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Assessing The Exports And Commodity Prices Linkage Amid Uncertainity

Belirsizlik Ortamında İhracat ve Emtia Fiyatları İlişkisinin Değerlendirilmesi

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Abstract

In this article, the impact of commodity prices on export volume under uncertainty shocks has been examined for the period of 1990Q1-2022Q4. According to the findings, the Maki cointegration test with multiple breaks indicates that all variables are in a co-integration relationship. The cointegration coefficients suggest global uncertainties and commodity prices have a adverse impact on exports, and cause to fluctuations. But they have lasted nearly six querters according to impulse-response functions from the VAR model and than it disappeared. We also estimate Vector Error Correction model and the findings indicate that uncertainties and commodity prices have significant and negative effect on exports in the long run. We lastly proved that there is one-way causality, goes from uncertainty toward commodity prices and exports marktes in the long term according to Frequency Domain test. In this frame, we need to multidimensional and comprehensive policy measures to reduce uncertainty in the global markets.

Keywords: *Economic and Policy Uncertainity, Exports, Commodity Prices, Time Series Econometrics.*

Öz

Bu çalışmada belirsizlik şokları altında, emtia fiyatlarının ihracat hacmi üzerindeki etkisi 1990Q1-2022Q4 dönemi için incelenmiştir. Bulgulara göre, çoklu yapısal kırılmaya izin veren Maki eş bütünleşme testi, tüm değişkenlerin uzun dönemde bir denge ilişkisi içinde olduğunu göstermektedir. Eş bütünleşme katsayıları, küresel belirsizliklerin ve emtia fiyatlarının yapısal kırılma altında, ihracatı negatif yönde etkilediğine ve dalgalanmalara neden olduğuna işaret etmektedir. Ancak VAR modelinden gelen Etki-Tepki fonksiyonlarına göre değişkenlerdeki dışsal şoklar yaklaşık altı çeyreklik dönemde sönmektedir. Diğer yandan VAR modeline dayalı olarak hesaplanan Vektör Hata Düzeltme modeli sonuçlarına göre belirsizliklerin ve emtia fiyat artışlarının ihracatı uzun dönemde negatif etkilediği tespit edilmiştir. Uzun ve kısa dönem ayrımının yapılabildiği frekans bazlı nedensellik testine göre uzun vadede belirsizliklerden emtia piyasaları ve ihracata doğu tek yönlü bir nedensellik gözlemlenmiştir. Bu çerçevede, küresel piyasalardaki belirsizlikleri gidermek için çok boyutlu ve kapsayıcı politika tedbirlerine ihtiyaç duyulduğu söylenebilir.

Anahtar Kelimeler: *Ekonomik ve Politik Belirsizlikler, İhracat, Emtia Fiyatları, Zaman Serisi Ekonometrisi*

JEL Codes: *B17, D8, F14, C22.*

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Introduction

The effects of uncertainty on the global economy have attracted considerable attention from researchers and policymakers during the last decades. Uncertainty can be defined as the conditional volatility of disturbances from negative shocks that are impossible to forecast. It arises from changes in the political, financial, commercial, or economic environment, often caused by unexpected events in the macro economy, policy shifts, or disagreements between countries. Moreover, uncertainty is a self-reinforcing process: negative shocks that induce it can further exacerbate the situation by creating a downward spiral of declining expectations. Predicting the future economic environment is difficult because unknown parameters introduce a high degree of risk. As a result, economic agents face challenges in forecasting future economic policies, including their timing and potential consequences. (Carballo et al., 2022: 2-3).

Uncertainty is measured according to different methods. Bloom, Phillip, Paul, Pavel and Gregory (2018), Jurado, Sydney and Ng (2015), formulated their approaches by utilizing the volatility of crucial economic and financial factors. Another method is based on text-searching newspaper archives. Baker, Bloom, and Davis (2013) introduced the EPU (Economic and Policy Uncertainty) index using information from newspaper articles for major economies. Samely, Caldara and Iacoviello (2021) developed the GRI (Geopolitical Risk Index) and also Baker, Bloom, Davis and Renault (2021) derived the Twitter based indicators.

There are various types of economic uncertainty stemming from political, financial, or business developments. The most prominent indexes in the literature are Monetary Policy Uncertainty (MPU), WUI (World Uncertainty Index), VIX index, TPU (Trade Policy Uncertainty), and the Global Risk Index (GRI) (Ahir et al., 2022: 6-8). These indicators capture fluctuations resulting from the unpredictability of political, fiscal, or monetary policies. For example, corruption investigations, coup attempts, outbreaks of war, political tensions, rising polarization, trade wars, financial crises, debt crises, disruptions, and volatility in commodity prices are common examples of uncertainty observed in different parts of the world. As a leading example, Fig. 1 shows the annotated index for global uncertainty (Ahir et al., 2022: 39). Both the uncertainties of globalization (Çetiner, 2008: 36-40) and concrete events, The Gulf War (1991), the 9/11 attacks (2001), the Financial Crisis of 2008, Brexit (2016) and COVID-19 pandemic (2020) confronted policymakers with extraordinary and complex challenges. Nowadays, the War in Ukraine continues to be the dominant of global uncertainty (Davis, 2016: 2).

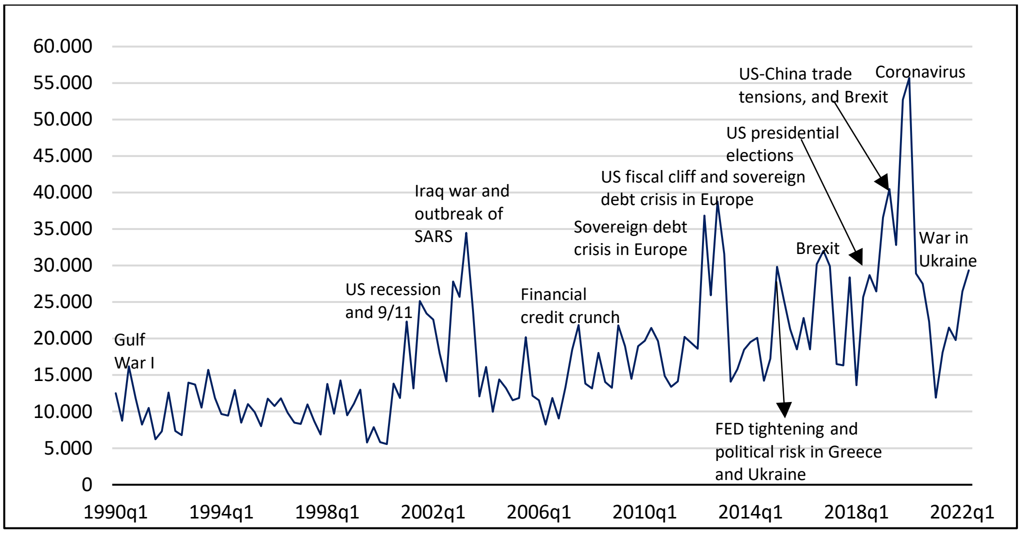


Figure 1. World Incertainty Index (WUI, GDP Weighted)

In various theoretical and empirical contexts, such as Novy and Taylor (2020), Handley and Limao (2015, 2017), global uncertainties exert a substantial impact on international trade due to increased integration between countries. Economic policy changes in one country can easily affect its trading partners, resulting in macroeconomic effects for both. Several studies have identified a significant correlation between trade and volatility at different levels of aggregation, with the main finding being that uncertainty tends to decrease trade flows, affecting both the range of exported products and overall trade (Kirchner, 2019: 179). Uncertainty has a direct effect on the decisions made by firms engaged in international trade. As uncertainty level increases, firms face higher fixed and irreversible investment costs, as well as an increased option value of waiting. In this setting, risk-averse economic agents tend to adopt a more conservative approach and opt for the traditional "wait and see" strategy. Firms and individuals postpone production, consumption, and investment decisions until the uncertainty has been resolved. These firms may delay or slow down production for external markets, reduce capital investment, increase cash holdings, decrease new sales agreements, and face higher risk premiums until the situation becomes clearer. Higher levels of uncertainty can also lead to delays in incurring sunk costs associated with exporting in an uncertain environment, such as searching for foreign suppliers, integrating foreign inputs into domestic processes, acquiring import licenses, and navigating customs procedures (Greenland et al., 2019: 1249).

The mere existence of economic uncertainty can significantly dampen economic activity. Additionally, it can lead to an increase in risk premiums (such as CDS), a decrease in debt issuances, and a rise in unemployment. Ultimately, all of these factors have a negative impact on the overall economy (Şahinöz & Coşar, 2018: 1517). According to Bloom (2009), heightened uncertainty leads firms to temporarily suspend their investment and hiring. It means wit and see strategy. In addition, productivity level falls due to the temporary halt in reallocation process across production factors. In the medium term, the rising volatility triggers an excessive increase in output, employment, and productivity. Consequently, uncertainty shocks lead to brief but intense periods of recession followed by recoveries in global economic activity.

The rise in global uncertainty has adverse effects on the international trade, contributing to increased external operating risks and trade costs. Hence, firms tend to adopt a cautious approach, delaying their entry into new foreign markets. Foreign orders are particularly affected, with the higher costs associated with maintaining inventory for foreign inputs prompting a more significant reduction compared to domestic orders. This cautious behavior can result in a contraction of trade. Importers also feel the impact of uncertainty, as it acts as a demand shock for countries relying on imports, leading to a decline in aggregate demand and a decrease in new purchase agreements (Zhao, 2022: 104). Under these conditions, future expectation perspective of both exporters and importers will be deteriorate. The transmission mechanism at the end, has generally resulted with negative outcomes. For instance, Grier and Smallwood (2007), Handley and Limao (2015) have addressed the impacts of uncertainty on external trade. They proposed that there is a strong negative trade-uncertainty linkage and uncertainty shocks negatively affect exports. Economic uncertainties not only affect exports but also have a negative impact on imports through substitution effect. According to the Novy and Taylor (2020), firms have the option to utilize domestic or foreign intermediate inputs. But, during periods of uncertainty, firms may choose to decrease dependence on foreign inputs and increase usage of domestic inputs. This is due to the higher inventory costs associated with imported inputs, which can result in a decrease in imports (Sharma & Paramati, 2021: 139).

Commodities can impact export volumes through uncertainty. Firstly, commodities refer to raw materials or primary agricultural and mining products that can be bought and sold. They are essential lifelines for modern society, and play a crucial role as the foundation of real sectors. In this manner they are traded in substantial amounts worldwide. Commodities exert an immediate influence on global food security, particularly in low-income, food-deficit nations. The volatility of international commodity prices brings immense uncertainty, posing a threat not only to global food security but also to economic and social stability (Long et al., 2022: 2). Commodities can be broadly classified into two categories: physical and financial. Physical commodities, known as hard and soft commodities, are directly linked to production within agricultural, metal, and energy sectors. On the other hand, financial commodities, such as gold, silver, or crude oil, are characterized by strong financial properties rather than being driven solely by supply and demand from industries. Historically, these financial commodities have served as a hedge against inflation and market volatility. In this regard, they contribute to diversifying investment portfolios for investors in financial markets through commodity futures (Song et al., 2022: 1-2).

The relationship between uncertainty and commodity prices is a complex and multifaceted one. Commodity prices are known to be highly volatile, and one important factor driving this volatility is economic uncertainty as they affect the supply and demand balance in the market. When uncertainty rise, investors become more cautious and risk-averse, leading to increased demand for safe-haven assets such as gold or US treasury bonds. This shift in investment patterns can lead to a decrease in demand for physical commodities, resulting in lower prices. Conversely, during periods of low uncertainty, investors are more willing to take on risk, leading to increased demand for commodities and driving prices higher. Higher prices make commodity markets have been a key source of uncertainty once again (Ahmed & Sarkodie, 2021: 3). Uncertainty can also influence commodity prices through supply-side channels, leading to disruptions in supply chains such as transportation, production, and distribution, resulting in shortages and price spikes. Instability in commodity-producing countries can contribute to supply disruptions and price fluctuations. For instance, geopolitical tensions may disrupt supply chains, causing delays or interruptions in the production and transportation of commodities, leading to decreased supply and increased commodity prices. Additionally, natural disasters can have a significant impact. Overall, understanding and managing the impact of economic uncertainty on commodity prices are crucial for both producers and consumers of commodities, as well as for policymakers and investors in the commodity markets (Karabulut, et al., 2020: 276-277).

Hence, the exploration of the correlation between exports and commodity prices under uncertainty holds significant importance due to various factors. First, commodity prices are often subject to significant volatility due to changes in supply and demand, geopolitical tensions, weather conditions, and economic indicators. Uncertainties in these factors can lead to fluctuations in commodity prices, creating an environment of market instability. Market instability impact the cost of production for exporters. When commodity prices are high, exporting countries may enjoy increased revenues from their exports, making their products more competitive in international markets. Conversely, during periods of low commodity prices, export competitiveness may decrease. Many countries heavily rely on commodities as key export products. Growing volatility of commodity prices, have created serious difficulties for the economic policies of commodity-oriented countries (Nikonenko et al., 2020: 440-441). Second, changes in commodity prices can alter a country's terms of trade, affecting its purchasing power in international markets. A rise in commodity prices may improve the terms of trade for commodity-exporting countries, leading to increased import capacity and potential economic benefits. Conversely, declining commodity prices may deteriorate terms of trade, posing challenges for exporters. Volatility in prices can impact investment decisions in commodity-related industries, such as mining, agriculture, and energy. Third, commodity prices play a crucial role in global supply chains, affecting the production costs and profitability of various industries worldwide. Uncertainties can disrupt supply chains, and leading to production delays. In summary, the importance of commodity prices for exports under uncertainty transcends individual nations and has far-reaching implications for global trade, economic growth, investment decisions, and policy responses. It can influence the overall economic stability and growth of exporting nation. Understanding and managing the relationship between commodity prices and exports amid uncertainty is essential for fostering economic resilience and sustainable development on a global scale (Boakye et. al., 2022: 2243-2246).

The remaining part of the study is organized as follows. In the following section, we provided theoretical basis for uncertainty in the economy including with business and investors behaviour. Section two review the related lieratue and outlines the contributions. Section three determines the main model and the data. Section four lays the groundwork for our presentation of the econometric exercise performed to provide input for the debate around this issue. Section five reports the findings from the econometric analysis. Conclusion of the study are presented in the last section.

1.Theoretical Basis

In the case of high uncertainty, businesses and individuals often find it challenging to make informed decisions regarding investment, production, consumption, and other economic activities. This uncertainty can result in a slowdown in economic growth, a decrease in the volume of trade, and an increase volatility in financial markets. Therefore, it is crucial to understand the behaviors and reveal the underlying transmission mechanisms. In this regard, the theoretical foundation of policy uncertainty is grounded in the notion that uncertainty shocks have negative effects on various macroeconomic variables.

The economy encompasses a complex system of production and consumption, with outcomes of today's decisions often realized much later. During this time gap, we have to face various unknown parameters and risks. Starting from the 19th century, global markets have undergone significant evolution characterized by growing complexity, specialization, and emphasis on the production process further amplified by interdependencies and the ever-expanding involvement of diverse economic actors, including investors, corporations, financial institutions, and governments. This expansion has introduced a variety of risks and unknown parameters into the equation. However, classical economists assume "Perfect Certainty" in the economy. Similar to the principles of Newton's celestial mechanics, the field of economics once operated under the assumption of a linear development path, where changes were not influenced by human actions. Economic agents were presumed to have complete and accurate knowledge of a predetermined program. Thus, they never made errors in their choices, and production and consumption decisions were made with the highest certainty (Davidson, 1999: 30-31).

Unlike classical economists, the *'Keynesian Uncertainty Theory,'* introduced by John Maynard Keynes, emphasizes the role of uncertainty in shaping economic decision-making and outcomes. According to this theory, the future is inherently unpredictable, and economic agents, such as consumers and investors, face fundamental uncertainty when making choices. In contrast to risk, which can be quantified and managed through probability assessments, uncertainty involves situations where the probabilities of different outcomes are unknown or unknowable. Keynes argued that under conditions of high uncertainty, individuals and businesses become more cautious and prone to hoarding cash rather than investing or spending. This cautious behavior, known as 'animal spirits,' can lead to a lack of aggregate demand, economic stagnation, and prolonged recessions. Consequently, the Keynesian Uncertainty Theory highlights the importance of confidence, expectations, and sentiment in driving economic activity. This theory has significantly influenced macroeconomic thought and policy, particularly during economic downturns, emphasizing the need for countercyclical measures such as fiscal stimulus and active government intervention to restore confidence and bolster aggregate demand in the face of pervasive uncertainty. By recognizing the pervasive role of uncertainty, policymakers can develop strategies to manage its impact and mitigate adverse effects on economic performance (Dow, 2015: 34-38).

Alchian (1950) contributed to the understanding of uncertainty's impact on economic theory. He presented an evolutionary approach that incorporates principles of natural selection to explain firms' behavior and their success and survival in uncertain markets. Despite the challenges posed by uncertainty and imperfect foresight, economists can analyze firms' behavior by assuming profit maximization. Positive returns or profits are crucial for long-term survival, enabling economists to retrospectively identify behaviors conducive to success. Firms that imitate successful counterparts can create the perception of consciously maximizing profits, even if their strategies were developed without the specific criteria that led to success. In uncertain environments, surviving firms may behave as if they possess information and foresight, swiftly emulating successful firms to enhance their chances of survival. Conversely, firms that fail to adapt or do so slowly face a higher risk of failure. Despite contemporaneous firms having limited knowledge and foresight, the principles of evolution and competition for scarce resources ensure that surviving firms tend to exhibit behaviors that maximize their chances of survival (Alchian, 1950: 212-218).

Another approach is traditional *"Wait-and-See"* effect of uncertainty shocks. In the typical framework, economic agents adjust their approach in response to an increase in uncertainty. The first mechanism is supply-demand channel. The rise of uncertainty coincides with a decline in production motivation and a deterioration in demand decisions. These factors contribute to significant fluctuations in commodity markets. In this environment, households may reduce their spending, and aggregate demand falls due to precautionary motivation. In turn, it can lead to negative effects on output and employment in the long run. Antonakakis, Chatziantoniou, and Filis (2014) demonstrated that uncertainty stemming from economic policy decisions has the effect of dampening demand and finally reduce investment expenditure as firms may be hesitant to invest in new projects or expand existing ones in an uncertain environment. It provides the opportunity to resolve the situation before committing to any course of action. This delay in decision-making can be incentivized by the potential benefits of waiting to make more informed decisions in the future, which can mitigate the risks associated with uncertain economic conditions and creates a trade-off between the potential gains from waiting and the costs of delaying (Basher, et al., 2019: 2). Besides, it can lead to a decline in capital accumulation, which can have negative effects on productivity and economic growth. Second, uncertainty affects tariffs that increases the variance of future desired prices. When uncertainty-driven fluctuations are substitutes, production function will be asymmetric, because losses from overpricing are smaller than losses from under-pricing. Third, firms raise prices to avoid being stuck with relatively low price in the future and it gives rise to increase mark-ups and higher mark-ups reduce labor supply and consumption. In particular, wholesale companies tend to raise their mark-ups due to a pricing bias that leads to upward adjustments. Additionally, both intermediate goods firms and intermediate goods firms experience reduced profitability in their export activities. In turn, This process creates spillover effect through trading partner and eventually, global commodity markets and international trade volume will not be better. According to Bernanke's (1983), and Dixit's (1989) theories, high levels of uncertainty can discourage firms from investing and hiring, especially when the investments are difficult to reverse or workers are expensive to hire and fire. Investment demand falls because, potential increase in tariffs lower expected asset prices. Carballo et al. (2022) consider a scenario involving a small exporting country, negligible domestic entry costs, and a consistent domestic mass of potential firms. Accordingly, the expected value from exporting for any firm v after entry;

$$\Pi_e(a_s, c) = \pi(a_s, c) + E_s \sum_{t=1}^{\infty} \beta^t \, \pi(a_s', c) \quad (1)$$

Where, a_s shows market condition observed by firm. If a firm determines that entering the market with an entry cost, K, will optimize its anticipated profits, it will choose to enter and maintain its exports in the subsequent period with a probability of β, where β is less than 1. E_S represents the anticipation considering potential future conditions based on the available information set pertaining to the current state. In the face of uncertain future conditions, non-exporters find themselves at a crossroads: should they make the decision to enter or wait until conditions show signs of improvement? The best choice for a firm's entry decision in state "s" maximizes its projected value, as defined by the Bellman equation presented below (Handley & Limao, 2017: 2738).

$$\Pi_e(a_s, c) = max\{\Pi_e(a_s, c) - K, \beta E_s \Pi(a_s', c)\} \quad (2)$$

To address the optimal stopping problem, we examine intervals of "a" encompassing the firm's actions. If economic conditions are sufficiently good, a firm decides according to following condition;

$$\Pi_e(a_t, c_t^u, r) - K = \Pi_w(c_t^u, r) \quad (3)$$

where a_t the is current condition, r is demand regime in which the firm takes as given and c_t^U is general cost. According to cost cutoff condition, the difference between the expected value of export Π_e and the sunk cost K should be at least equal to the anticipated value of waiting, Π_w. Uncertainty rise the cost cut-off condition and firms may be hesitant to engage in cross-border transactions in an uncertain environment. It's evident that uncertainty has a stronger dissuasive effect on risk-averse firms when it comes to engaging in foreign markets, compared to risk-taking firms. Increasing uncertainty discourage investments in physical capital, increases firms' cash holdings, dampens trade credit and hence, impede international trade (Caldara, et al., 2019: 26-27). Therefore, theories regarding the effects of uncertainty have evolved from classical economists to the late 20th century, coinciding with globalization and the financialization of economies, which introduced new economic actors and increased complexity. Consequently, examining these theories is crucial for identifying relevant variables and proxies, predicting the expected directions of explanatory factors, and reinforcing the foundation for empirical analysis and discussion.

2. Related Literature

The economic outcomes of global uncertainties have become important focal points in both empirical and theoretical studies, particularly following the Brexit, USA-China Trade wars and the Covid-19 pandemic. Since the introduction of standardized measures by Baker et al. (2013), the empirical literature in this field has grown substantially. The expanding body of research primarily concentrates on examining the impact of various uncertainty measures (GUI, TPU, EPU, VIX index, Geopolitic or Political Risks index, etc.) on macroeconomic variables. These variables include economic growth, international trade, financial markets, energy usage, carbon emissions, firm behavior, or commodity prices. The majority of these studies have found evidence supporting a negative relationship. While some directly employ measures of uncertainty series, numerous papers rely on proxies such as the VIX index, firm profits, stock returns, volatility in markets, or productivity (Jurado et al. 2015: 1178).

A substantial body of research investigates the effects of uncertainties on economic growth. Rising uncertainty is widely recognized as having adverse effects on output. Following uncertainty shocks, reductions in investment and consumption significantly contribute to the slowing of real GDP growth. In this regard, Lensink et al. (1999), Wu et al. (2008), Fauntas and Karanaros (2006), Bredin et al. (2009), Baker and Bloom (2013), Christensen et al. (2018), Şahinöz and Coşar (2018), Mendeya and Ho (2021), Bhowmik et al. (2021) suggest that rising uncertainty or unexpected shocks can affect economic activity negatively through investment and consumption decisions, risk premiums, and expectations.

In the context of the uncertainty relationship with commodities, the existing literature either utilizes commodity prices directly or employs proxies such as gold prices, oil prices or grain prices to analyse the correlation between the variables. At this strand, Wang et al. (2015a), Bakas and Triantafyllou (2018), Chen et al. (2019), Adekoya et al. (2021), Ahmed and Sarkodie (2021), Xiao et al. (2022), Song et al. (2022) assert that uncertainty leads to volatility in the commodity markets and commodity prices are sensitive to uncertainty. Also price shocks from commodities impose statistically significant effect on various uncertainty measures. So it's important to stabilize (reduce uncertainty) the world economy to ensure food security and to promote exports earnings for low income developing countries.

Uncertainty and exports&imports relationship in the context of international trade has been extensively studied. Handley and Limao (2014), Wang and Zu (2015b), Limao and Maggi (2015), Constantinescu (2017), Crowley et al. (2018), Caldara et al. (2019), Greenland et al. (2019), Novy and Taylor (2020), Görüş and Akyüz (2023), Ahmad et al. (2020), Sharma and Paramati (2021), Zhao (2022), Carballo et al. (2022) provides insights on the subject relationship. They indicated that international trade is so volatile in response to uncertainty shocks. Besides, trade volume growth and new export entry are positively associated with uncertainty reduction and reduction in uncertainty reduces the volatility of firm-level exports. On the other hand, Grier and Smalwood (2007), Chen and Zhao (2021) shown that economic uncertainty has an insignificant effect on export volatility and export growth in aggregate level.

Scholars have provided extensive literatures concerning the nexus between exports and commodity prices. The relationship between commodity prices and exports is complex, and influenced by uncertainties such as supply disruptions, demand fluctiations, risk perception and market volatility. Its generally accepted in the study of Mork et al. (1994), Le et al. (1995), Céspedes and Velasco (2012), Baumann (2013), Gruss (2014), Gruss and Kebhaj (2019), Knop and Vesğignani (2014), Aponte (2016), Fernández, Schmitt-Grohé, and Uribe (2017), Inoue and İkimoto (2017), Schmitt-Grohé and Uribe (2018), Nikonenko et. al. (2020), Cunha et al. (2022), that there is a strong and statistically significant long-run relationship between exports and commoditiy prices. In addition, commodity price fluctuations can significantly impact the sustainable development of macroeconomics, and an increase in commodity prices (e.g. oil, natural gas, mining products) channels an improvement in export revenues, hence, boosting the economy while commodity importers have suffered.

There are also type of papers on the effetc of uncertainty on credit markets, stock prices and transmission of volatilities from one market to another. Kang and Ratti (2013), Liu and Zhang (2015), Gülen and Ion (2016), Christou et al. (2017), Arouri et al. (2018), Ferreira et al. (2018), Basher et al. (2019), Chiang (2019), Wang et al. (2020), Phan et al. (2021), Mokni et al. (2022) found that increase in economic policy uncertainty decreases financial stability, and an unanticipated increase in policy uncertainty reduces real stock returns, deteriorates credit markets and increase volatilities. When credit markets deteriorate, it becomes more difficult for businesses to access financing. Exporters may struggle to secure the necessary funds to produce goods for export or to expand their operations to meet demand in foreign markets. If overseas buyers face tighter credit conditions, they may reduce their purchases of goods and services from exporters, leading to a decline in export volume. Also exporters may face higher borrowing costs or be forced to use alternative, more expensive financing options, which can reduce their competitiveness in international markets. Thus, we can expect that uncertainty will produce harmful effects on trade through credit markets.

Unlike the previous studies, we have several contributions and aims to fill some gaps in the literature. First, we contribute on how exports react to global commodity prices and uncertainty shocks in a “multivariate framework” with latest data. However, majority of previous studies are limited in scope and emphasized on specific markets such as gold, oil or grain. The limitation is due to the failure to include commodity market in global level. It’s important to infer global policy recommendation on exports and commodity price movements under unexpected shocks. In this fashion, our study contributes to the contemporary body of research on policy uncertainty and international trade, a field initially pioneered by Handley and Limao (2014, 2015). Secondly, we consider the “structural beraks” in the co-integration analysis by incorporating structural changes in the parameters of models. It offers an improvement over traditional methods since numerous models assume a consistent relationship between variables throughout the entire period. Nevertheless, there are instances where structural breaks can lead to alterations in the fundamental relationship between the variables.

Alternatively, inaccurate forecasts could arise, leading to potentially misleading policy recommendations. Prior research has neglected the reciprocal impact of these two factors and has not explored whether structural shifts could influence this causality. Lastly, it would be better to distinguish between Global Uncertainty (GU) and Economic Policy Uncertainty (EPU). Global uncertainty arises from a variety of random and unpredictable factors that lie outside the realm of policymakers' influence. As an illustration, weather conditions, natural disasters, conflicts, pandemics, technological breakthroughs, and other unforeseen events can exacerbate economic activity cycles, often lying beyond the direct control of policymakers. Economic Policy Uncertainty (EPU) encompasses the uncertainty stemming from unexpected policy actions, shifts in policy instruments, and alterations in economic policies, all of which can significantly affect economic activity. By acknowledging these separate origins of uncertainty, policymakers can enhance their comprehension of the associated impacts and formulate effective strategies to mitigate them.

Our subject is important from several aspects. Uncertainties play a crucial role in the dynamics of exports and commodity markets. They provide insights into risk assessment, market volatility, investment decisions, trade policies, and macroeconomic effects. Understanding and assessing uncertainties helps evaluate risks associated with international trade and commodity markets. Volatility introduced by uncertainties affects market dynamics, necessitating strategies to manage risks. Within this framework, our objective is to investigate whether uncertainty genuinely has an impact on commodity prices and also we try to explain the response of exports volume which stem from uncertainty changes. For this purpose, we “hypothesize” that uncertainty and commodity prices have a significant impact on export volume. It can be argued that high level of uncertainty poses significant risks to exporting firms in overseas markets. Yin and Han (2014), Bakas and Triantafyllou (2018), and Hailemariam et al. (2019) suggest policy uncertainty can have an adverse impact on exports. Second, we hypothesize that uncertainty and commodity prices are co-integrated with exports in the long run, and commodity prices benefit exporting countries. More clearly, fluctuations in the commodity price index will influence the direction of export volume based on whether the country’s position as a net exporter or net importer in the commodity market.

For example, sharp fluctuations in energy prices have exerted significant impacts, as rapid price declines are detrimental to energy-exporting countries. Conversely, sharp price increases pose challenges for energy-importing countries, while exporting nations are susceptible to energy price vulnerability (Zhang et. al., 2022; Aponte, 2016; Wang et al., 2022). Lastly, we address three “research questions”. Do global uncertainty and commodity prices exert a noteworthy economic influence on export volume?, If so, do variables respond differently to such uncertainty? and what role do unexpected shocks play in elucidating structural breaks throughout the sample period have emerged as a research questions in our study.

3. The Model And Data

Advancements in the narrative identification of economic policy uncertainty have empowered researchers to model its economic implications. Specifically, in a time series context, our empirical baseline models (export model and commodity model) can be expressed as the following regressions;

$$LnExp_t = \beta_0 + \beta_1 LnWUI_t + \beta_2 LnCPI_t + \varepsilon_t \tag{4}$$

As is seen, all variables converted into natural logarithms to mitigate the influence of scale and skewness. Additionally, by interpreting the coefficients as elasticities, we can enhance our comprehension of how variations in the variables affect the uncertainty. In this specification, β_0 is the constant parameter of the model, ε is the stochastic error term, and subscript *t* refers to the quarterly time span from 1995Q1 to 2022Q4**.** In the study, we more focused on post-2000 period to be able to see the effects of the important global development such as 2001 U.S.A. Recession and 9/11 attack, Gulf War II, outbreak of SARS, global financial downturn of 2007/2008, Sovereign debt crisis in Europe, Brexit, USA-China Trade Wars, and Coronavirus pandemics. As depicted in Figure 1, the World Uncertainty Index remained relatively stable until the 2000s; however, post-2000 period, it embarked on a significantly volatile path. In the quation (4), *LnEXP* is modelled as dependent variable and indicates quarterly global exports in billions of the nominal US dollars. *LnWUI* denotes unbalanced GDP weighted World Uncertainty Index (WUI) for 142 countries that measures overall uncertainty across the globe and β_1 is parameter of WUI. It is computed by counting the percent of word "uncertain" or its variant. The WUI is subsequently adjusted by being multiplied by 1,000,000. A larger value indicates greater uncertainty, while a smaller value suggests lower uncertainty. Lastly, *LnCPI* is commodity indicators that shows free market commodity price indices, quarterly (2015=100). We retrieved data from UNCTAD Statistics, UN Trade Statistics, World Trade Organization (WTO) statistics and Uncertainty Database.

4. Econometric Framework

In the main analysis, we run the co-integration equation firstly whether a long-term equilibrium relationship exists among the variables. We specify co-integration test that derived from the time series estimation model specified in equation (1). But in this equation, we consider the structural breaks. In time series analysis, it is common for structural breaks to occur. These breaks predominantly arise from economic shocks that create significant uncertainties. If the analysis is conducted using traditional methods such as Engle and Granger (1987) or Johansen (1991) without taking these breaks into account, the results may not be reliable. In this manner, Gregory and Hansen (1996a), Bai and Peron (1998), Hatemi-J (2008) introduced several tests. However, since the researcher does not have prior knowledge about break number, it is necessary to use a test that can provide accurate results. Thus, we employed the residual based Maki co-integration test, (Maki, 2012) which allows for testing long-run relationships under an unknown number of structural breaks. The term *"structural"* model in econometrics was initially described by Hurwicz (1962). A model is considered structural if it allows us to predict the effects of intentional policy actions or changes in the economy or nature. To make such predictions, the model needs to explain how the intervention relates to changes in model elements (parameters, equations, observable or unobservable variables). In this context, the *MAKI* test operates on the assumption that the undisclosed count of breaks in the co-integrating vector is less than or equal to the maximum number of breaks. We consider the following regression models according to different level;

$$y_t = \mu + \sum_{t=1}^{k} \mu_i D_{i,t} + \beta' x_t + u_t \tag{5}$$

$$y_t = \mu + \sum_{t=1}^{k} \mu_i D_{i,t} + \beta' x_t + \sum_{i=1}^{k} B_i' x_t D_{i,t} + u_t \tag{6}$$

$$y_t = \mu + \sum_{t=1}^{k} \mu_i D_{i,t} + \gamma t + \beta' x_t + \sum_{i=1}^{k} B_i' x_t D_{i,t} + u_t \tag{7}$$

$$y_t = \mu + \sum_{t=1}^{k} \mu_i D_{i,t} + \gamma t + \sum_{i=1}^{k} \gamma_i t D_{i,t} \beta' x_t + \sum_{i=1}^{k} B_i' x_t D_{i,t} + u_t \tag{8}$$

Where observation number *t=1,2,….T*. Scalar y_t and *m x 1* vector x_t $(x_{1t}…x_{mt})$ are dependent and independent variables in which both of them are integrated at order one, u_t is the error term. μ, μ_i ,γ, γ_i, $\beta' = (\beta_1….\beta_m)$ and $\beta_i' = (\beta_{i1} …\beta_{im})$ are parameters of the model. T_B is break date, *k* represents break number and *D* denotes break dummy which is 1 if $t > T_{Bi}$ $(i=1, \cdots, k)$ and of 0 otherwise. accordingly, equation 5 is the first model with level shift, model 6 shows level + regime shift, equation 7 stands for level shift with trend and lastly model 8 considers the breaks in level, regime and trend. We have to estimate $\tau_{\min}^{k}$ test statistic by employing the equation 5 to test the cointegration with i breaks $(i \leq k)$;

$$y_t = \mu + \sum_{i=1}^{k} \mu_i D_{i,t} + \beta' x_t + u_t$$
(9)

Than we get OLS residual from the regression error term $\hat{u}_t$ and imply the ADF test for null hypothesis of $\rho=0$ against the alternative hypothesis of $\rho < 0$ in equation 10;

$$\Delta\tilde{u}_t = \rho\tilde{u}_{t-1} + \sum_{j=1}^{p} \propto_j \Delta\tilde{u}_{t-1} + \varepsilon_t$$
(10)

For all possible potential break points, the presence of a single break is investigated under the assumption of $p=0$, and the corresponding t-statistic is calculated. The observation corresponding to the minimum t-statistic in τ_1 represents the break date if $k = 1$. In other words, minimizing the sum of squared residuals will be the first break point for equation 9;

$$SSR_1 = \sum_{t=1}^{T} (y_t - \hat{\mu} - \hat{\mu}_1 D_{1,t} - \hat{\beta}' x_t)^2$$
(11)

In equation 11, the first break point is set as $\hat{b}p_1 = \text{argmin}_{\tau_1^\alpha} SSR_1$.To get second possible break point from the subsamples we use the following regression and error term are as follow;

$$y_t = \mu + \hat{\mu}_1 D_{1,t} + \hat{\mu}_2 D_{2,t} + \beta' x_t + u_t$$
(12)

$$\Delta\tilde{u}_t = \rho\tilde{u}_{t-1} + \sum_{j=1}^{p} \propto_j \Delta\tilde{u}_{t-1} + \varepsilon_t$$
(13)

Than, we need to define sub samples T_2^a and t statistic of the parameters of error term τ_2. We can determine the second break point (bp_2) by minimizing SSR_2 over T_2^a;

$$SSR_2 = \sum_{t=1}^{T} (y_t - \hat{\mu} - \hat{\mu}_1 D_{1,t} - \hat{\mu}_2 D_{2,t} - \hat{\beta}' x_t)^2$$
(14)

According to equation 14, second break point is $\hat{b}p_2 = \text{argmin}_{\tau_2^\alpha} SSR_2$. We applied bp_1 and bp_2 to sub-sample and get the break date. The procedure described in equations 8, 9, and 10 can be iterated until a total of k break points have been estimated.

At the second stage, we estimate the VAR model to identify impulse-response functions (IRFs). If variables are co-integrated, they are move together in the long run and unexpected shocks that arise from one variable may effect another. For this purpose we can employ IRFs. These functions show how each of the uncertainty shocks affect the respective variables in an autoregressive structure. But the variable ordering and structure of the VAR estimation that we used to calculate IRFs could lead to substantial bias. Second, the error terms in a VAR model are generally correlated. There are some inefficiencies with regards to the utilization of exogeneity tests and graphical representations of impulse response functions when drawing policy implications. Furthermore, the results obtained from VAR models are not robust with respect to the number of variables, trends in the series, lag numbers, and the frequency employed in the model. Due to such problems, the structural VAR models (S-VAR) have been developed. This method is based on the principle of imposing constraints on the coefficients of the VAR model while taking into account the economic theory. Second, it allows us to examine the causal relationships between variables. Third, it can be used to examine the impact individual shocks will have on other variables. Unlike conventional VAR models, the estimated parameters can be interpreted as an economic policy implication (Sims, 2002: 3-7). In regards to our study, we can represent standard VAR model in structural form;

$$WUI_t = \emptyset_{11} + \emptyset_{12} WUI_{t-1} + \emptyset_{13} CPI_{t-1} + \emptyset_{14} EXP_{t-1} + \varepsilon_{1t}$$
$$CPI_t = \emptyset_{21} + \emptyset_{22} WUI_{t-1} + \emptyset_{23} CPI_{t-1} + \emptyset_{24} EXP_{t-1} + \varepsilon_{2t}$$
(15)
$$EXP_t = \emptyset_{31} + \emptyset_{32} WUI_{t-1} + \emptyset_{33} CPI_{t-1} + \emptyset_{34} EXP_{t-1} + \varepsilon_{3t}$$

In equation system 15, error terms are white noise with constant variance. We can re-write the standard VAR model as structural way by using endogenous variables of dependent variable as follows;

$WUI_t = \emptyset_{11} + \emptyset_{12}CPI_t + \emptyset_{13}EXP_t + \emptyset_{14}WUI_{t-1} + \emptyset_{15}CPI_{t-1} + \emptyset_{16}EXP_{t-1} + \varepsilon_{1t}$
$CPI_t = \emptyset_{21} + \emptyset_{22}WUI_t + \emptyset_{23}EXP_t + \emptyset_{24}WUI_{t-1} + \emptyset_{25}CPI_{t-1} + \emptyset_{26}EXP_{t-1} + \varepsilon_{2t}$
(16)
$EXP_t = \emptyset_{31} + \emptyset_{32}WUI_t + \emptyset_{33}CPI_t + \emptyset_{34}WUI_{t-1} + \emptyset_{35}CPI_{t-1} + \emptyset_{36}EXP_{t-1} + \varepsilon_{3t}$

It is also assumed that, ε_{1t}, ε_{2t} and ε_{3t} are uncorrelated, which would allow for us to identify the effect of each independent shock. Re-writing the equation set 16 by moving the lags and constants to the other side of the equation, it yields to matrix form;

$$\begin{bmatrix} 1 & \emptyset_{12} & \emptyset_{13} \\ \emptyset_{22} & 1 & \emptyset_{23} \\ \emptyset_{32} & \emptyset_{11} & 1 \end{bmatrix} * \begin{bmatrix} WUI_t \\ CPI_t \\ EXP_t \end{bmatrix} = \begin{bmatrix} \emptyset_{11} \\ \emptyset_{12} \\ \emptyset_{13} \end{bmatrix} + \begin{bmatrix} \emptyset_{14} & \emptyset_{15} & \emptyset_{16} \\ \emptyset_{24} & \emptyset_{25} & \emptyset_{26} \\ \emptyset_{34} & \emptyset_{35} & \emptyset_{36} \end{bmatrix} * \begin{bmatrix} WUI_t \\ CPI_t \\ EXP_t \end{bmatrix} + \begin{bmatrix} \delta_{11} & 0 & 0 \\ 0 & \delta_{22} & 0 \\ 0 & 0 & \delta_{33} \end{bmatrix} * \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}$$
(17)

The primary objective of structural VAR estimation is to achieve orthogonalization of the error terms for conducting impulse response analysis. A constrained structural VAR model establishes the connection among the residuals. This refers to unforeseen shocks as well as structural shocks, both of which are exogenous and devoid of correlation with each other. Thus, ε_{1t}, ε_{2t} and ε_{3t} are unobservable and zero-mean white noise processes and they are serially uncorrelated and independent of each other. Equation 17 allowed us to transform the structural form in equation 15 to reduced form in the vector x_t;

$$Ax_t = A_0 + A_1x_{t-1} + \delta\varepsilon_t \tag{18}$$

"A" is coefficient matrix that shows structural parameters, x_{t-1} is variable matrix, *"δ"* is the variance covariance matrix and ε_t is the error term. We can use equation (18) to estimate structural parameters but firstly we have to impose restriction (set it zero) on coefficient matrix. In this matrix, to observe the effect of a specific variable on the dependent variable, we set the coefficients of other independent variables to zero. This identification structure allows for variables to react contemporaneously to other domestic and external variables (Villaverde & Ramirez, 2010: 304-307). In this study, we aim to estimate the effect of uncertainity and commodity prices. Thus, the coefficient φ_{22} and φ_{32} would describe the contemporaneous effect of a change in uncertainty on both commodity prices and exports markets. Samely, the coefficient φ_{33} would describe the contemporaneous effect of a change in commodity prices on exports. Lastly, we can estimate the effect shock on the variables by plotting a dynamic multipliers on a diagram. To achieve this objective, we can employ impulse response functions (IRFs). Impulse responses to distinct structural shocks are a prevalent method for illustrating the dynamic characteristics of macroeconomic models. To achieve this, we adopt the structural moving average (SMA) representation of the VAR model;

$$y_t = v + \sum_{j=0}^{\infty} \Theta_j \varepsilon_{t-j}$$
(19)

Where Θ_j is independent variable matrix and ε is i.i.d error term. In the matrix form, it yields;

$$\begin{bmatrix} y_{1t+s} \\ y_{2t+s} \\ y_{3t+s} \end{bmatrix} = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} + \begin{bmatrix} \emptyset_{11,0} & \emptyset_{12,0} & \emptyset_{13,0} \\ \emptyset_{21,0} & \emptyset_{22,0} & \emptyset_{23,0} \\ \emptyset_{31,0} & \emptyset_{32,0} & \emptyset_{33,0} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t+s} \\ \varepsilon_{2t+s} \\ \varepsilon_{3t+s} \end{bmatrix} + \cdots + \begin{bmatrix} \emptyset_{11,s} & \emptyset_{11,s} & \emptyset_{11,s} \\ \emptyset_{21,s} & \emptyset_{22,s} & \emptyset_{23,s} \\ \emptyset_{31,s} & \emptyset_{32,s} & \emptyset_{33,s0} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}$$
(20)

The structural dynamic multipliers (impulse responses) can be similarly found as;

$$\frac{\partial y_{1t+s}}{\partial \varepsilon_{1t}} = \emptyset_{11,s} \;\; ; \;\; \frac{\partial y_{1t+s}}{\partial \varepsilon_{2t}} = \emptyset_{12,s} \;\; ; \;\; \frac{\partial y_{2t+s}}{\partial \varepsilon_{1t}} = \emptyset_{21,s} \;\; ; \;\; \frac{\partial y_{2t+s}}{\partial \varepsilon_{2t}} = \emptyset_{22,s}$$
(21)

As seen from equation 21, $\varphi_{ij,s}$ will give the plots of the IRF's foe each j. Generally, the IRF measures the dynamic response of a particular variable to externalor unpredicted shocks keeping all the other variables of the system constant. By this way, we can figure out how unit impulses of the structural shocks at time t impact the other variables during the sample period (Björnland, 2000: 9).

In the last stage of the analysis we examined the causal linkage and it's direction between variables by employing *"Frequency Domain"* approach. We use this method because it has some advantages against "*Time Domain"* approach. The time-varying approach treats time series as a function of time, whereas in the context of frequency domain analysis, the series under consideration is treated as a function of frequency. Hosoya (1991), Breitung and Candelon (2006) stated that traditional time domain tests fail to determine causal relationships for different frequencies. Causal dynamics can yield different responses at different frequencies, and standard Granger causality tests are unable to capture them. They are not sensitive to the different causality relationships exhibited at different frequencies. It assumes that a single Wald statistic holds the causality relationship between variables across the entire frequency distribution. However, the causality relationship can vary depending on the "*short or long term*". A relationship that exists in the short term may disappear in the long term (Görüş & Aydın, 2019: 818). So, instead of time domain tests, the frequency-domain method offers a broader view of the direction and strength of causality in different frequencies. To consider different frequencies, Hosoya (1991), Yao and Hosoya (2000) introduced Wald-type causality test based on spectral density. They defined a two-dimensional vector of the time series $z_t = [x_t; y_t]'$, observed at *t = 1,….T.* z_t is ordered at a finite number of lags *(p)* of standard VAR model;

$$z_t = \propto_1 z_{t-1} + \propto_2 z_{t-2} + \cdots + \propto_p z_{t-p} + \varepsilon_t$$
(22)

we move the error term to the other side of the equation and use the lag operator (L) ;

$$\varepsilon_t = \propto_1 z_{t-1} + \propto_2 z_{t-2} + \cdots + \propto_p z_{t-p} - z_t$$
(23)

$$\varepsilon_t = z_t(I - \alpha_1 L^1 - \alpha_1 L^2 -. \ldots - \alpha_p L^p)$$
(24)

Where, polynomial function $\theta = 1 - \alpha_1 L^1 - \alpha_2 L^2 - \ldots . \alpha_p L^p$ and error term $\varepsilon_t = \theta(L) z_t$. We can denote 2x2 sized autoregressive polynomial function, $\theta(L) = I - \theta_1 L^1 - \theta_2 L^2 - \ldots . - \theta_p L^p$ with $L^k z_t = z_{t-k}$. The ε_t is white noise error term that means *E(εt) = 0* and *E (εε') = Σ* is positively defined sum. We define lower triangular matrix G from cholesky decomposition. *GG'= Σ-1*. Its expected value is $E(\eta_t : \eta_t') = I$ and $\eta_t = G\varepsilon_t$. If this process is stationary, the moving average representation would be as follows;

$$z_t = \Phi(L)\varepsilon_t = \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$
(25)

$$\psi(L)\eta_t = \begin{bmatrix} \psi_{11}(L) & \psi_{12}(L) \\ \psi_{21}(L) & \psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix}$$
(26)

Where $\Phi(L) = \theta(L)^1$ and $\Psi(L) = \Phi(L)G^{-1}$. In this respect the spectral density of x_t is expressed as;

$$f_x(w) = \frac{1}{2\pi}\{|\psi_{11}(e^{iw})|^2 + |\psi_{21}(e^{iw})|^2\}$$
(27)

where w is the frequency of the spectral density. Based on this equation, Gweke (1982) and Hosoya (1991) defined the measure of causality test as;

$$My \to x(w) = \left[log \frac{2\pi fx(w)}{\psi_{11}(e^{-iw})^2}\right] = log \left[log \frac{\psi_{12}(e^{-iw})^2}{\psi_{11}(e^{-iw})^2}\right]$$
(28)

If $|\Psi_{12}(e^{-iw})^2 = 0$ or *log (1)=0* we say that y does not cause x at frequency w. If the elements of t z_t are integrated at order one and indicate co-integration relationship, *θ(L)* has unit root. If we subtract z_t from both side of the equation $\varepsilon_t = \theta(L) z_t$ we have;

$$\Delta z_t = (\theta_1 - I) z_{t-1} + \theta_2 z_{t-2} + \cdots + \theta_p z_{t-p} + \varepsilon_t = \tilde{\theta}(L) z_{t-1} + \varepsilon_t$$
(29)

In this equation autoregressive polynomial function is $\theta(L) = \theta_1 - I + \theta_2 L^1 + \ldots . + \theta_p L^p$. When the $\theta(L)$ or $\tilde{\theta}(L)$ are equal to zero it means y is not the cause of x according to Granger non-causality. In this process we test the null hypothesis of $H_0 : M_{y\to x}(w) = 0$ (it means there is no causality runs from x to y at frequency w) against the alternative $H_1 : M_{y\to x}(w) \neq 0$.

5. Empirical Findings

At this stage, we reported the estimation results. We begin our analysis by assessing the summary statistics of the variables. Table 1 describes data characteristics with logarithmic transformation. The results show that the *LnEXP* has the highest volatility and the *LnCPI* has the lowest. Regarding our variable of interest, the mean value of *LnWIU* is 9,74 while the min. and max. values are 8,62 and 10,9 respectively. Second, standard deviation of *WUI* is larger than other variables proportionally (9,74 / 0,47 = 20.72) according to their mean value. Thirdly, to assess the normality of the dataset. In this frame, we calculate the skewness, kurtosis, and Jarque-Bera statistics.

According to the test statistics, all variables exhibit negative skewness, with each variable's value being close to zero. Also the kurtosis of all the variables are positive and all close to the value of three. According to J-B test, the null hypothesis about normal distribution has not been rejected for *LnCPI* and *LnWUI* at least %5 confidence level (0.07 and 0.82 > 0.05). At the right side, the pair-wise correlation analysis indicates a strong relationship (0.80) between commodity and export variable but moderate relationship between uncertainty and the other two variables as the probability value is 60% and 39% respectively. Additionally, the negative covariance coefficient between LnEXP (dep. variable) and LnWUI indicates that they move in opposite direction. However positive covariance between LnCPI and LnEXP points out a movement in the same direction.

Table 1. Summary Statistics

Statistics	LnCPI	LnEXP	LnWUI	Correlation Matrix			
Mean	4.48	14.84	9.74	-	LnCPI	LnEXP	LnWUI
Median	4.52	15.07	9.79	LnCPI	1	-	-
Maximum	5.06	15.65	10.92	LnEXP	0.80	1	-
Minimum	3.94	13.79	8.62	LnWUI	0.39	-0.60	1
Std. Dev.	0.39	0.77	0.47	**Covariance Matrix**			
Skewness	-0.09	-0.11	-0.03	-	LnCPI	LnEXP	LnWUI
Kurtosis	2.92	2.63	2.72	LnCPI	0.08	-	-
Jarque-Bera	5.54	12.52	0.38	LnEXP	0.14	0.33	-
Prob.	0.07	0.00	0.82	LnWUI	0.05	-0.16	0.21

Than we test for unit root to restrain from any spurious regression results. For this purpose we employed traditional Dickey and Fuller (1981) ADF, Phillips and Perron (1988) PP and Elliot et al. (1996) DF-GLS tests in addition to Carrion-i-Silvestre et al. (2009) multiple approach that takes structural breaks into consideration. The existence of a structural break can cause standard tests to lean towards not rejecting the presence of a unit root. Accordingly, both for the corresponding results of tests are reported in Table 2.

Table 2. Unit Root Tests

Part 1	***Level***			**First Difference**		
Test	LnCPI	LnEXP	LnWUI	LnCPI	LnEXP	LnWUI
ADF	-1.24 (0.65)	-1.24 (0.65)	-3.01 (0.02)	-7.54 (0.00)	-9.67 (0.00)	-15.17 (0.00)
PP	-0.86 (0.79)	-1.24 (0.65)	-4.19 (0.00)	-7.12 (0.00)	-9.64 (0.00)	-26.45 (0.00)
DF-GLS	-1.16	1.1	-2.35	-7.24	-2.77	-14.37

Part 2	**LnCPI**		**LnEXP**		**LnWUI**	
Test	Test Statistics	C.V. (5%)	Test Statatistics	C.V. (5%)	Test Statatistics	C.V. (5%)
PT	10.57	7.59	9.76	7.37	6.03	5.34
MPT	10.28	7.59	9.55	7.37	5.82	5.34
MZA	-26.24	-34.41	-28.12	-35.58	-30.72	-31.4
MSB	0.13	0.12	0.13	0.11	0.12	0.12
MZT	-3.59	-4.14	-3.73	-4.21	-3.91	-3.94
Break Points & Dates	28 (2001Q4) / 67 (2011Q3) / 99 (2019Q3)		23 (2000Q3)/ 55 (2008Q3) / 80 (2014Q2)		22 (2001Q3) /35 (2011Q2) / 73 (2013Q1)	

Note: The probability of rejecting the null hypothesis (unit root) is provided in parenthesis in Part 1. Critical values in DF-GLS are 2.58 1.94 and 1.61 for 1%, 5% and 10% significance level respectively. The maximum lag number used to calculate the long-term variance in the multiple break test is set as four, due to the quarterly frequency.

According to findings from the traditional tests in Part 1, *LnCPI* and *LnEXP* are nonstationary in their levels, as we could not reject the null hypothesis. In contrast, we can reject the null of unit root for LnWUI or we can conclude that it is stationary at both for level and first difference. But according to the structural break tests (breaks in level) in Part 2, all series are integrated at order one. It means the LnWUI is deemed non-stationary in the presence of a structural break due to the sudden and significant jump or unexpected shocks which observed during the full period. With this outcomes, we can proceed and run the co-integration procedure. Because, they can be combined in a way that their linear combination is stationary and have a long run equilibrium. For this purpose we employed Maki co-integration test with multiple breaks.

Table 3. Maki Test

Models	Test Statistics	Break Points and Dates	Critical Values		
			10%	5%	1%
Level shift (Model 0)	-6.511***	60 /2009Q4 88 / 2016Q4 100 / 2019Q4	-5.125	-5.392	-5.943
Level shift with trend (Model 1)	-6.621***	60 / 2009Q4 88 / 2016Q4 99 / 2019Q3	-6.169	-5.691	-5.408
Regime shift (Model 2)	-7.103***	27 / 2001Q3 75 / 2013Q3 100 / 2019Q4	-7.031	-6.516	-6.211
Level, trend & regime shift (Model 3)	-6.620	22 / 2000Q2 29 / 2002Q1 60 / 2009Q4	-7.673	-7.145	-6.873

Notes: *** and ** indicate that the test statistic value lies above the Maki's critical value at 1%, 5% and 10% significance level. Sample size is 112 and the trimming parameter is 0.05. Critical values are provided in Table 1 of Maki (2012).

Table 3 shows the findings of the co-integration test with critical values. We determined the maximum lag length for *p=4* due to quarterly data and set the trimming parameter 0.05. The empirical findings provide co-integration relationship between variables in the model with level shift (we reject the null hypothesis in model 0), level shift with trend (we reject the null hypothesis at 1% confidence level in model 1) and the regime shift (we reject the null hypothesis at 10% level in model 2). But model 3 is statistically insignificant. The results also show three structural break dates. Under the model 0 and the model 1 in which they coincides with 2008-2009 global financial turmoil, trade war between China and USA with the start of the Trump era and the outbreak of Coronavirus-19 pandemic. In addition, the regime shift model indicates a structural break during US recession in 2001 and 9/11 events, US fiscal cliff and sovereign debt crisis in Europe in 2013 and the outbreak of Coronavirus-19 pandemic (see Fig. 1). As seen, military, political or economic events have caused structural breaks in co-integration relationship. However model 3 does not provide any evidence for cointegration among the variables.

After determining the co-integration relationship, we estimate long run coefficients using FMOLS (Fully Modified Ordinary Least Squares), DOLS (Dynamic OLS) and CCR (Cannonical Co-integration Regression) estimators. It is known that traditional OLS estimator would be super-consistent and there would be endogeneity problem (it means disturbance terms are correlated in the model) due to cointegration. Thus, β coefficients from traditional OLS estimation cannot be unbiased. To overcome these problems, it would be better to use asymptotically equivalent and efficient estimators such as FMOLS, DOLS and CCR (Hayakawa & Kurozumi, 2006: 2).

Table 4. Results of the Co-integration Coefficients (D*ependent Variable: LnEXP*)

Estimat	Variable	Coefficient	Std. Error	t-Statistics	Prob.	Adj R2	*Remarks on Coefficients*
OLS	LnCPI	0.48	0.042	11.42***	0.00	0.98	*Significant and Positive*
	LnWUI	-0.06	0.025	-2.48**	0.01		*Significant and Positive*
	C	12.17	0.318	38.26**	0.01		*Significant and Positive*
FMOLS	LnCPI	-0.45	0.075	6.06***	0.00	0.97	*Significant and Positive*
	LnWUI	-0.08	0.044	-1.81*	0.07		*Significant and Negative*

	C	12.45	0.56	22.165	0.00		*Significant and Positive*
DOLS	LnCPI	0.43	0.079	5.44***	0.00		*Significant and Positive*
	LnWUI	-0.09	0.061	-1.47	0.15	0.96	*Significant and Negative*
	C	12.75	0.711	17.93***	0.00		*Significant and Positive*
CCR	LnCPI	-0.42	0.073	5.75***	0.00		*Significant and Positive*
	LnWUI	-0.07	0.041	-1.70*	0.06	0.97	*Significant and Negative*
	C	12.50	0.609	20.52***	0.00		*Significant and Positive*

Note: "*","**", and "***" indicates 1%, 5% and 1% significance level respectively.

In table 4, we report the results according to FMOLS, DOLS and CCR in addition to traditional OLS. They provide both coefficients and long-run elasticies. The coefficients of uncertainty and commodity prices are statistically significant at 10% and 1% confidence level respectively for all estimators. The results show that uncertainty has a negative and significant effect on exports according to the all estimators except DOLS. In other words, LnWUI is negatively correlated with exports under these estimators. Because businesses become cautious and postpone international trade transactions under ubiquitous uncertainties. Firms may delay or reduce their export orders due to concerns about market stability, disrupted supply chains, or heightened risks associated with the uncertainties. Also, the coefficients point out an inelastic relationship. Specifically, a 1% increase in uncertainty would decrease exports by 0.08% for FMOLS, 0.07% for CCR, in addition to 0.09% for DOLS. When we consider commodity price index, it has negative and statistically significant effect on exports for FMOLS and CCR but it has positive and significant effect as for DOLS. Under uncertainty, the demand for financial commodities often rises as businesses and investors seek hedging mechanisms to manage risks. As businesses engage in hedging strategies to mitigate uncertainties, they may require financial instruments such as futures contracts, options, or derivatives, which can drive up demand for these commodities. Thus, increased demand for financial commodities may have a positive effect on exports. The coefficents indicate in-elastic relationship with dependent variable that means a 1% increase in uncertainty would decrease exports by 0.45% for FMOLS, 0.42% for CCR but increase 0.43% for DOLS respectively.

After employing the co-integration test, we can construct the VEC model based on Structural VAR in equation 16 with an optimal lag order to avoid inconsistent results and ineffective estimation from the traditional VAR model. According to the LR, FPE, SC and AIC criteria, in table 5, the optimal lag order of the model is four.

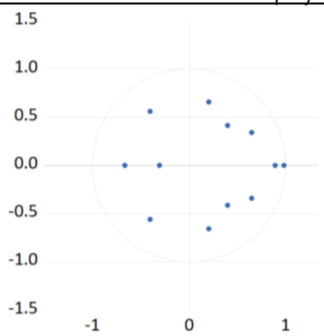
Table 5. Results of the Optimal Lag Order Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	255.11	NA	1.80E-06	-4.712	-4.637	-4.682
1	278.74	45.490	1.37E-06	-4.985	-4.686	-4.864*
2	284.73	11.197	1.45E-06	-4.929	-4.405	-4.716
3	289.73	9.066	1.57E-06	-4.85484	-4.105	-4.551
4	309.52	34.767*	1.28e-06*	-5.056*	-4.082*	-4.661

Table 6 show the robustness of the VAR (4) model. This model ensures stability conditions that means it is free from autocorrelation problem, there is no heterskedasticity and inverse roots are in unit circle.

Table 6. Test for Stability Condition of VAR (4) Model

Inverse roots of AR characteristic polynomial



Serial Correlation LM Test

Lags	LM-Stat.	Prob.
1	11.80	0.22
2	13.51	0.14
3	9.24	0.42
4	21.83	0.09

Res. Heteroscadasticity Test

Chi-Sq.	Df.	Prob.
135.38	120	0.15

According to optimum lag order, table 7 presents the estimation results of the S-VAR model from VAR (4). Unlike to the traditional VAR model, we can interpret these coefficients. In table 7, Matrix A indicates coefficients matrix and Matrix B is error correction variance-covariance matrix. As per equation 16, the effects of *LnWUI* on *LnCPI* (represented by ϕ_{24}) and *LnEXP* (represented by ϕ_{34}) are positive but they are "*not statistically significant*". On the other hand, exports equation shows an opposite relationship between commodity prices and exports volume (represented by ϕ_{35}), and it is statistically significant at the 1% level. It means one-unit increase in the CPI results in a 0.370 unit decrease in exports.

Table 7. Estimation Results of S-VAR Model

	Constant	Coefficients	Standard Error	z-Statistics	Probability
Matrix A					
	ϕ_{24}	0.008	0.016	0.52	0.59
	ϕ_{34}	0.018	0.014	1.26	0.21
	ϕ_{35}	-0.370	0.082	-4.48	0.00
Matrix B					
	b_{11}	0.332	0.022	14.62	0.00
	b_{22}	0.058	0.003	14.62	0.00
	b_{33}	0.049	0.003	14.62	0.00

In Figure 2, we plotted the impulse-response functions (IRF's) using the Cholesky identification with one standard deviation scheme, depicting the unexpected shocks observed from one variable to another. The x axis represents the periods and y axis shows the percentage variation. These functions enable us to depict the temporal trajectory of variables in our model due to a one-unit increase in the current value of one of the errors. We have the main diagonal where it's going to be showing the effects of a shock of the variable to itself. For example shock of *LnWUI* on *LnWUI* is present in the first column of the first figure, but we have more interested in watching the cross results. On that note, the second figure in the first column shows that *LnWUI* shock has decreasing positive impact on commodity markets during the first and half quarter due to increasing demand on financial commodities to need for hedge against uncertainties, than pass through negative zone and finally disappeared after six quarters. The third figure in the same column illustrates the response of exports. We can interpret that uncertainty shock decreases *LnEXP* slightly by 2% during the first and second quarter. After that, the shock has gradually decreased and it reaches steady state level around 7th quarters. In the second column of the figure one indicates that the response of LnWUI to a shock on LnCPI is statistically insignificant. The third figure illustrates that *LnEXP* response with %1 increase initially (these responses may have resulted from demand being brought forward or adjustment delays in response to the shock of uncertainty), followed by a decline of near 2%, and subsequently become insignificant starting from the second quarter. Eventually, they get back to their steady state level after 8 quarters. The figures in column three are completely statistically insignificant so we do not consider them in the analysis.

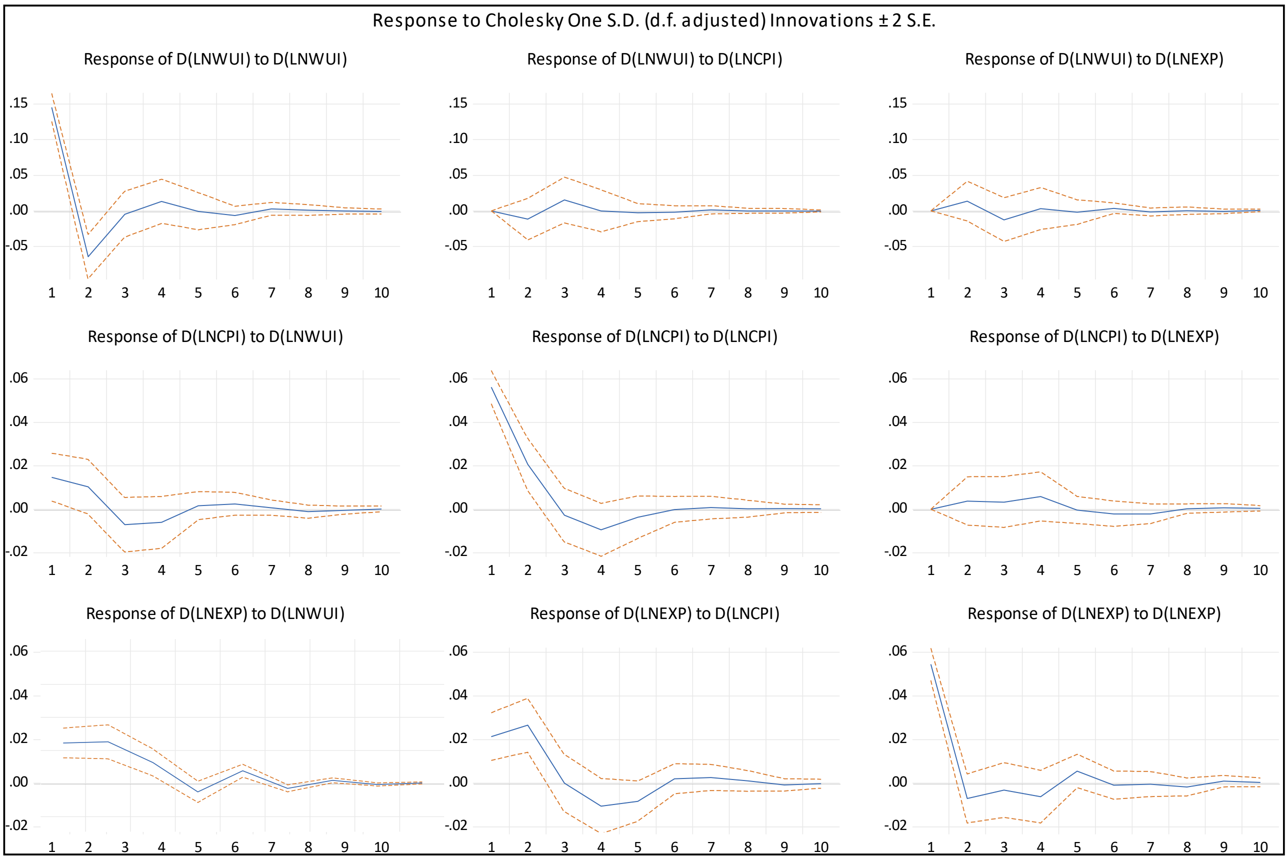


Figure 2. Impulse-Response Functions

After confirming co-integration, we can use a S-VAR model to analyze short and long-run dynamics. This allows us to observe how variables return to their long-run equilibrium path and identify the mechanisms that drive this adjustment process (Bekhet & Yusop: 2009: 160).

Table 8. Results of the VECM

	Long Run Parameters: Dependent Variable LnEXP			
Cointegrating Eq:	LnCPI(-1)	LnWUI(-1)	C	
	-0.853	-1.057	-0.698	
	[-3.01***]	[-5.23***]	[-0.37]	
	Speed of Adjustment			
Error Correction:	D(LnEXP)	D(LnCPI)	D(LnWUI)	
$CointEq_1$	-0.084	0.072	-0.277	
	[-1.71*]	[1.64*]	[3.56***]	
Stability Diagnostics:	LM Test[a]	R^2	White Test[b]	R. Reset Test[c]
	2.74 (0.25)	0.52	1.43 (0.11)	1.27 (0.26)

Note: The numbers in brackets refer to t-statistics and number in pranthesis show probability value. ***, **, and * indicate the null hypothesis to be rejected at 1% (2.58), 5%, (1.96) or 10% (1.64) significance level respectively. a- H_0: No serial correlation versus H_1: Serial correlation of k=2 lag order. b- H_0: Homoskedasticity versus H_1: Heteroskedasticity of unknown form. c- H_0: No misspecification versus H_1: Misspecification in the error term (non-linear combinations of the independent variables explain the dependent variable).

The long-run relationship between the cointegrated variables has now determined through a VECM. The first part of Table 8 shows the long-run dynamics and the second part gives the speed of adjustment to the longrun equilibrium. The long run relationship between variables for one cointegrating vector is $LnEXP = -0.853LnCPI_{t-1} - 1.057LnWUI_{t-1} - 0.698$. From this equation it can be seen that, other things equal, each percentage point increase in commodity price index and uncertainty will cause the decrease of 0.853 and 1.057 percentage points in exports respectively. Also all the coefficients in part 1 were significant at 1% level of significance except constant. Second part provides speed of adjustment within which the model will restore its equilibrium following from any disturbances. The coefficients of the ECT_{-1} with LnEXP and LnWUI are negative and statistically significant indicating that there is a convergence toward lon-run equilibrium. LnEXP remove %8.4 of generated shock and LnWUI corrects it by %27.7 in one quarter. On the other hand, LnCPI adjusts by %7.2 increase as per period to restore long-run equilibrium. To complement this study, we report also the diagnostic tests for serial correlation (LM test), F and R^2 to assess goodness of fit, autoregressive conditional heteroskedasticity (ARCH test), and Ramsey Reset test to check model specifications. These are provided at the bottom of the table. According to results, the observations confirm the stability of the model on the nexus between variables.

At the last section, the results of the causality tests in the frequency domain are presented in Fig. 3. We try to figure out the casual effect of uncertainty induced shock by decomposing the sample period as short and long run for all frequencies, ω, (which are expressed as a fraction of π) in the interval (0, π). In the figure, horizontal axis shows frequencies from long term to short term (left to right). In the test, π value is set as 3.14 unit. Therefore, it is given in the horizontal axis. Vertical axis represents Wald statistics and the dotted lines indicates 5.99 and 4.79 which is the 5% and 10% critical value of a χ2 distribution with 2 df. respectively. We calculated the period length based on the *2π / fx (ω)* formula.

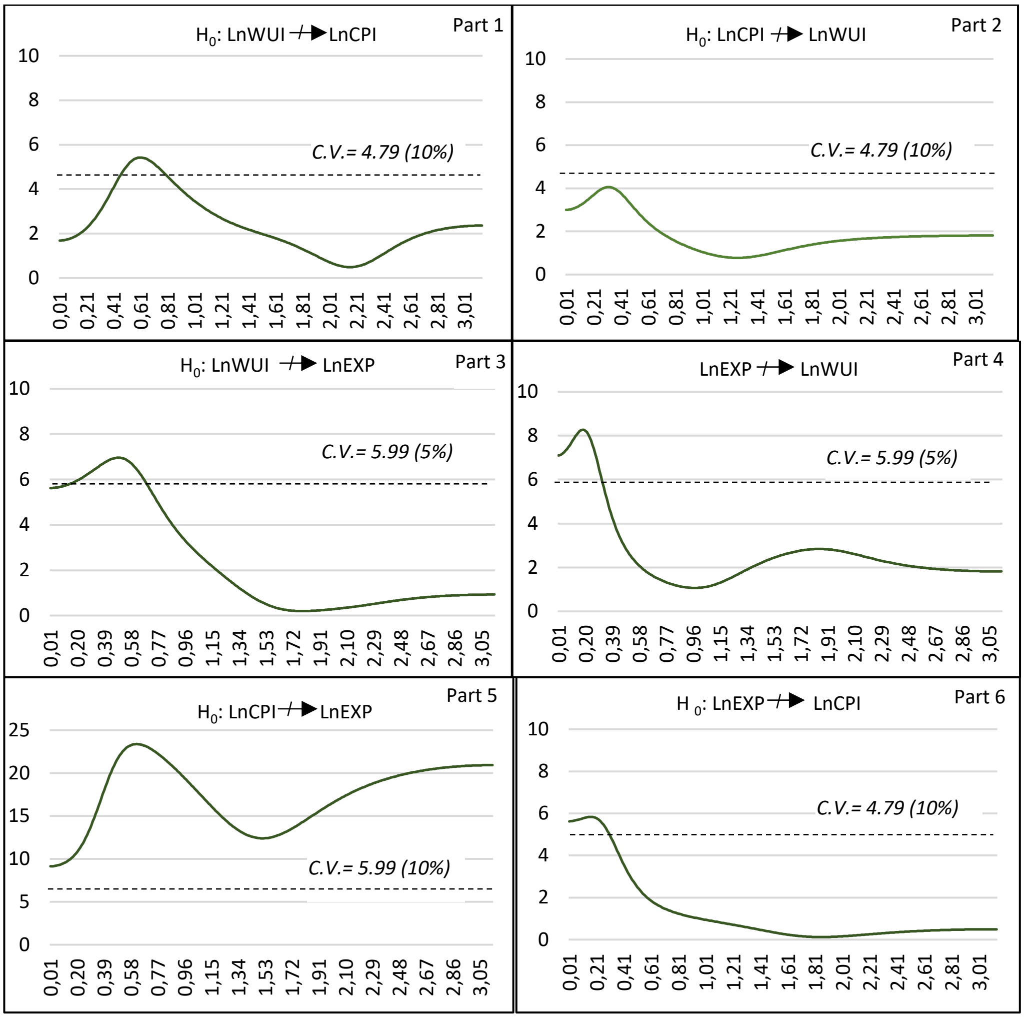


Figure 3. Plots of Wald Statistics from Frequency Domain Test

According to the Wald statistics, we detected one-way causality that runs from uncertainty to commodity prices in the long run as the Wald statistics exceed the dotted line for the frequency of ω ϵ 0.48 to 0.77 (in Part 1) at 10% confidence level. Part 3 and art 4 indicates a two-way causality linkage between exports and uncertainty in the long term at 5% confidence level. However, we couldn't find any evidence for short-term causality. When we consider export and commodity prices in Part 5, it indicates a causality linkage between them that can provide evidence from commodity price index to exports volume for all frequencies. This suggests that commodity prices are connected to exports at both the short and long term. But causality linkage from export to commodity index is only valid for the short range gaps between 0.01 to 0.31 at 10% level. On the contrary, from 0.31 to the rest of the frequencies, we cannot reject the null hypothesis of non-causality. Therefore, by decomposing the causality into different frequencies, our study offers a much deeper understanding of causal relationships.

Conclusion

In this paper, we aim to analyze the dynamic relationship between export and commodity prices under uncertainty shocks, covering the quarterly time span from 1995Q1 to 2022Q4. Initially, we apply the Maki co-integration test (Table 3), allowing for an unknown number of breaks in the investigated variables, to determine the long-run relationship between them. The results suggest a co-integration relationship between variables with multiple breaks. Furthermore, we present the co-integration coefficients from FMOLS, DOLS, and CCR estimators in Table 4. These estimators indicate that uncertainty is negatively correlated with export volume and it is consistent with the estimations from the S-VAR and VEC model in Table 7 and 8. Besides, commodity prices exhibit a positive effect on exports for DOLS but it is negative for FMOLS and CCR. Also, the VEC model shows exports variable is negatively related with independent variables. Lastly, we employ the *"Frequency Domain"* test to examine the causality linkage between variables. This approach provides additional insights compared to traditional "Time Domain" approaches. We present the results in Figure 3, depicting the test statistics along with their 5% and 10% critical values (represented by broken lines) for all frequencies in the interval (0, π). The results proved that uncertainty shocks influencing the commodity prices and export markets in the long term as seen in Part 1 and Part 3. Also there is strong causality linkage from commodity prices to exports volume for all frequencies in Part 5.

Empirical findings from the study present important implications for policy makers to enact better trade and economic policies. As seen from co-integration and causality tests, exports are accompanied by uncertainty. Notably, the impact of uncertainty on exports volume tends to effect negatively, indicative of diminished market confidence and cautious decision-making among exporters. However, the relationship with commodity prices is subject to heterogeneity across studies, with some revealing a positive correlation denoting risk-premium effects, while others highlight a negative nexus attributable to investor risk aversion and the inclination towards safe-haven assets. In this respect, maintaining the stability of economic policies is a prerequisite for the commodity trade and export growth especially for developing and emerging markets. In the global scale, these variables have a complex relationship with each other. Supply and demand dynamics of commodity prices and exports markets can be affected by changes in the global economic and political landscape. The inherent volatility and unpredictability associated with uncertainty, stemming from exogenous shocks and events, have profound implications for both exports volume and commodity prices. These uncertainties can disrupt supply chains, alter demand patterns, and introduce market inefficiencies, exerting a discernible influence on the interconnected dynamics of exports and commodities. For example, if a major oil-producing country experiences political unrest, this can lead to a decrease in supply and an increase in prices. Similarly, a global recession can lead to a decrease in demand for commodities, leading to a decrease in prices. So critical events such as geopolitical disruptions, financial crises, pandemics, and policy shifts often precipitate structural breaks, significantly transforming the relationships between these variables. Noteworthy instances encompass the emergence of the SARS virus, military interventions, and the unprecedented Covid-19 pandemic, all of which have instigated substantial perturbations within the relationship, reshaping market behavior and dynamics.

Exports volume is an important factor as it is closely linked to commodity prices. Higher exports volume can lead to an increase in demand for commodities, which can drive up prices. However, if uncertainty in the global scale increases at the same time, this can offset the positive effects of increased exports volume on commodity prices. For example, if there is political instability in a major trading partner, this can lead to a decrease in demand for exports and lower prices. Finally, uncertainty in the global scale can have a significant impact on both commodity prices and exports volume. When uncertainty increases, investors may become more risk-averse, leading to a decrease in demand for commodities and a decrease in prices. This can also lead to a decrease in exports volume as countries may be hesitant to engage in trade during uncertain times. Overall, it is important to consider all three factors when analyzing the global market. A comprehensive understanding of the relationships between commodity prices, exports volume, and uncertainty can help businesses and investors make informed decisions and navigate the complexities of the global economy. In conclusion, we need to multidimensional and comprehensive policy measures such as enhancing transparency, rising predictability, strengthening risk management tools, diversifying export markets, fostering trade agreements and stability, investing in infrastructure and logistics sectors, implementing risk mitigation programs, promoting research and development expenditure and strengthening crisis management mechanisms.

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