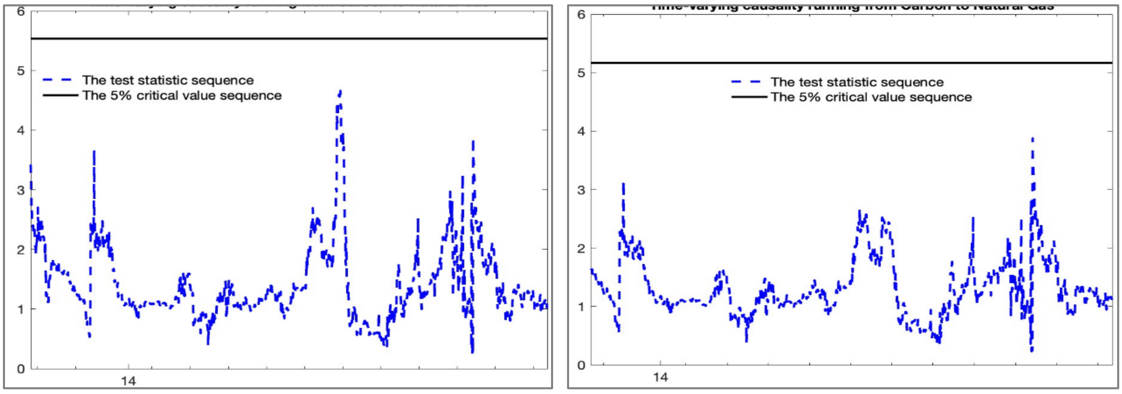
Figure 23. *TVGC Tests Between Natural Gas to Carbon*

TVGC relationship among prices of carbon and natural gas does not exist in all examined periods. This situation may be because natural gas is a cleaner fossil source than coal. In addition, Qiao et al. (2023) also state that natural gas pipelines and expenses depend on long-term investment decisions and are more abundant regarding reserves. Therefore, the reason why carbon prices do not affect natural gas prices may depend on long-term investment (such as pipelines and LNG terminals) and bilateral country agreements.



*The horizontal axis represents years.
i)Bivariate ii)Multivariate Stoxx iii)Multivariate GPR

Figure 24. *TVGC Tests Between Natural Gas to Carbon*



*The horizontal axis represents years.

i)Windows 0.2 ii)Windows 0.25

Figure 25. *Comparison of Window Size*

To sum up, based on these findings, we identify a causality relation between fossil energy contracts and carbon contracts, especially after 2016, followed by the declaration of the Paris Agreement. The volatility in energy prices affect carbon prices because of LNG surplus, oil price sanctions, the Covid-19 crisis, economic recovery after Covid, Russian-Ukranian war, political declarations. Therefore, these circumstances affect carbon prices. The causality relation from carbon price to fossil price, is more substantial after 2020. Our findings support Qiao et al. (2023) who explain the conclusion on the carbon contracts also coal along with oil contracts, is vital because after the economic revival and risk for contagion effect and low allowances in MSR system, the target of "carbon neutrality" also boost in energy demand. Our results also support Duan et al. (2021) who show that when the carbon evolves as a more mature market, the impact of energy prices is more prominent, allowing us to capture carbon market formation and fundamental factors better and state that this situation is more evident with Phase III.

2.5 CONCLUSIONS

With the initiation of the EU ETS, the European Commission has a great motivation to mitigate carbon emissions, mainly from fossil energy sources, and accelerate the regulation for supporting green energy transition that may impact the emergence of a unidirectional causal relation between carbon and fossil energy market. Assessing this relation will contribute to evaluating the functionality of the ETS-and its role in fossil energy. Besides, this study figures out how causality relations are affected by fossil energy prices, carbon prices, or vice versa under various market situations. In that vein, this paper aims to apply TVGC approach to determine a dynamic casual link and identify the reasons behind this association among energy along with the carbon market.

This paper presents and extends the carbon studies by applying the TVGC among carbon and fossil energy sources proposed by Shi et al. (2018) and Shi et al. (2020) from 10 March 2010 until 29 September 2023. We also compare the results using the methods of Thoma (1994) and Swanson (1998) who employ forward-expanding and rolling window approaches. Our results prove that the recursive system captures and detects more casual relations. Thus, the recursive approach surpasses the forward and rolling procedures over the examined period. In that regard, we also check our results for robustness purposes amid bivariate and multivariate structures consisting of additional data such as stock market prices and geopolitical risk index and also alter the window size whether the results change.

Based on the findings, we identify a causality relation between fossil energy contracts and carbon contracts, especially after 2016, followed by the declaration of the Paris Agreement. The reason behind the volatility in energy prices depends on LNG surplus, oil price sanctions, the Covid-19, boost in economy after Covid, the Russian-Ukranian war, political declarations, high natural gas prices because of stocks. Therefore, these circumstances affect carbon prices. The causal relation from carbon price to the coal and crude oil market, this casual relation is more substantial after 2020. Our result also support Qiao et al. 2023 that the carbon contract's impact on the coal and crude contracts is more substantial after the economic revival and risk for the contagion effect and low allowances in the MSR system. Also, they clarify that gas is a more abundant resource of investment decisions in the long period, which is a cleaner fossil source compared to coal and oil; therefore, it is normal that the carbon price effect is insignificant. According to our results, initiating the Emission Trading System phase 4 led to a stricter cap and revised allocations of free quantities. Also, market actors who use the carbon market as a hedging instrument trigger a steep carbon price, and therefore, it influences coal and oil refinery entities to manage emission amounts. Our findings are still robust when we add control variables and change the window size. The findings display the efficient level of the carbon market has increased in recent years, thanks to regulations, that it has an impact on fossil fuels with correct pricing, thus affecting the decisions of energy actors for power generation decisions and contributing to the aim of reducing carbon emissions. The effect of carbon contracts on conventional energy contracts differs in individual periods, which can present as a valuable benchmark for policymakers and also for market actors.

Furthermore, politicians should cautiously follow and understand the mechanism of carbon besides conventional energy commodities to promote a more effective carbon market. Our results show that more effective carbon markets give correct market signals, and thus, energy actors allocate power generation decisions, accustom energy consumption formation, and decide their positions to mitigate emissions according to the carbon prices.

Moreover, the aim of more efficient carbon market policymakers should constitute a system to observe fluctuations in price via risk monitoring tools or an early warning system to prevent the adverse influence on carbon market on the conventional energy market to boost the transition of low carbon emissions via changing structure of energy in the power generation. Future studies could also use clean energy indices and macro and micro variables to evaluate the carbon market more comprehensively.

CHAPTER 3

OIL PRICE SHOCKS AND SECTORAL UNEMPLOYMENT IN THE UNITED STATES

3.1 INTRODUCTION

From the beginning point of the oil crisis in the 1970s, a remarkable connection has been determined between crucial hikes in oil prices together with recessions in the United States. This relationship boosts the curiosity of economists together with policymakers, leading them to search how shifts in oil prices influence by economic indicators. In the past, these hikes in oil prices were often responsible for downturns in the country's economy, as highlighted in Hamilton's work in 1983. Therefore, studies generally examine the nexus among oil prices and macroeconomic indicators, along with how oil price shocks influence the national economy. Kilian (2009) demonstrates oil price spikes may emerge from worldwide economic expansion.

Moreover, the most studies centralize analyzing the consequence on oil price shocks, particularly on industrial production. A limited studies check into the survey of how oil prices affect shifting in the labor market. For instance, Loungani' work (1986) shows that oil price volatility throughout the 1970s oil crisis mitigating employment for various sectors, and that this was mainly because extensive labor redistribution. Lee et al. (1995) consider oil price volatility scenarios, state that oil price shocks considerably affect unemployment. Ferderer (1996) states oil price shocks present as beneficial indicators for forecasting employment growth rate. Recently, Alsalman (2023) searches the consequence of oil price shocks on aggregate U.S. unemployment as well as various timings of unemployment spells. The outcomes affirm negative oil supply shocks constitute a recessionary impact, notably elevating aggregate unemployment metrics aligned with the count of individuals unemployed for more or equal to five weeks. Koirala and Ma (2020) also search how oil price fluctuations impact both overall and sector-specific employment growth in the U.S. regarding the switch uncertainty linked with oil prices over time. Research conducted by Herrera et al. (2017) highlights substantial variability among industries in how they react to an unforeseen decline in the oil price, particularly job creation and destruction. A significant portion of the literature centers around searching the labor market responses to oil price shocks through aggregate unemployment rates (as observed in studies like Karaki (2018)). Therefore, exploring the relationship between sectoral unemployment and structural oil shocks can offer a more comprehensive insight into the intricacies of the labor market dynamics, providing pertinent information essential for formulating an effective policy response. In that aim, we investigate understanding the reactions of sectoral unemployment to structural shocks of the oil market together with whether there is a notable variability among different unemployment sectors. Compared to prior research, this study investigates the conclusion of oil price shocks on unemployment within diverse sectors of the U.S. economy. It employs a combination of theoretical simulations and empirical estimation techniques to address this inquiry.

Our contribution is examining how oil specific shocks influence sectoral unemployment in the United States. Three shocks link to the oil determine as: “shocks to the current physical availability of crude oil (oil supply shocks), shocks to the current demand for crude oil driven by fluctuations in the global business cycle (aggregate demand shocks)', and shocks driven by shifts in the precautionary demand for oil (precautionary demand shocks). Precautionary demand arises from the uncertainty about shortfalls of expected supply relative to expected demand. It reflects the convenience yield from having access to inventory holdings of oil that can serve as insurance against an interruption of oil supplies” (Kilian, 2009, p. 1054).

Therefore, structural VAR technique leads to scrutinize the shocks of oil price in detail along with gives more perspective about oil price shocks. This is the first study investigating the reaction of the labor market segments to these shocks by applying the structural VAR methodology by Kilian and Park (2009). First, we categorise unemployment into sectors such as total unemployment, nonagriculture, mining, quarrying, and oil and gas extraction, government, transportation and utilities, manufacturing, information, leisure and hospitality, education and health services, financial activities. The analyze highlights the significant diversity in how sector-specific unemployment responds to oil price shocks in the United States. Specifically, various unemployment sectors may show unique responses, in the account of the direction also magnitude, to shocks in oil supply. For instance, the transportation and utilities unemployment sector display a negative response during the six months following the shock, albeit with a statistically insignificant outcome. Moreover, the reactions of both the information and non-agricultural unemployment sectors to the oil supply shock lack statistical significance. The unemployment in the manufacturing industry affected the most compare to the other sectors, responses positively to shock of oil supply, and this positive impact remains significant for a period of 15 months. Concerning an aggregate demand shock, unemployment in all sectors follow a consistent negative trend, albeit with variations in the magnitude of the impact. Each unemployment sector exhibits distinct responses, including an insignificant horizon and a combination positive and negative trend, along with variations in magnitude degrees. Sectoral unemployment responds significantly in all sectors to the aggregate demand shock.

The diverse conclusion of an oil price shocks on sectoral unemployment could be attributed to the unique features of each sector. Initially, the influence of oil price uncertainty can vary among sectors with various degrees of oil reliance, reflecting the extent that whether or not oil is utilized as an input into the construction processes. Choi et al. (2018) state the uncertainty at the aggregate level has a more pronounced negative effect on growth in industries which rely significantly on exterior finance. Hence, it is plausible that sectors exhibiting greater reliance on external finance may experience more substantial effects from oil price shocks. Nonetheless, the extent of these effects differs across sectors, probably due to the distinct components within each sector, bringing on differing responses to shifts in oil prices along with shocks linked with oil prices. Especially, sectors that exhibit a more substantial reliance on oil seem to suffer more severe adverse effects. Overall, the findings indicate which the U.S. unemployment respond irregularly to oil price shocks establish sector-specific characteristics. Our research provides to the current literature by searching the impact of these three structural shocks to the price of oil on unemployment in the United States.

Given its substantial contribution to the macroeconomic inconstancy within the U.S., our focus lies on the labor market. The link among oil price shocks together with unemployment is crucial to policymakers due to its implications. This chapter underscores the significance of oil price shocks in influencing the dynamics of the U.S. labor market.

The form of this study is as follows: Section 2 examine the prior literature briefly, Section 3 explains data in the model, such as the global oil market variables alongside sectoral unemployment metrics, and Section 4 elaborates on the structural VAR model approach, Section 5 presents the findings regarding the reactions of diverse sectoral unemployment to shocks of the oil market, and Section 6 represents the conclusion.

3.2 LITERATURE REVIEW

From the beginning of 1970s, experiencing the dramatic influence on oil price shocks on macroeconomy scholars started to research this nexus. Several scholars compromise that boost in oil prices, the adverse conclusion on the U.S. economy shows significantly overbalanced compared to the positive effects caused by reductions in oil prices by the starting of the 2000s. These transmission channels of oil price shocks on economy, especially sectoral reallocation of labor, have been extensively analyzed by various theoretical models by Herrera and Karaki (2015). Oil price fluctuations would activate a transition of labor along with assets from the sectors the most influenced to the least for a country that imports oil heavily (Karaki, 2018). Thus, these transition disruptions would deepen the harmful adverse impacts of boosted oil prices while diminishing the beneficial responses connected to decreased oil prices (Davis and Haltiwanger, 2001). The importance of a precautionary saving approach to clarify the asymmetry channel in how economic facilities reply to oil price variations (Edelstein and Kilian, 2009). In detail, when oil prices rise, it accelerates uncertainty among individuals' future income, which leads to saving more as a precautionary measure, resulting in less. Conversely, when oil prices drop, individuals still exhibit a similar behaviour pattern.

Moreover, Bernanke et al. (1997) include monetary procedures in theory that explain the asymmetries in the reaction of economic actions to oil price shocks in both ways (positive and negative) due to the implementation of stringent contractionary measures in reaction of higher oil prices, while being less persistent in reaction of decreasing oil prices. Bernanke (1983) and Pindyck (1991) show the irreversible investment framework because the asymmetry in the production reacts to oil price shocks which boosted oil prices together with affected consumers' habits of transferring goods away from energy-intensive usage.

Lately, two main concerns have emerged regarding prior empirical study on the influence on oil price shocks. Firstly, Kilian and Vigfusson (2011) highlighted the approaches employed in research formed on censored VAR techniques are prone generating irregular projections. They suggest the slope-based methods employed in previous papers to assess the symmetry of the attitude of economic actions to oil price shocks lack informative value. Alternatively, Kilian and Vigfusson (2011) introduced a symmetry technique on impulse response functions as they could not detect any proof contradicting the idea of symmetry concerning unemployment. Herrera et al. (2011) search the link among oil price shocks and industrial production employing the symmetry technique estimate by Kilian and Vigfusson (2011) and conclude that proof against the symmetry, particularly within industries that heavily rely on energy, both in their operational activities and in their production procedures. More analyses applying disaggregated data have revealed the impact of positively also negatively oil price variations on stock returns as well as job movements tends to display symmetry. In addition, the outcome of studies highlights the importance of assessing the primary pathway by which oil prices impact the economy and determining whether there have been alterations in the circulation system of oil prices across different time frames.

Furthermore, before Kilian's study in 2009, researchers considering the economic influence on oil price shocks mainly centered on approaches that account for oil prices as externally specified or external. When treating oil prices exogenously, drawbacks emerge. Initially, Barsky and Kilian (2001) paper explains the rises in oil prices in the 1970s were predominantly a reaction to economic inconsistencies activated by strategies that present as proof of a contrary causality among oil prices together with the U.S. economy, boosting skepticism about the oil prices as externally excepted or exogenous. Another view is the historical ups and downs in oil prices have been primarily influenced by shocks in supply/demand within the oil market. Kilian and Park (2009) indicate how these shocks affect both the price of oil and economic activities, which vary considerably.

When we focus on the previous studies on how oil price shocks explain the shifts in the labor market. The high oil prices fluctuations during the 1970s oil crisis led to mitigating employment and largely labor movement (Loungani, 1986). The influence on oil price shocks in on unemployment are meaningful regardless of volatility level (Lee et al., 1995). Oil price shocks serve as projection factors for predicting the employment growth rate (Ferderer, 1996). Herrera et al. (2017) highlight substantial variability among industries in how they respond to unforeseen fluctuations in oil prices, particularly in terms of job constitution as well as demolition. Karafaki (2018) searched oil price shocks association with unemployment across the U.S., when faced with an unfavorable supply shock, the unemployment rate hikes. Kandemir Kocaaslan (2019) affirms positive as well negative oil price shocks influence on unemployment rate. Michieka and Gearhart (2019) search oil prices affect on four employment sector mining, construction, manufacturing as well a service respectively counties in the U.S. which produce oil. They display if oil price rise one percent, employment sectors hike by 1.45 percent.

Alsalman (2023) searched the impact of structural oil price shocks on U.S. aggregate unemployment rates along with the period of unemployment spells, and the findings show heterogeneity of each shock. Alsalman (2023), similarly to our study, follows Kilian and Park (2009), and analyzing oil price supply as well as demand shocks, the research examines their impact on unemployment spells. The results suggest that concentrating on aggregate variables may obscure certain variations at the individual unemployment spell level. We search the consequences of structural oil price shocks on different unemployment sectors in the United States. We find that each sector responds oil price shocks in various mannitude level and pace.

3.3 DATA

The research, first has considered the influence of oil price shocks sectoral unemployment spanning from January 2000 to August 2023 in the United States. The dataset regarding the U.S. unemployment obtained from the FRED[15] dataset sourced by the Federal Reserve Bank which shows unemployed persons in each sector namely unemployment, nonagriculture, mining, quarrying, and oil and gas extraction, government, transportation and utilities, manufacturing, information, leisure and hospitality, education and health services, financial activities. The measurement of the oil price relies on the composite refiner acquisition cost (RAC) of crude oil, a metric collected by the U.S. Energy Information Administration[16] (EIA). We deflate the RAC using the U.S. CPI Consumer Price Index[17] (CPI) from the Bureau of Labor Statistics, aiming to get real oil prices in our research. The monthly global oil production dataset the gathered from Energy Information Administration (EIA)[18]. For measuring world economic activity, we apply the monthly global economic conditions (GECON) index by Baumeister et al. (2020) rather than Kilian's (2009) global real economic activity index. Baumeister et al. (2020) propose a Global Economic Condition[19] (GECON) indicator, which encompasses a collection of variables designed to capture crucial information about the global economy which include energy linked indicators consisting long period of oil price uncertainty. Because of its pronounced volatility post-2010 and other contributing factors, numerous studies now suggest that Kilian's (2009) global real economic activity index is flawed. (see Baumeister et al., (2020); Baumeister and Guérin, (2021); Hamilton, (2021)).

3.4 METHODOLOGY OF THE STRUCTURAL VAR MODEL

Kilian (2009) highlights oil price shocks resulting from the shifts in demand and supply dynamics have diverse impacts on the actual economy. Therefore, we use Kilian and Park's (2009) theoretical method, which demonstrates three fundamental shocks, to

[15] Source: https://fred.stlouisfed.org/series/LNU03032238
[16] Source: https://www.eia.gov/dnav/pet/pet_pri_rac2_dcu_nus_m.htm
[17] Source: https://www.bls.gov/cpi/
[18] Source: https://www.eia.gov/dnav/pet/PET_CRD_CRPDN_ADC_MBBL_M.htm
[19] Source: https://sites.google.com/site/cjsbaumeister/datasets

evaluate how oil price shocks affect unemployment. We estimate the following structural VAR(p) model:

$$B_{0w_{t}=} z_0 + \sum_{i=1}^{p} B_{iw_{t-i}} + \varepsilon_t \quad (1)$$

The vector w_t comprises the log difference of the the worldwide crude oil production, the global economic conditions index, the logarithm of real oil price, and the log of the sectoral unemployment. We employ GECON index in level form. B_0 demonstrates a matrix of contemporaneous coefficients without singularity. z_0 represents the constant term also B_i shows the autoregressive coefficient matrix. Structurally autonomous as well as sequentially uncorrelated shocks present as ϵ_t in the below illustrated in detail.

$$\epsilon_t = (\epsilon_t^{\Delta\text{world oil production}}, \epsilon_t^{\text{global economic condition}}, \epsilon_t^{\text{real oil price}}, \epsilon_t^{\text{US unemployment}})'. \quad (2)$$

Assuming the presence of B^{-1}, we carry out to calculate the simplified interpretation of Equation (1) as follows:

$$w_{t=} c + \sum_{i=1}^{p} X_{iw_{t-i}} + \varepsilon_t \quad (3)$$

In the equation $c = B^{-1}z_0$, $X_i = B^{-1}B_i$ along with the simplified interpretation present as $\varepsilon_t = B^{-1}\epsilon_t$. Initially, we proceed with the simplified outlined in Equation (3) to extract the inhibit structural shocks as $\boldsymbol{\varepsilon}_t$. Employing a method of Kilian and Park (2009), a block-recursive arrangement introduces the simultaneous connection among the structural disruptions as well as the changes within the simplified version of VAR.

$$\epsilon_t = \begin{bmatrix} \epsilon_t^{\Delta\text{world oil production}} \\ \epsilon_t^{\text{global economic condition}} \\ \epsilon_t^{\text{real oil price}} \\ \epsilon_t^{\text{US unemployment}} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^{\text{oil supply shock}} \\ \varepsilon_t^{\text{aggregate demand shock}} \\ \varepsilon_t^{\text{oil specific demand shock}} \\ \varepsilon_t^{\text{other shocks to unemployment}} \end{bmatrix} \quad (4)$$

Equation (4), includes two distinct components. In this context, the initial part constituting the first three equations interprets the representation of the oil market.

Notwithstanding, the latter part contains the final equation, elucidating the characteristics of the U.S. sectoral employment.

More specifically, the real oil price variations fall apart in three distinct shocks: 'shocks to the global crude oil supply, shocks to the global demand for all industrial commodities (including crude oil), and oil-market specific demand shocks which designed to capture the changes in precautionary demand for crude oil in response to a possible future oil supply shortfall' (Kilian, 2009, p. 1053). In Kilian's (2009) paper, these shocks are referred to as the 'oil supply shock,' the 'aggregate demand shock,' along with the 'oil-specific demand shock' yet 'precautionary demand shock.'

It is depicted that the first row's last three components are zero which means $B^{-1}\ is\ 0$, suggesting that the GECON index, real oil prices, along with sectoral employment do not propound an immediate consequence on world oil supply. Instead, their influence on world oil supply with a delay ($b_{12} = b_{13} = b_{14} = 0$). This situation emanates because oil-exporting nations confronting challenges in promptly adapting to rapid switches in oil demand, principally because of substantial adjustment costs as well as considerable uncertainty encircling the market demand. Therefore, in a short period, variations in oil construction may not be expeditiously actualized by reacting to unpredictable or random shocks. Although, the oil market is dominated by giant producers with crucial power and externally govern the oil supply. Consequently, an oil export nation's production decision can affect by certain external events, for instance, political or military conflicts, which are often infrequent at the same time, unexpectable for a short period (Wang et al., 2014).

The imposition of the second restrain $b_{23} = b_{24} = 0$, indicates that global output production cannot directly reciprocate to precautionary demand shocks as well as other shocks in sectoral employment. Kilian (2009) highlighted that despite the compelling impacts of oil supply disruptions on world real economic activity, shifts in the oil price over the exact duration do not stimulate a reciprocal response in world real economic activity.

The third constraint, b_{34}= 0, considers the oil price reacts concurrently to oil-linked shocks although responds to shocks in sectoral employment with a delay.

This hypothesis was determined in Kilian and Park (2009), where innovations in oil prices are recognized as predisposed to economic variables.

3.5. EMPIRICAL RESULTS: EFFECTS OF OIL PRICE SHOCK ON U.S. UNEMPLOYMENT

3.5.1 The Responses of Oil Prices to Three Structural Shocks

First, we iniate our research by scrutunizing how the real oil price reacts to the three distinct shocks as illustrated in Figure 26. In this illustration, the solid lines demonstrate the responses, while the dashed lines depict the one-standard error band that three distinct structural shocks have diverse impacts on the real price of oil. In our demonstration, an surprising hike in oil supply exhibits a notably negative although relatively mild power on the real oil price. However, the real oil price hiked and affected immediately because of increase in global aggregate demand. In a similar vein, the real oil price increased rapidly along with after constantly declined due to a surprising wave in the prudent oil demand.

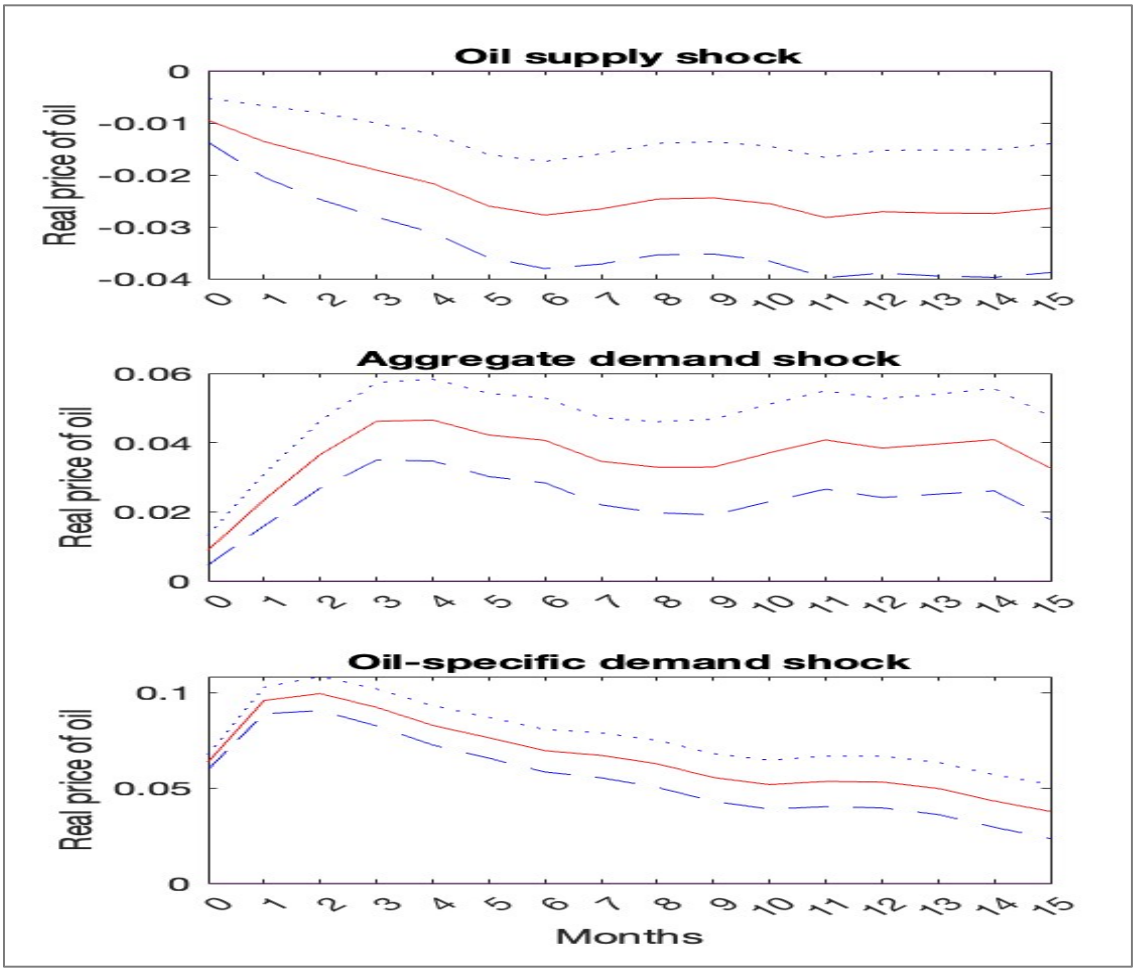


Figure 26. *Responses of the Real Oil Prices to Three Structural Shocks*

3.5.2 The Responses of Sectoral Unemployment to Three Structural Shocks

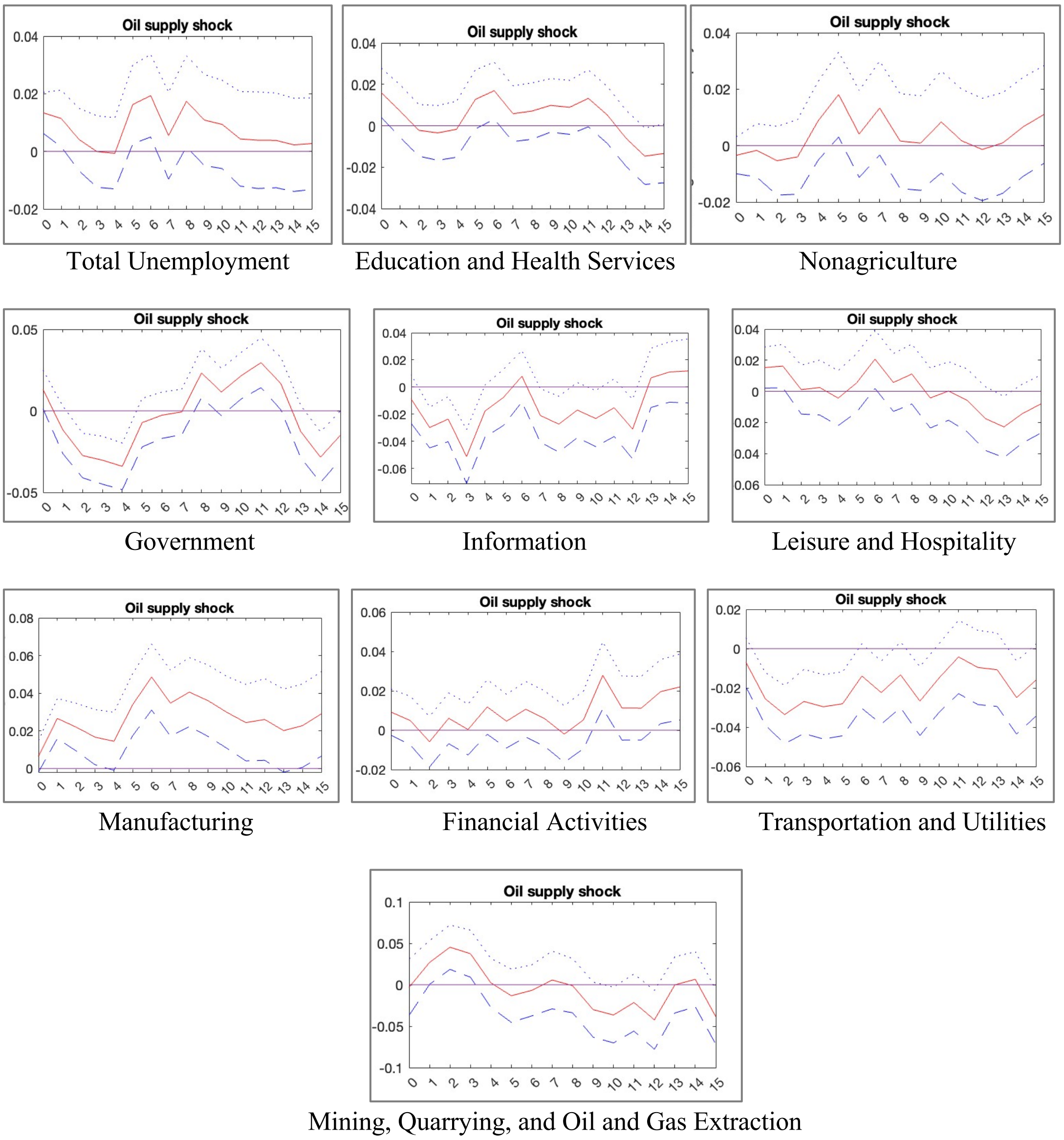


Figure 27. *Responses of Sectoral Unemployment Level to Oil Supply Shocks*

In Figure 27, we demonstrate the responses of U.S. unemployment level on an industrial basis to a positive oil supply shock. The manufacturing sector responses episodically significant as well as positive to oil supply shock. Transportation and utilities sector responds to oil supply shock negatively during five months which mitigates the number of unemployment. All other sectors are statistically insignificant.

Overall, our findings state that the diverse impacts of oil supply shock across sectors might stem from variations in sector-specific characteristic. As highlighted by Davis and Haltiwanger (2001) also Herrera and Karaki (2015), sectors characterized by greater energy intensity, for instance manufacturing.

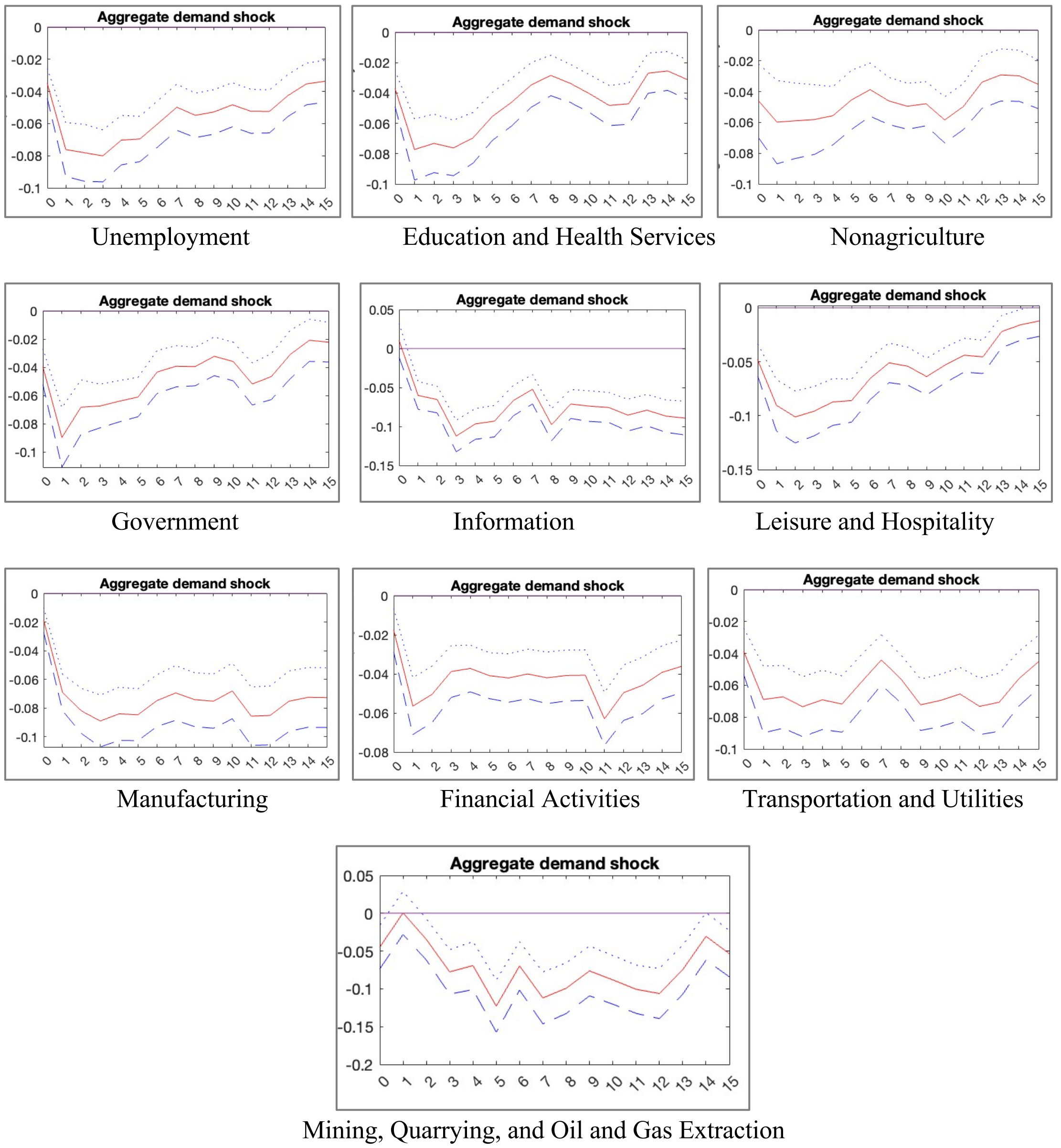


Figure 28. *Responses of Sectoral Unemployment Level to-Aggragate Demand Shocks*

In Figure 28, we illustrate the responses of sectoral unemployment to a positive aggregate demand shock. All unemployment sectors significantly and negatively respond to an aggregate demand shocks. The most affected sector is mining, quarrying, and oil and gas extraction followed by leisure and hospitality sector, the magnitude levels are higher than the other sectors. It is seen that in each sector reaction trend behaviour is different.

Result of a hike in global economic activity cause decreased unemployment, yet the impact degree can be differed for each sector. According to Kilian (2009), positive aggregate demand shocks, which boost oil prices, can lead to prompting as well as growth retardation impacts on economic growth. The preceding factor activates economic growth by amplifying the real global economic activity. In our case we notice the conclusion of aggregate demand shock on sectoral unemployment are negative persistently and significant. This phenomenon occurs because heightened economic activity leads to an increased demand for labor in each sector. We observe that as time passes, the conclusion of the aggregate demand shock become less strong and consequential for certain subsectors. Kilian and Park (2009) consider this issue because the first favorable effects on aggregate demand are partially countered by the higher oil prices brought on by rises in aggregate demand, which mitigate global economic activity.

Alsalman (2023) also points out that a sudden hike in global real economic activity, leading to a boost in the real oil price, correlates with a temporary decrease in the unemployment rate (a stimulating impact) initially, followed by a subsequent rise of approximately 12 months after the shock (a growth-retarding impact). Our outcomes show the impact of higher global economic activity on sectoral unemployment tends to be negative and persistent. Kairola and Ma (2020) states the effects of shocks in oil prices can vary among sectors based on their distinct levels of oil dependence. Additionally, they point out the level of impact can vary depend on which sector is utilized oil as a production input. In this context, a boost in global economic activity led to diminished unemployment, yet this effect can be varied in the sector.

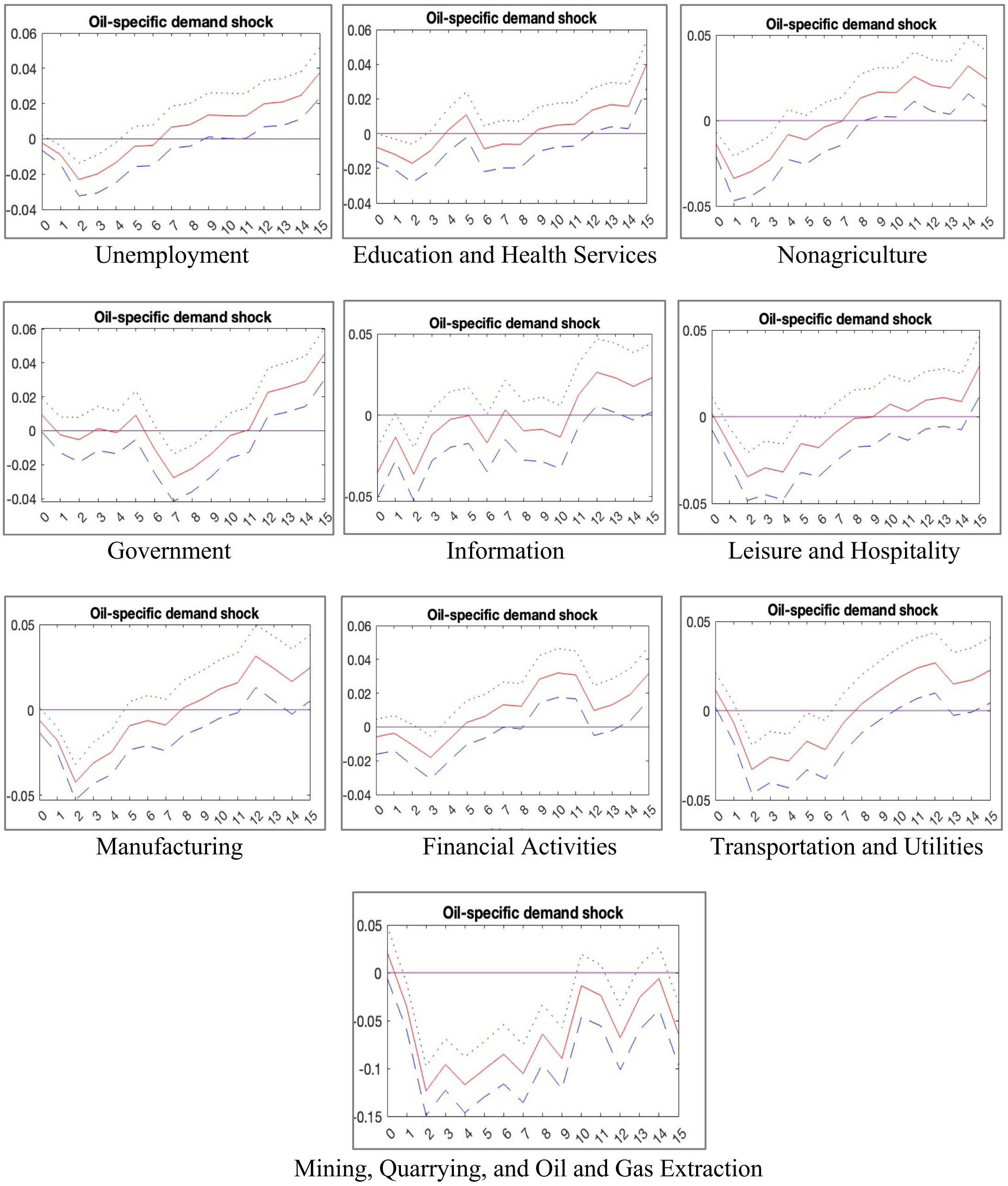


Figure 29. *Responses of Sectoral Unemployment Level to oil Specific Demand Shocks*

Next, in Figure 29, we present the responses of sectoral unemployment to 'precautionary demand shock' which encapsulates the changes in the precautionary demand for oil in instances of increased uncertainty regarding potential future oil supply shortages. Unemployment sector reacts to the precautionary demand shock significantly negative between the first and fourth months after twelveth month it turns positive. Nonagriculture unemployment sector responses significantly negative in the short term then statistically insignificant, after ninth month it reacts significantly positive.

Moreover, government sector responses the precautionary demand shock marginally positively significant in the long term. Both manufacturing and leisure and hospitality sectors respond negatively for the first fourth months to shock of precautionary demand afterwards statistically insignificant. Financial activities sector is marginally positively significant in the long term. The period between second and sixth months, transportation and utilities sector response to the precautionary demand shock is significantly negative. Mining, quarrying, and oil and gas extraction industry reacts precautionary demand shock persistenly negatively between second month and tenth month also the magnitude level of reaction is the strongest. The responses of education and health services and information sectors are statistically insignificant.

On the whole, mainly unemployment sectors respond to the precautionary demand shock negatively and significant in the short period, while in the long period statistically insignificant. Because over time, it becomes apparent when the influence on oil-specific shocks weaken and turn positive in certain sub-sectors. This phenomenon occurs because the elevated oil prices, resulting from rises in aggregate demand as well as precautionary demand, subsequently contribute to a downturn in global economic activity, partly counteracting the primary positive impacts on unemployment.

To sum up, the findings demonstrate that US sectoral unemployment reacts very different to oil price shocks base on sectors. This highlights the significance of breaking down unemployment based on various industries and emphasizes that various oil price shocks affect various magnitudes also directions of the response of sectoral unemployment in unique ways. This heterogeneity forms because of oil dependence of each sector, if one sector heavily depends on oil in production, then the level and impact size getting larger or vice versa.

3.6 CONCLUSION

A substantial body of studies examines oil prices and how the shocks can fundamentally impact vital macroeconomic factors, for instance, investment, consumption, etc. Only a few studies have specifically investigated how oil price shocks affect the labor market.

Therefore, this research investigates how oil price shocks affect sectoral unemployment in the United States. We employ a structural VAR technique that divides shocks to oil prices into three separate fundamentals: oil supply shocks; global aggregate demand shocks, and precautionary demand shocks that are especially connected to the oil market, that is intended to monitor shifts in oil prices brought on the increased demand for precaution. In this context, by isolating the conclusions of aggregate demand shocks from the impacts of shocks to the oil supply and precautionary demand, this model allows one to analyze how sectoral unemployment reacts to different oil price shocks.

Kilian (2009) highlights that alteration in oil prices, determined by shocks of oil supply as well as demand, bring about different impacts on the economic indicators, which are also probable to have various impacts on sectoral unemployment. To this end, building upon Kilian's work in 2009, our main aim in this study break down the real oil price into three distinct components: specific demand shocks within the crude oil market, global demand shocks along with oil supply shocks. Subsequently, we aim to figure out the effect of these three types of shocks on sectoral unemployment in the US.

The findings of sectoral unemployment demonstrate important heterogeneity that various sectors respond differently to each oil supply shocks. The manucafturing sector responses episodically significant as well as positive to oil supply shock. Transportation and utilities sector responds to oil supply shock negatively for the first five months which mitigates the number of unemployment. All other sectors are statistically insignificant. Afterwards unemployment of each sector responds to aggregate demand shock consistently negative, although the extent of its impact varies across industries. The findings of precautionary demand shock of each sector also demonstrate various heterogeneity behaviour. For instance, total unemployment reacts to the precautionary demand shock significantly negative between the first and fourth months after twelveth month it turns positive. Nonagriculture unemployment sector responses significantly negative in the short term then statistically insignificant, after ninth month it reacts significantly positive.

The primary response of unemployment sectors to precautionary demand shocks is negative and significant in the short term. Nevertheless, over the long term, this response becomes statistically insignificant. As time progresses, it becomes evident that the effects of oil-specific shocks diminish and exhibit positive trends in specific sub-sectors. When we compare to the unemployment behaviour of each sector shows heterogeneity that is a proof of each sector has own special character to reflect to the oil shocks.

Briefly, this research demonstrates oil supply along with demand shocks generate different impacts on uneployment, depending on the sector. This states the significance of oil price shocks on sectoral unemployment. In comparison with other structural shocks, aggregate demand shocks have the most crucial influence on revealing the responses for both sectoral unemployment. This aligns with Kilian's (2009) perspective, highlighting that the impacts originating from the demand part of the oil market have greater noticeable presence in the tangible economy. Furthermore, it emphasizes the crucial role of the primary determinants of oil price shocks, particularly surprising price fluctuations, underlining importance in producing effective along with suitable policy considerations for the labor market.

CONCLUSION

In the global economy, fluctuations in energy prices significantly influence both macroeconomic and microeconomic factors, potentially leading to economic downturns or overall welfare improvements. Therefore, it is essential to understand the energy asset's behaviour for economists and policymakers. Starting with this motivation, this thesis is structured as three energy economics and finance essays exploring different aspects of energy commodities from various perspectives. The question of research in the first chapter, whether hubs with varying development levels and the same pricing mechanism might have significantly varied numbers of speculative gas price bubbles. Our findings offer a distinct insight, indicating that more developed hubs exhibit higher efficiency and are associated with a lower occurrence of price bubbles. In addition, the key contributors to gas price bubbles in European hubs include unforeseen weather conditions, the economic development level, supply disruptions, oversupply, oil indexation, cross-commodity prices, and exceptional circumstances for instance the Covid-19 pandemic. Moreover, this study demonstrates the evidence of integration in the EU gas market because the timings of the price bubbles are similar. According to our empirical outcomes, certain policy implications can be stated. Initially, creating a hub does not guarantee the establishment of an effective gas-on-gas price mechanism. Therefore, in well-functioning markets, occurrences of price bubbles are less common. Several essential elements needed to attain the status of a benchmarking hub are outlined in prior hub review methodologies (e.g., in ACER, 2020; Shi, 2016). In our study, we observe that for experiencing less price bubbles there should be need for various instruments such as supply divergence, LNG facilities to connect to global markets, various interconnection points with different countries, and multiple supply/demand instruments as storage facilities, political willingness to trade at hubs, low level of market concentration and high competition. Therefore policy makers should focus on to facilitate first various supply instruments afterwards political willingness to trade at hubs, low level of market concentration and high competition to experience fewer gas price bubbles. Further, if the long-term gas contracts tie to the oil price rather than being its intrinsic value, whenever the oil price experiences a bubble gas price also experience as well.

The European Union emphasizes diversifying gas supply and trading operations in the realm of gaseous renewables. It actively engages in substantial investments in renewable gas, including blue hydrogen, biogas, and biomethane, with the aim of enhancing trading activities. Therefore, through evaluations of the gas market as well as the analysis of price bubbles will contribute a significant role in facilitating decarbonized gas market transition. This, in turn, will stimulate the trading of low-carbon gas at hubs that support clean energy transition, fostering energy and environmental sustainability and for future research could investigate price bubbles after renewable gases initiated to trade at natural gas hubs.

The second chapter investigates the impact of a causal association among conventional energy prices and carbon prices. We proof a causal association among energy contracts and carbon contracts, particularly becoming evident after 2016, coinciding with the announcement of the Paris Agreement. The volatility in energy prices can be attributed to factors such as an excess of liquefied natural gas (LNG), sanctions impacting oil prices, the repercussions of the Covid-19 pandemic, the Russian-Ukrainian conflict, political announcements, and elevated natural gas prices due to stock levels. The commencement of Phase 4 in the Emission Trading System resulted in a more stringent cap and updated allocations of free quantities. Furthermore, market participants utilizing the carbon market as a hedging tool contribute to a significant increase in carbon prices, thereby influencing coal and oil refinery entities to actively manage their emission levels. A more efficient carbon market provides accurate market signals, leading energy stakeholders to adjust power generation choices, tailor energy consumption patterns, and strategically position themselves to reduce emissions in alignment with prevailing carbon prices, which should cautiously observe the impact of carbon trade in future research. Moreover, policymakers should attentively monitor and comprehend the dynamics of carbon along with conventional energy commodities, to enhance the effectiveness of the carbon market. Carbon markets with greater effectiveness provide accurate market signals. Therefore, energy stakeholders should adjust power generation decisions, tailor energy consumption patterns, along with formulate their positions to address emissions mitigation in alignment with carbon prices. Furthermore, in the pursuit of a more efficient carbon market, policymakers should establish a system to monitor price fluctuations through risk monitoring tools or an early warning system. This is crucial to prevent adverse effects on the carbon market from impacting the conventional energy market along with to facilitate the transition to low carbon emissions by reshaping the energy structure in power generation. Subsequent research endeavors could employ clean energy indices along with macro and micro variables to conduct a more comprehensive evaluation of the carbon market.

The third chapter investigates how oil price shocks influence sectoral unemployment in the United States. The findings demonstrate heterogeneity in each sector; in other words, each sector reacts differently to oil price shocks. This underlines the importance of oil prices in influencing sectoral unemployment. When contrasted with three structural shocks, it becomes evident that aggregate demand shocks had the greatest impact in revealing the responses of sectoral unemployment. As expected, positive demand shock mitigates the unemployment for each sector.

The primary reaction of unemployment sectors to precautionary demand shocks is negatively significant in the short period; however, over the long period, this response becomes statistically insignificant. As time progresses, the impacts of precautionary demand shock diminish along with it become positive in specific sub-sectors. The decrease in unemployment could also indicate shifts in labor market reallocation, thereby magnifying the influence on oil price shocks. Especially for the case of precautionary demand shock, each industry conducts differently to the expectations of oil shock. Therefore, policymakers should cautiously consider the sector response to the unemployment when oil price shocks occur. It highlights the vital role played by the primary factors influencing oil price shocks, especially in unexpected price fluctuations, underscoring their significance in formulating practical and appropriate policy considerations for the labor market.

BIBLIOGRAPHY

ACER, 2017. Statistical compendium of ACER Gas Target Model metrics for the year 2016.

ACER, 2019. Annual Report on the Results of Monitoring the Internal Electricity and Natural Gas Markets in 2019 D, 1–274.

ACER, 2020. Annual Report on the Results of Monitoring the Internal Electricity and Natural Gas Markets in 2020 1–274.

Ajmi, A.N., Hammoudeh, S., Mokni, K., 2021. Detection of bubbles in WTI, brent, and Dubai oil prices: A novel double recursive algorithm. Resour. Policy 70, 101956. https://doi.org/10.1016/j.resourpol.2020.101956

Alsalman, Z., 2023. Oil price shocks and US unemployment: evidence from disentangling the duration of unemployment spells in the labor market. Empir. Econ. 65, 479–511. https://doi.org/10.1007/s00181-022-02351-0

An, P., Li, H., Zhou, J., Li, Y., Sun, B., Guo, S., Qi, Y., 2020. Volatility spillover of energy stocks in different periods and clusters based on structural break recognition and network method. Energy 191, 116585. https://doi.org/10.1016/j.energy.2019.116585

Asche, F., Misund, B., Sikveland, M., 2013. The relationship between spot and contract gas prices in Europe. Energy Econ. 38, 212–217. https://doi.org/10.1016/j.eneco.2013.02.010

Asche, F., Osmundsen, P., Tveterås, R., 2002. European market integration for gas? Volume flexibility and political risk. Energy Econ. 24, 249–265. https://doi.org/10.1016/S0140-9883(02)00003-8

Balcilar, M., Demirer, R., Hammoudeh, S., Nguyen, D.K., 2016. Risk spillovers across the energy and carbon markets and hedging strategies for carbon risk. Energy Econ. 54, 159–172. https://doi.org/10.1016/j.eneco.2015.11.003

Barnes, A., 2021. The Challenges and Prospects for Carbon Pricing in Europe, The Oxford Institute for Energy Studies.

Barsky, R.B., Kilian, L., 2001. Do We Really Know that Oil Caused the Great Stagflation? A Monetary Alternative. NBER Macroecon. Annu. 16, 117–183. https://doi.org/10.1162/088933601320224900

Baum, C.F., Hurn, S., Otero, J., 2021. The dynamics of U.S. industrial production: A time-varying Granger causality perspective. Econom. Stat. https://doi.org/10.1016/j.ecosta.2021.10.012

Baumeister, C., Guérin, P., 2021. A comparison of monthly global indicators for forecasting growth. Int. J. Forecast. 37, 1276–1295. https://doi.org/10.1016/j.ijforecast.2021.02.008

Baumeister, C., Lee, T.K., Korobilis, D., 2020. Energy Markets and Global Economic Conditions Data Sources and Variable Selection.

Bernanke, B.S., 1983. Irreversibility , Uncertainty , and Cyclical Investment Author (s): Ben S . Bernanke Stable URL : https://www.jstor.org/stable/1885568 REFERENCES Linked references are available on JSTOR for this article : reference # references _ tab _ contents You may. Q. J. Econ. 98, 85–106.

Bernanke, B.S., Gertler, M., Watson, M., 1997. Systematic monetary policy and the effects of oil price shocks. Brookings Pap. Econ. Act. 1997, 91–157. https://doi.org/10.2307/2534702

Brigida, M., 2014. The switching relationship between natural gas and crude oil prices. Energy Econ. 43, 48–55. https://doi.org/10.1016/j.eneco.2014.01.014

Broadstock, D.C., Cao, H., Zhang, D., 2012. Oil shocks and their impact on energy related stocks in China. Energy Econ. 34, 1888–1895. https://doi.org/10.1016/j.eneco.2012.08.008

Broadstock, D.C., Li, R., Wang, L., 2020. Integration reforms in the European natural gas market: A rolling-window spillover analysis. Energy Econ. 92. https://doi.org/10.1016/j.eneco.2020.104939

Brown, S.P.A., Yücel, M.K., 2008. What drives natural gas prices? Energy J. 29, 45–60. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol29-No2-3

Byun, S.J., Cho, H., 2013. Forecasting carbon futures volatility using GARCH models with energy volatilities. Energy Econ. 40, 207–221. https://doi.org/10.1016/j.eneco.2013.06.017

Caldara, D., Iacoviello, M., 2018. Measuring Geopolitical Risk, International Finance Discussion Papers. https://doi.org/10.17016/ifdp.2018.1222r1

Caporin, M., Fontini, F., 2017. The long-run oil–natural gas price relationship and the shale gas revolution. Energy Econ. 64, 511–519. https://doi.org/10.1016/j.eneco.2016.07.024

Caspi, I., 2016. RTADF: Testing for Bubbles with EVIEWS.

Caspi, I., Katzke, N., Gupta, R., 2018. Date stamping historical periods of oil price explosivity: 1876–2014. Energy Econ. 70, 582–587. https://doi.org/10.1016/j.eneco.2015.03.029

Chen, J., Liang, Z., Ding, Q., Liu, Z., 2022. Quantile connectedness between energy, metal, and carbon markets. Int. Rev. Financ. Anal. 83, 102282. https://doi.org/10.1016/j.irfa.2022.102282

Cheng, I.H., Xiong, W., 2014. Financialization of commodity markets. Annu. Rev. Financ. Econ. 6, 419–941. https://doi.org/10.1146/annurev-financial-110613-034432

Chevallier, J., 2009. Carbon futures and macroeconomic risk factors: A view from the EU ETS. Energy Econ. 31, 614–625. https://doi.org/10.1016/j.eneco.2009.02.008

Choi, S., Furceri, D., Huang, Y., Loungani, P., 2018. Aggregate uncertainty and sectoral productivity growth: The role of credit constraints. J. Int. Money Financ. 88, 314–330. https://doi.org/10.1016/j.jimonfin.2017.07.016

Creti, A., Nguyen, D.K., 2015. Energy markets' financialization, risk spillovers, and pricing models. Energy Policy 82, 260–263. https://doi.org/10.1016/j.enpol.2015.02.007

Davis, S.J., Haltiwanger, J., 2001. Sectoral job creation and destruction responses to oil price changes. J. Monet. Econ. 48, 465–512. https://doi.org/10.1016/S0304-3932(01)00086-1

Dickey, D.A., Fuller, W.A., 1979. Distribution of the Estimators for Autoregressive Time Series With a Unit Root. J. Am. Stat. Assoc. 74, 427–431. https://doi.org/10.1080/01621459.1979.10482531

Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ. J. 119, 158–171. https://doi.org/10.1111/j.1468-0297.2008.02208.x

Dolado, J.J., Lütkepohl, H., 1996. Making wald tests work for cointegrated VAR systems. Econom. Rev. 15, 369–386. https://doi.org/10.1080/07474939608800362

Dowds, J., Hines, P.D.H., Blumsack, S., 2013. Estimating the impact of fuel-switching between liquid fuels and electricity under electricity-sector carbon-pricing schemes. Socioecon. Plann. Sci. 47, 76–88. https://doi.org/10.1016/j.seps.2012.09.004

Duan, K., Ren, X., Shi, Y., Mishra, T., Yan, C., 2021. The marginal impacts of energy prices on carbon price variations: Evidence from a quantile-on-quantile approach. Energy Econ. 95, 105131. https://doi.org/10.1016/j.eneco.2021.105131

Edelstein, P., Kilian, L., 2009. How sensitive are consumer expenditures to retail energy prices? J. Monet. Econ. 56, 766–779. https://doi.org/10.1016/j.jmoneco.2009.06.001

EURACOAL, 2023. EURACOAL Market Report 2023 no . 1.

EURACOAL, 2022. EURACOAL Market Report 2022 2022.

EURACOAL, 2019. EURACOAL Market Report 2 / 2019.

EURACOAL, 2017. EURACOAL Market Report 2 / 2017.

European Commission, 2012. Directorate-General for Energy, Market Observatory for Energy, Brussels, 2012. Quarterly Report on European Gas Markets Market Observatory for Energy DG Energy Volume 4 (issue 4; fourth quarter of 2011) and Volume 5 (issue 1; first quarter of 2012).

European Commission, 2013. Directorate-General for Energy, Market Observatory for Energy, 2013. Quarterly Report on European Gas Markets Market Observatory for Energy DG Energy Volume 6 (issue 1, first quarter of 2013).

European Commission, 2014a. Directorate-General for Energy, Market Observatory for Energy, 2014. Quarterly Report on European Gas Markets Market Observatory for Energy DG Energy Volume 7 (issue 4; fourth quarter of 2014).

European Commission, 2014b. Directorate-General for Energy, Market Observatory for Energy, 2014. Quarterly Report on European Gas Markets Market Observatory for Energy DG Energy Volume 7 (issue 3; third quarter of 2014).

European Commission, 2016. Directorate-General for Energy, Market Observatory for Energy, 2016. Quarterly Report on European Gas Markets Market Observatory for Energy DG Energy Volume 9 (issue 1; fourth quarter of 2015 and first quarter of 2016).

European Commission, 2017. Directorate-General for Energy, Market Observatory for Energy, 2017. Quarterly Report on European Gas Markets Market Observatory for Energy DG Energy Volume 10 (issue 4; fourth quarter of 2017).

European Commission, 2018. Directorate-General for Energy, Market Observatory for Energy, 2018. Quarterly Report on European Gas Markets Market Observatory for Energy DG Energy Volume 11 (issue 3, third quarter of 2018).

European Commission, 2019. Directorate-General for Energy, Market Observatory for Energy, 2019. Quarterly Report on European Gas Markets Market Observatory for Energy DG Energy Volume 13 (issue 3, third quarter of 2019).

European Commission, 2020. Directorate-General for Energy, Market Observatory for Energy, 2020. Quarterly Report on European Gas Markets Market Observatory for Energy DG Energy Volume 13 (issue 2, second quarter of 2020).

European Commission, 2022. Directorate-General for Energy, Market Observatory for Energy, 2022. Quarterly Report on European Gas Markets Market Observatory for Energy DG Energy Volume 15 (issue 4; fourth quarter of 2022).

European Parliament and Council of the European Union, 2009. Directive 2009/73/EC of 13 July 2009 concerning common rules for the internal market in natural gas and repealing Directive 2003/55/EC. Off. J. Eur. Union L 211, 94–136.

Fama, E.F., 1991. Efficient Capital Markets: II The comments of Fischer Black. J. Financ. * XLVI.

Fan, J.H., Akimov, A., Roca, E., 2013. Dynamic hedge ratio estimations in the European Union Emissions offset credit market. J. Clean. Prod. 42, 254–262. https://doi.org/10.1016/j.jclepro.2012.10.028

Fantazzini, D., 2016. The oil price crash in 2014/15: Was there a (negative) financial bubble? Energy Policy 96, 383–396. https://doi.org/10.1016/j.enpol.2016.06.020

Ferderer, J.P., 1996. Oil price volatility and the macroeconomy. J. Macroecon. 18, 1–26. https://doi.org/10.1016/S0164-0704(96)80001-2

Figuerola-Ferretti, I., McCrorie, J.R., Paraskevopoulos, I., 2020. Mild explosivity in recent crude oil prices. Energy Econ. 87, 104387. https://doi.org/10.1016/j.eneco.2019.05.002

Filimonov, V., Sornette, D., 2013. A stable and robust calibration scheme of the log-periodic power law model. Phys. A Stat. Mech. its Appl. 392, 3698–3707. https://doi.org/10.1016/j.physa.2013.04.012

Franza, L., 2014. Long-Term Gas Import Contracts in Europe: The Evolution in Pricing Mechanisms 40.

Geuder, J., Kinateder, H., Wagner, N.F., 2019. Cryptocurrencies as financial bubbles: The case of Bitcoin. Financ. Res. Lett. 31, 179–184. https://doi.org/10.1016/j.frl.2018.11.011

Gianfreda, A., Grossi, L., Carlotto, A., 2012. The European hubs for natural gas: An integration towards a single area? 9th Int. Conf. Eur. Energy Mark. EEM 12. https://doi.org/10.1109/EEM.2012.6254707

Gong, X., Shi, R., Xu, J., Lin, B., 2021. Analyzing spillover effects between carbon and fossil energy markets from a time-varying perspective. Appl. Energy 285, 116384. https://doi.org/10.1016/j.apenergy.2020.116384

Grandi, L., 2014. European gas markets: From oil indexation prices to spot prices?

Gronwald, M., 2016. Explosive oil prices. Energy Econ. 60, 1–5. https://doi.org/10.1016/j.eneco.2016.09.012

Gronwald, M., Ketterer, J., Trueck, S., 2011. The Dependence Structure between Carbon Emission Allowances and Financial Markets - A Copula Analysis. SSRN Electron. J. https://doi.org/10.2139/ssrn.1824224

Hamilton, J.D., 2021. Measuring global economic activity. J. Appl. Econom. 36, 293–303. https://doi.org/10.1002/jae.2740

Hammoudeh, S., Lahiani, A., Nguyen, D.K., Sousa, R.M., 2015. An empirical analysis of energy cost pass-through to CO2 emission prices. Energy Econ. 49, 149–156. https://doi.org/10.1016/j.eneco.2015.02.013

Harvey, D.I., Leybourne, S.J., Sollis, R., Taylor, A.M.R., 2016. Tests for explosive financial bubbles in the presence of non-stationary volatility. J. Empir. Financ. 38, 548–574. https://doi.org/10.1016/j.jempfin.2015.09.002

Heather, P., 2015. The Evolution of European Gas Hubs.

Heather, P., 2020. European traded gas hubs: the supremacy of TTF.

Heather, P., Oxford Institute for Energy Studies., 2010. The evolution and functioning of the traded gas market in Britain. Oxford Institute for Energy Studies.

Herrera, A.M., Karaki, M.B., 2015. The effects of oil price shocks on job reallocation. J. Econ. Dyn. Control 61, 95–113. https://doi.org/10.1016/j.jedc.2015.08.006

Herrera, A.M., Karaki, M.B., Rangaraju, S.K., 2017. Where do jobs go when oil prices drop? Energy Econ. 64, 469–482. https://doi.org/10.1016/j.eneco.2016.02.006

Herrera, A.M., Lagalo, L.G., Wada, T., 2011. Oil price shocks and industrial production: Is the relationship linear? Macroecon. Dyn. 15, 472–497. https://doi.org/10.1017/S1365100511000290

Hintermann, B., 2010. Allowance price drivers in the first phase of the EU ETS. J. Environ. Econ. Manage. 59, 43–56. https://doi.org/10.1016/j.jeem.2009.07.002

Honore, A., 2019. Decarbonization and industrial demand for gas in Europe.

Hulshof, D., van der Maat, J.P., Mulder, M., 2016. Market fundamentals, competition and natural-gas prices. Energy Policy 94, 480–491. https://doi.org/10.1016/j.enpol.2015.12.016

IEA, 2013. Developing a natural gas trading hub in China.

IEA, 2016. Energy Policies of IEA Countries - Italy 2016 Review.

IEA, 2019. The United Kingdom 2019 - Energy Policy Review.

IEA, 2020a. The Netherlands 2020 - Energy Policy Review.

IEA, 2020b. Germany 2020 - Energy Policy Review.

IEA, 2020c. Austria 2020 - Energy Policy Review.

Irfan, M., Elavarasan, R.M., Ahmad, M., Mohsin, M., Dagar, V., Hao, Y., 2022. Prioritizing and overcoming biomass energy barriers: Application of AHP and G-TOPSIS approaches. Technol. Forecast. Soc. Change 177, 121524. https://doi.org/10.1016/j.techfore.2022.121524

Ji, Q., Zhang, D., Geng, J. bo, 2018. Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. J. Clean. Prod. 198, 972–978. https://doi.org/10.1016/j.jclepro.2018.07.126

Jiang, W., Liu, Y., Xue, W., 2023. How do fossil energy markets and carbon markets affect each other? Based on the grainger causal relationship on quantiles. J. Clean. Prod. 423, 138799. https://doi.org/10.1016/j.jclepro.2023.138799

Johansen, A., Ledoit, O., Sornette, D., 2000. Crashes As Critical Points. Int. J. Theor. Appl. Financ. 03, 219–255. https://doi.org/10.1142/s0219024900000115

Johansen, A., Sornette, D., 2001. Finite-time singularity in the dynamics of the world population, economic and financial indices. Phys. A Stat. Mech. its Appl. 294, 465–502. https://doi.org/10.1016/S0378-4371(01)00105-4

Kandemir Kocaaslan, O., 2019. Oil price uncertainty and unemployment. Energy Econ. 81, 577–583. https://doi.org/10.1016/j.eneco.2019.04.021

Känzig, D.R., Konradt, M., 2023. Climate Policy and the Economy: Evidence from Europe's Carbon Pricing Initiatives. SSRN Electron. J. 1–50. https://doi.org/10.2139/ssrn.4454880

Karaki, M.B., 2018. The Energy Journal. Energy J. 39, 25–50.

Khan, I., Zakari, A., Dagar, V., Singh, S., 2022a. World energy trilemma and transformative energy developments as determinants of economic growth amid environmental sustainability. Energy Econ. 108, 105884. https://doi.org/10.1016/j.eneco.2022.105884

Khan, I., Zakari, A., Zhang, J., Dagar, V., Singh, S., 2022b. A study of trilemma energy balance, clean energy transitions, and economic expansion in the midst of environmental sustainability: New insights from three trilemma leadership. Energy 248, 123619. https://doi.org/10.1016/j.energy.2022.123619

Khan, K., Su, C.W., Khurshid, A., 2022. Do booms and busts identify bubbles in energy prices? Resour. Policy 76, 102556. https://doi.org/10.1016/j.resourpol.2022.102556

Khan, K., Su, C.W., Umar, M., Yue, X.G., 2021. Do crude oil price bubbles occur? Resour. Policy 71, 101936. https://doi.org/10.1016/j.resourpol.2020.101936

Kilian; Park, 2009. The impact of oil price shocks on the U.S. Stock market. Int. Econ. Rev. (Philadelphia). 50, 425–430. https://doi.org/10.1201/b18660-95

Kilian, L., 2009. American Economic Association Not All Oil Price Shocks Are Alike : Disentangling Demand and Supply Shocks in the Crude Oil Market Author (s): Lutz Kilian Source : The American Economic Review , Vol . 99 , No . 3 (Jun ., 2009), pp . 1053-1069 Published. Am. Econ. Rev. 99, 1053–1069.

Kilian, L., Vigfusson, R.J., 2011. Are the responses of the U.S. economy asymmetric in energy price increases and decreases? Quant. Econom. 2, 419–453. https://doi.org/10.3982/qe99

Koirala, N.P., Ma, X., 2020. Oil price uncertainty and U.S. employment growth. Energy Econ. 91, 104910. https://doi.org/10.1016/j.eneco.2020.104910

Lammerding, M., Stephan, P., Trede, M., Wilfling, B., 2013. Speculative bubbles in recent oil price dynamics: Evidence from a Bayesian Markov-switching state-space approach. Energy Econ. 36, 491–502. https://doi.org/10.1016/j.eneco.2012.10.006

Lee, K., Ni, S., Ratti, R.A., 1995. Oil shocks and the macroeconomy: the role of price variability. Energy J. 16, 39–56. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol16-No4-2

Li, M.F., Hu, H., Zhao, L.T., 2022. Key factors affecting carbon prices from a time-varying perspective. Environ. Sci. Pollut. Res. 65144–65160. https://doi.org/10.1007/s11356-022-20376-x

Li, Y., Chevallier, J., Wei, Y., Li, J., 2020. Identifying price bubbles in the US, European and Asian natural gas market: Evidence from a GSADF test approach. Energy Econ. 87. https://doi.org/10.1016/j.eneco.2020.104740

Lin, B., Li, J., 2015. The spillover effects across natural gas and oil markets: Based on the VEC-MGARCH framework. Appl. Energy 155, 229–241. https://doi.org/10.1016/j.apenergy.2015.05.123

Liu, H.H., Chen, Y.C., 2013. A study on the volatility spillovers, long memory effects and interactions between carbon and energy markets: The impacts of extreme weather. Econ. Model. 35, 840–855. https://doi.org/10.1016/j.econmod.2013.08.007

Liu, T.Y., Lee, C.C., 2018. Will the energy price bubble burst? Energy 150, 276–288. https://doi.org/10.1016/j.energy.2018.02.075

Loungani, P., 1986. Oil Price Shocks and the Dispersion Hypothesis Author (s): Prakash Loungani Source : The Review of Economics and Statistics , Vol . 68 , No . 3 (Aug ., 1986), pp . 536-539 Published by : The MIT Press Prakash Loungani *. Rev. Econ. Stat. 68, 536–539.

Lovcha, Y., Perez-Laborda, A., Sikora, I., 2022. The determinants of CO2 prices in the EU emission trading system. Appl. Energy 305, 117903. https://doi.org/10.1016/j.apenergy.2021.117903

Mac Kinnon, M.A., Brouwer, J., Samuelsen, S., 2018. The role of natural gas and its infrastructure in mitigating greenhouse gas emissions, improving regional air quality, and renewable resource integration. Prog. Energy Combust. Sci. 64, 62–92. https://doi.org/10.1016/j.pecs.2017.10.002

Mansanet Bataller, M., Pardo Tornero, Á., Valor, E., 2006. CO2 Prices, Energy and Weather. SSRN Electron. J. https://doi.org/10.2139/ssrn.913964

Michieka, N.M., Gearhart, R.S., 2019. Oil price dynamics and sectoral employment in the U.S. Econ. Anal. Policy 62, 140–149. https://doi.org/10.1016/j.eap.2019.02.001

Miriello, C., Polo, M., 2015. The development of gas hubs in Europe. Energy Policy 84, 177–190. https://doi.org/10.1016/j.enpol.2015.05.003

Neumann, A., Cullmann, A., 2012. What's the story with natural gas markets in Europe? Empirical evidence from spot trade data. 9th Int. Conf. Eur. Energy Mark. EEM 12 1–6. https://doi.org/10.1109/EEM.2012.6254679

Nick, S., Thoenes, S., 2014. What drives natural gas prices? - A structural VAR approach. Energy Econ. 45, 517–527. https://doi.org/10.1016/j.eneco.2014.08.010

Pastor, D.J., Ewing, B.T., 2022. Is there evidence of mild explosive behavior in Alaska North Slope crude oil prices? Energy Econ. 114, 106259. https://doi.org/10.1016/j.eneco.2022.106259

Perron, P., Phillips, P.C.B., 1988. Testing for a Unit Root in Time Series Regression. Biometrika.

Phillips, P.C.B., Shi, S., Yu, J., 2014. Specification sensitivity in right-tailed unit root testing for explosive behaviour. Oxf. Bull. Econ. Stat. 76, 315–333. https://doi.org/10.1111/obes.12026

Phillips, P.C.B., Shi, S., Yu, J., 2015. Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500. Int. Econ. Rev. (Philadelphia). 56, 1043–1078. https://doi.org/10.1111/iere.12132

Phillips, P.C.B., Shi, S.P., 2018. Financial bubble implosion and reverse regression. Econom. Theory 34, 705–753. https://doi.org/10.1017/S0266466617000202

Phillips, P.C.B., Wu, Y., Yu, J., 2011. EXPLOSIVE BEHAVIOR IN THE 1990s NASDAQ : WHEN DID EXUBERANCE ESCALATE ASSET VALUES ? Author (s): Peter C . B . Phillips , Yangru Wu and Jun Yu Published by : Wiley for the Economics Department of the University of Pennsylvania and Institute of Social an. Int. Econ. Rev. (Philadelphia). 52, 201–226.

Pindyck, R., 1991. Irreversibility, Uncertainty, and Investment. J. Econ. Lit. XXIX, 1110–1148. https://doi.org/10.1093/acprof:oso/9780198270140.003.0001

Prest, B.C., 2018. Explanations for the 2014 oil price decline: Supply or demand? Energy Econ. 74, 63–75. https://doi.org/10.1016/j.eneco.2018.05.029

Qiao, S., Dang, Y.J., Ren, Z.Y., Zhang, K.Q., 2023. The dynamic spillovers among carbon, fossil energy and electricity markets based on a TVP-VAR-SV method. Energy 266, 126344. https://doi.org/10.1016/j.energy.2022.126344

Reboredo, J.C., Ugando, M., 2015. Downside risks in EU carbon and fossil fuel markets. Math. Comput. Simul. 111, 17–35. https://doi.org/10.1016/j.matcom.2014.12.001

Regnard, N., Zakoïan, J.M., 2011. A conditionally heteroskedastic model with time-varying coefficients for daily gas spot prices. Energy Econ. 33, 1240–1251. https://doi.org/10.1016/j.eneco.2011.02.004

Schultz, E., Swieringa, J., 2013. Price discovery in European natural gas markets. Energy Policy 61, 628–634. https://doi.org/10.1016/j.enpol.2013.06.080

Shahzad, U., Madaleno, M., Dagar, V., Ghosh, S., Doğan, B., 2022. Exploring the role of export product quality and economic complexity for economic progress of developed economies: Does institutional quality matter? Struct. Chang. Econ. Dyn. 62, 40–51. https://doi.org/10.1016/j.strueco.2022.04.003

Sharma, S., Escobari, D., 2018. Identifying price bubble periods in the energy sector. Energy Econ. 69, 418–429. https://doi.org/10.1016/j.eneco.2017.12.007

Shi, S., Hurn, S., Phillips, P.C.B., 2020. Causal change detection in possibly integrated systems: Revisiting the money-income relationship. J. Financ. Econom. 18, 158–180. https://doi.org/10.1093/JJFINEC/NBZ004

Shi, S., Phillips, P.C.B., Hurn, S., 2018. Change Detection and the Causal Impact of the Yield Curve. J. Time Ser. Anal. 39, 966–987. https://doi.org/10.1111/jtsa.12427

Shi, X., 2016. Development of Europe's gas hubs: Implications for East Asia. Nat. Gas Ind. B 3, 357–366. https://doi.org/10.1016/j.ngib.2016.11.001

Shi, X., Variam, H.M.P., 2018. Key elements for functioning gas hubs: A case study of East Asia. Nat. Gas Ind. B 5, 167–176. https://doi.org/10.1016/j.ngib.2018.03.001

Sornette, D., Woodard, R., Zhou, W.X., 2009. The 2006-2008 oil bubble: Evidence of speculation, and prediction. Phys. A Stat. Mech. its Appl. 388, 1571–1576. https://doi.org/10.1016/j.physa.2009.01.011

Stern, J., 2014. International gas pricing in Europe and Asia: A crisis of fundamentals. Energy Policy 64, 43–48. https://doi.org/10.1016/j.enpol.2013.05.127

Stern, J., Rogers, H. V, 2014. The Dynamics of a Liberalised European Gas Market :

Su, C.W., Khan, K., Tao, R., Nicoleta-Claudia, M., 2019. Does geopolitical risk strengthen or depress oil prices and financial liquidity? Evidence from Saudi Arabia. Energy 187, 116003. https://doi.org/10.1016/j.energy.2019.116003

Su, C.W., Wang, K.H., Chang, H.L., Dumitrescu-Peculea, A., 2017. Do iron ore price bubbles occur? Resour. Policy 53, 340–346. https://doi.org/10.1016/j.resourpol.2017.08.003

Swanson, N.R., 1998. Money and output viewed through a rolling window. J. Monet. Econ. 41, 455–474. https://doi.org/10.1016/s0304-3932(98)00005-1

Tan, X.P., Wang, X.Y., 2017. Dependence changes between the carbon price and its fundamentals: A quantile regression approach. Appl. Energy 190, 306–325. https://doi.org/10.1016/j.apenergy.2016.12.116

Tang, C., Irfan, M., Razzaq, A., Dagar, V., 2022. Natural resources and financial development: Role of business regulations in testing the resource-curse hypothesis in ASEAN countries. Resour. Policy 76, 102612. https://doi.org/10.1016/j.resourpol.2022.102612

Thoma, M., 1994. Subsample instability and asymmetries in money income causality.pdf. J. Econom.

Toda, H.Y., Yamamoto, T., 1995. Statistical inference in vector autoregressions with possibly integrated processes. J. Econom. 66, 225–250. https://doi.org/10.1016/0304-4076(94)01616-8

Wang, M., Fu, Z., 2022. A new method of nonlinear causality detection: Reservoir computing Granger causality. Chaos, Solitons and Fractals 154, 111675. https://doi.org/10.1016/j.chaos.2021.111675

Wang, T.T., Zhang, D., Clive Broadstock, D., 2019. Financialization, fundamentals, and the time-varying determinants of US natural gas prices. Energy Econ. 80, 707–719. https://doi.org/10.1016/j.eneco.2019.01.026

Wang, Y., Wu, C., Yang, L., 2014. Oil price shocks and agricultural commodity prices. Energy Econ. 44, 22–35. https://doi.org/10.1016/j.eneco.2014.03.016

Wątorek, M., Stawiarski, B., 2016. Log-Periodic Power Law and Generalized Hurst Exponent Analysis in Estimating an Asset Bubble Bursting Time. e-Finanse 12, 49–58. https://doi.org/10.1515/fiqf-2016-0001

Wu, Y., Zhu, Q., Zhu, B., 2018. Decoupling analysis of world economic growth and CO2 emissions: A study comparing developed and developing countries. J. Clean. Prod. 190, 94–103. https://doi.org/10.1016/j.jclepro.2018.04.139

Xie, M., Irfan, M., Razzaq, A., Dagar, V., 2022. Forest and mineral volatility and economic performance: Evidence from frequency domain causality approach for global data. Resour. Policy 76, 102685. https://doi.org/10.1016/j.resourpol.2022.102685

Yang, H., Han, X., Wang, L., 2021. Is there a bubble in the shale gas market? Energy 215, 119101. https://doi.org/10.1016/j.energy.2020.119101

Yu, L., Li, J., Tang, L., 2015. Dynamic volatility spillover effect analysis between carbon market and crude oil market: A DCC-ICSS approach. Int. J. Glob. Energy Issues 38, 242–256. https://doi.org/10.1504/IJGEI.2015.070265

Zhang, C., Khan, I., Dagar, V., Saeed, A., Zafar, M.W., 2022. Environmental impact of information and communication technology: Unveiling the role of education in developing countries. Technol. Forecast. Soc. Change 178, 121570. https://doi.org/10.1016/j.techfore.2022.121570

Zhang, D., 2017. Oil shocks and stock markets revisited: Measuring connectedness from a global perspective. Energy Econ. 62, 323–333. https://doi.org/10.1016/j.eneco.2017.01.009

Zhang, D., Wang, T., Shi, X., Liu, J., 2018. Is hub-based pricing a better choice than oil indexation for natural gas? Evidence from a multiple bubble test. Energy Econ. 76, 495–503. https://doi.org/10.1016/j.eneco.2018.11.001

Zhang, Y.J., Sun, Y.F., 2016. The dynamic volatility spillover between European carbon trading market and fossil energy market. J. Clean. Prod. 112, 2654–2663. https://doi.org/10.1016/j.jclepro.2015.09.118

Zhang, Y.J., Wei, Y.M., 2010. An overview of current research on EU ETS: Evidence from its operating mechanism and economic effect. Appl. Energy 87, 1804–1814. https://doi.org/10.1016/j.apenergy.2009.12.019

APPENDIX 1. ETHICS BOARD FORM

	HACETTEPE ÜNİVERSİTESİ SOSYAL BİLİMLER ENSTİTÜSÜ	Doküman Kodu *Form No.*	FRM-DR-12
		Yayım Tarihi *Date of Pub.*	22.11.2023
	FRM-DR-12 **Doktora Tezi Etik Kurul Muafiyeti Formu** *Ethics Board Form for PhD Thesis*	Revizyon No *Rev. No.*	02
		Revizyon Tarihi *Rev.Date*	25.01.2024

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

Date:22/02/2024

ThesisTitle (In English):Empirical Essays On Energy Economics

My thesis work with the title given above:
1. Does not perform experimentation on people or animals.
2. Does not necessitate the use of biological material (blood, urine, biological fluids and samples, etc.).
3. Does not involve any interference of the body's integrity.
4. Is not a research conducted with qualitative or quantitative approaches that require data collection from the participants by using techniques such as survey, scale (test), interview, focus group work, observation, experiment, interview.
5. Requires the use of data (books, documents, etc.) obtained from other people and institutions. However, this use will be carried out in accordance with the Personal Information Protection Law to the extent permitted by other persons and institutions.

I hereby declare that I reviewed the Directives of Ethics Boards of Hacettepe University and in regard to these directives it is not necessary to obtain permission from any Ethics Board in order to carry out my thesis study; I accept all legal responsibilities that may arise in any infrigement of the directives and that the information I have given above is correct.

I respectfully submit this for approval.

Begüm AKÇORA

Student Information			
Name-Surname	Begüm AKÇORA		
Student Number	N15242514		
Department	Economics		
Programme	Doctor of Philosophy in Economics		
Status	PhD x	Combined MA/MSc-PhD ☐	

SUPERVISOR'S APPROVAL

APPROVED
Prof. Dr. Özge KANDEMİR KOCAASLAN

	HACETTEPE ÜNİVERSİTESİ SOSYAL BİLİMLER ENSTİTÜSÜ	Doküman Kodu *Form No.*	FRM-DR-12
		Yayım Tarihi *Date of Pub.*	22.11.2023
	FRM-DR-12 **Doktora Tezi Etik Kurul Muafiyeti Formu** *Ethics Board Form for PhD Thesis*	Revizyon No *Rev. No.*	02
		Revizyon Tarihi *Rev.Date*	25.01.2024

HACETTEPE ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
İKTİSAT ANABİLİM DALI BAŞKANLIĞINA

Tarih:22/02/2024

Tez Başlığı: Enerji Ekonomisi Üzerine Ampirik Makaleler

Yukarıda başlığı verilen tez çalışmam:
1. İnsan ve hayvan üzerinde deney niteliği taşımamaktadır.
2. Biyolojik materyal (kan, idrar vb. biyolojik sıvılar ve numuneler) kullanılmasını gerektirmemektedir.
3. Beden bütünlüğüne veya ruh sağlığına müdahale içermemektedir.
4. Anket, ölçek (test), mülakat, odak grup çalışması, gözlem, deney, görüşme gibi teknikler kullanılarak katılımcılardan veri toplanmasını gerektiren nitel ya da nicel yaklaşımlarla yürütülen araştırma niteliğinde değildir.
5. Diğer kişi ve kurumlardan temin edilen veri kullanımını (kitap, belge vs.) gerektirmektedir. Ancak bu kullanım, diğer kişi ve kurumların izin verdiği ölçüde Kişisel Bilgilerin Korunması Kanuna riayet edilerek gerçekleştirilecektir.

Hacettepe Üniversitesi Etik Kurullarının Yönergelerini inceledim ve bunlara göre çalışmamın yürütülebilmesi için herhangi bir Etik Kuruldan izin alınmasına gerek olmadığını; aksi durumda doğabilecek her türlü hukuki sorumluluğu kabul ettiğimi ve yukarıda vermiş olduğum bilgilerin doğru olduğunu beyan ederim.

Gereğini saygılarımla arz ederim.

Begüm AKÇORA

Öğrenci Bilgileri				
	Ad-Soyad	Begüm AKÇORA		
	Öğrenci No	N15242514		
	Enstitü Anabilim Dalı	İktisat		
	Programı	İngilizce İktisat		
	Statüsü	**Doktora** x		**Lisans Derecesi ile (Bütünleşik) Dr** ☐

DANIŞMAN ONAYI

UYGUNDUR.
Prof. Dr. Özge KANDEMİR KOCAASLAN

APPENDIX 2. ORIGINALITY REPORT

	HACETTEPE ÜNİVERSİTESİ SOSYAL BİLİMLER ENSTİTÜSÜ	Doküman Kodu *Form No.*	FRM-DR-21
		Yayım Tarihi *Date of Pub.*	22.11.2023
	FRM-DR-21 **Doktora Tezi Orijinallik Raporu** *PhD Thesis Dissertation Originality Report*	Revizyon No *Rev. No.*	00
		Revizyon Tarihi *Rev.Date*	

TO HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

Date:22/02/2024

Thesis Title (In English):Empirical Essays on Energy Economics

According to the originality report obtained by my thesis advisor by using the Turnitin plagiarism detection software and by applying the filtering options checked below on 21/02/2024 for the total of 88 pages including the a) Title Page, b) Introduction, c) Main Chapters, and d) Conclusion sections of my thesis entitled above, the similarity index of my thesis is 7%.

Filtering options applied**:

1. ☒ Approval and Decleration sections excluded
2. ☒ References cited excluded
3. ☒ Quotes excluded
4. ☐ Quotes included
5. ☐ Match size up to 5 words excluded

I hereby declare that I have carefully read Hacettepe University Graduate School of Social Sciences Guidelines for Obtaining and Using Thesis Originality Reports that according to the maximum similarity index values specified in the Guidelines, my thesis does not include any form of plagiarism; that in any future detection of possible infringement of the regulations I accept all legal responsibility; and that all the information I have provided is correct to the best of my knowledge.

I respectfully submit this for approval.

Begüm AKÇORA

Student Information				
Name-Surname	Begum AKCORA		**Student Number**	N15242514
Department	Economics			
Programme	Economics in English			
E-mail/Phone Number	05331615341		begumakcora@gmail.com	
Status	**PhD**	x	**Combined MA/MSc-PhD**	☐

SUPERVISOR'S APPROVAL

APPROVED
Prof. Özge KANDEMIR KOCAASLAN

**As mentioned in the second part [article (4)/3]of the Thesis Dissertation Originality Report's Codes of Practice of Hacettepe University Graduate School of Social Sciences, filtering should be done as following: excluding refence, quotation excluded/included, Match size up to 5 words excluded.

2

FRM-DR-21 Rev.No/Tarih: 00/22.11.2023

	HACETTEPE ÜNİVERSİTESİ SOSYAL BİLİMLER ENSTİTÜSÜ	Doküman Kodu *Form No.*	FRM-DR-21
		Yayım Tarihi *Date of Pub.*	22.11.2023
	FRM-DR-21 **Doktora Tezi Orijinallik Raporu** *PhD Thesis Dissertation Originality Report*	Revizyon No *Rev. No.*	00
		Revizyon Tarihi *Rev.Date*	

HACETTEPE ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
İKTİSAT ANABİLİM DALI BAŞKANLIĞINA

Tarih: 22 /02/2024

Tez Başlığı*Enerji Ekonomisi Üzerine Ampirik Makaleler

Yukarıda başlığı verilen tezimin a) Kapak sayfası, b) Giriş, c) Ana bölümler ve d) Sonuç kısımlarından oluşan toplam 88 sayfalık kısmına ilişkin, 21/02/2024 tarihinde tez danışmanım tarafından Turnitin adlı intihal tespit programından aşağıda işaretlenmiş filtrelemeler uygulanarak alınmış olan orijinallik raporuna göre, tezimin benzerlik oranı % 7 'dir.

Uygulanan filtrelemeler**:

1. ☒ Kabul/Onay ve Bildirim sayfaları hariç
2. ☒ Kaynakça hariç
3. ☒ Alıntılar hariç
4. ☐ Alıntılar dâhil
5. ☐ 5 kelimeden daha az örtüşme içeren metin kısımları hariç

Hacettepe Üniversitesi Sosyal Bilimler Enstitüsü Tez Çalışması Orijinallik Raporu Alınması ve Kullanılması Uygulama Esasları'nı inceledim ve bu Uygulama Esasları'nda belirtilen azami benzerlik oranlarına göre tezimin herhangi bir intihal içermediğini; aksinin tespit edileceği muhtemel durumlarda doğabilecek her türlü hukuki sorumluluğu kabul ettiğimi ve yukarıda vermiş olduğum bilgilerin doğru olduğunu beyan ederim.

Gereğini saygılarımla arz ederim.

Begüm AKÇORA

Öğrenci Bilgileri				
	Ad-Soyad	Begüm AKÇORA	**Öğrenci No**	N15242514
	Enstitü Anabilim Dalı	İktisat		
	Programı	İngilizce İktisat		
	E-posta/Telefon	05331615341	begumakcora@gmail.com	
	Statüsü	**Doktora** x	**Lisans Derecesi ile (Bütünleşik) Dr** ☐	

DANIŞMAN ONAYI

UYGUNDUR.
Prof. Dr. Özge KANDEMİR KOCAASLAN)

*Tez **Almanca** veya **Fransızca** yazılıyor ise bu kısımda tez başlığı **Tez Yazım Dilinde** yazılmalıdır
**Hacettepe Üniversitesi Sosyal Bilimler Enstitüsü Tez Çalışması Orjinallik Raporu Alınması ve Kullanılması Uygulama Esasları İkinci bölüm madde (4)/3'te de belirtildiği üzere: Kaynakça hariç, Alıntılar hariç/dahil, 5 kelimeden daha az örtüşme içeren metin kısımları hariç (Limit match size to 5 words) filtreleme yapılmalıdır.