Biofuel Policies and Their Ripple Effects: An Analysis of Vegetable Oil Price Dynamics and Global Consumer Responses

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Abstract

The paper analyzes the price dynamics of Palm, Soybean, Rapeseed, and Sunflower oils due to their extensive uses in the food and fuel sectors and recent considerable price increases. We consider the impact of biofuel policies and consumers' responses. Using Johansen cointegration and VECM, we identify two long-term equilibrium relationships that arise from biofuel policies as our first key finding. In our second insight, an asymmetric AR-EGARCH-DCC model results show heightened volatility and correlation responses to vegetable oil price deviations, especially post-biofuel. Biofuel policies significantly influence shifts in time-varying correlations among these price shocks. Finally, we examine how household consumers in nine countries respond to price shocks with a structural VAR model. The post-biofuel policy era markedly influenced consumer reactions regarding vegetable oil price fluctuations. While most nations show decreased sentiment with price hikes, China and Germany see increased consumer sentiment. South Africa's response varies by oil type. Biofuel policies amplify these effects on consumer confidence across all studied countries. These findings have significant implications for policymakers trying to balance the energy transition and global food security while promoting sustainable growth in vegetable oil demand across both sectors and ensuring price stability for global agricultural commodities.

Keywords: Biofuel policy; Long run; Consumer confidence; transition; EGARCH-DCC; VECM;

JEL Classification: Q41, Q42, Q02, Q18, D12, C32, C58

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1 Introduction

The prices of vegetable oils have significantly risen in recent years due to their amplified use in the food and fuel sectors (Azam et al.; 2020 and Priyati and Tyers; 2016). This upsurge has ignited an intense discussion on the interplay between vegetable oils and energy transition. Advocates suggest biofuels can reduce the adverse effects of fossil fuels, including pollutant emissions, resource depletion, and dependency on unstable foreign suppliers. However, critics argue that leveraging vegetable oils as biofuels could augment disparities within the global food system, benefitting major agribusinesses while disadvantaging small-scale farmers. Undoubtedly, vegetable oils serve as a sustainable, renewable energy source, offering a path to decreased greenhouse gas emissions and a chance to address climate change. Conversely, their use as biofuels raises concerns about food security, as increased demand may reassign land and resources from food production to biofuel production, potentially causing food shortages and a rise in food prices.

This study contributes to the literature on energy transition and the global food security debate. Historically, energy prices have influenced agricultural costs and recently, this interaction has been reversed due to the burgeoning use of agricultural commodities in biofuel production (Peri and Baldi; 2010). This leads to the simultaneous growth of major vegetable oil prices. Similarly, uncertainty related to price changes and volatility might be another concern for consumers, producers, and policymakers. The use of food crops for biofuels, as highlighted by López-Cabrera and Schulz (2016), has raised concerns about biofuels' sustainability and sparked a global food security debate, especially during high food prices (2010-2014) and the 2008 food crisis.[1] Critics link biofuels to increasing food costs and volatility. Motivated by these phenomena, our research seeks to address three fundamental questions largely overlooked by previous studies: the implications of biofuel policies on vegetable oil price comovement and long-run dynamics, the effects of such policies on vegetable oil short-run and long-run volatility and correlation dynamics, and household consumers responses to uncertainties surrounding price changes following biofuel policy implementation. Amid shedding light on these issues, we document several significant findings.

[1] The debate surrounding global food security has been addressed by several researchers (e.g., Tadesse et al.; 2014; Baffes and Haniotis; 2010; Boly and Sanou; 2022; Martínez-Jaramillo et al.; 2019; Subramaniam et al.; 2019, amongst others). They conclude that biofuel policies are one of the culprits, along with other factors causing concerns about global food security. However, as Araujo et al. (2016) outlines, abolishing biofuel policies would not necessarily increase global food security due to the competing uses of crop production, such as feed and industrial use.

Previous studies find mixed results when investigating the interrelationships between agricultural commodities in general and biofuels. For example, Zhang et al. (2009, 2010), Yu et al. (2006), and Owen et al. (1996) indicate no direct long-run price relations between biofuel and agricultural commodity prices, while Peri and Baldi (2010), Paris (2018), and Nazlioglu and Soytas (2012) conclude that long-run relationships exist among the prices of vegetable oils, other commodities, and biofuels. Unlike these studies, we only investigate the biofuel policy implementation's effect on major vegetable oils' price dynamics. Understanding the long-run dynamics of vegetable oil prices is essential for stable and affordable biofuel production, thereby enhancing the sustainability of renewable energy policies (Ebadian et al.; 2020). Our analysis uses the Johansen cointegration approach on Palm, Soybean, Rapeseed, and Sunflower oil price data from January 1990 to August 2021. It reveals no long-term price relationships among these oils before biofuel policy implementation but identifies two such relationships afterward. We argue that these dynamics largely depend on the analyzed period, and biofuel policy implementation tends to induce long-run relationships.

Additionally, we investigate short-run price deviations from the long-run equilibrium using the Vector Error Correction Model (VECM). The results reveal a 3% to 16% correction speed for equilibrium short-run deviations post-biofuel policy implementation. This aligns with the findings of several studies (Chiu et al.; 2016; Yoon; 2022; Natanelov et al.; 2011, Paris; 2018), which found both short-run and long-run relationships among biofuels and agricultural commodities. Moreover, we study the substitution effect among vegetable oils under biofuel policies. This is done by imposing restrictions within the VECM and normalizing the long-run coefficients. Our results indicate a long-run comovement of vegetable oils in the same direction, signifying their high substitution nature due to the biofuel policies. This finding resonates with a substitution effect between biofuels and agricultural commodities highlighted in Kumar et al. (2023). Likewise, Natanelov et al. (2011) point out that the change in energy policy, which stimulated the growth of the energy feedstocks market, has indeed impacted the comovement of crude oil and agricultural commodities.

Our comprehensive analysis delves into these oils' intricate interrelations and sensitivities, examining how changes in one market reverberate throughout the others. Using the Diebold and Yilmaz (2009) method, our study provides a deep understanding of the spillover effects over a span of 100 months, both before and after the onset of biofuel policies. A standout revelation is the pronounced dominance of Palm oil, which exerts a significant influence on the volatility of other vegetable oil markets. Moreover, the aftermath of biofuel policy implementation has only intensified the interdependence of these markets, as evident from the notable increase in the sensitivity of various vegetable oil markets to price shocks. Such intricate interlinkages suggest the potential for rapid cascading effects in response to market shocks, emphasizing the imperative of harmonized risk management strategies.

The surge in demand for vegetable oils as renewable energy resources also introduces questions regarding price volatility (Brahma et al.; 2022 and Pickl; 2019). To address this, we apply an asymmetric AR(1)-EGARCH(1,1)-DCC model to the cointegrated residuals derived from the long-run equilibrium relationships prompted by the biofuel policy implementation. This analysis delves into the extent of unexpected short-run equilibrium price deviations. It examines if the uncertainty surrounding these deviations fluctuates over time while considering the impacts of positive and negative shocks. On the one hand, the EGARCH analysis reveals that unexpected short-term equilibrium price deviations are significantly influenced by ARCH and GARCH effects, to which the vegetable oil market's volatility is highly sensitive. The impacts of these fluctuations on conditional variance have prolonged effects. On the other hand, the DCC model estimates indicate significant ARCH-like coefficients in both full (0.265) and post-biofuel (0.736) subsamples, suggesting that unexpected short-run price deviations in vegetable oil influence the conditional correlation among varying prices, more so in the post-biofuel period compared to the full dataset. Notably, a significant leverage coefficient behaves differently between the samples, implying that biofuel policies have changed the correlation patterns among vegetable oil price shocks. This change may be due to shifts in supply and demand brought about by these policies. Hence, there's a call for a thorough assessment of these policies' effects on market links and risks by stakeholders and policymakers. This finding aligns with the results of Cheng et al. (2023), Tiwari et al. (2022), and Serletis and Xu (2019), who report that the oil market and the biofuel feedstock markets are closely intertwined and that biofuel policies have intensified their linkages in terms of volatility spillovers.

Lastly, the competitive demand for vegetable oils between household consumers and energy oil producers, enhanced by biofuel policies, highlights the need to understand consumer responses to vegetable oil price fluctuations. Insights from studying consumer responses can guide policymakers in devising strategies to mitigate adverse effects on food security, especially in developing countries where food expenditure is a major part of household income (Das and Gundimeda; 2022). Using the consumer confidence index from nine countries as a sentiment measure, we rely on the Diebold and Yilmaz spillover analysis and a structural VAR model to explore how household consumers respond to price shocks in the vegetable oil market. Our findings depict a robust connection between vegetable oil price shocks and shifts in consumer sentiment, especially in the biofuel policy era. Remarkably, the spillover effects exhibit considerable variations across countries, emphasizing the global importance of these market dynamics. The structural VAR model reveals a positive relation between consumer confidence and vegetable oil price shocks in China and Germany. In contrast, a negative correlation is observed in the remaining countries except South Africa. The African nation presents a dichotomy where Palm oil price hikes elevate consumer confidence while Sunflower oil price shocks diminish it.

The remainder of the paper is structured as follows. The next section shows the history of biofuel policies and a literature review of the relationships and volatility of vegetable oils and other commodities. The third section describes the data and preliminary analyses. Section four discusses the short-run and long-run relationships among vegetable oils. Section five highlights the volatility and correlation analyses. Section six presents household consumers' reactions to vegetable oil price uncertainty. The last section discusses policy implications and concludes the article.

2 History of biofuel policies and empirical literature review

We first provide a brief but comprehensive summary of the regulations and targets that have encouraged the growth of the biofuel industry worldwide, as outlined by Sorda et al. (2010). We survey the initial policies implemented between 2000 and 2010 and their sustainable objectives and long-term targets. Next, we present two main strands of literature regarding vegetable oils.

2.1 Global biofuel policies overview

Biofuel policies vary across regions, shaped by specific national needs, goals, and resources. These policies largely aim to increase the use of renewable fuels, reduce greenhouse gas (GHG) emissions, and promote energy independence. This overview summarizes the main biofuel policies across different regions. It provides insight into various mandates and goals set by different countries, from the United States and Canada to China, India, and nations across the African continent.

2.1.1 North and South American biofuel policies

The Energy Policy Act of 2005 introduced the Renewable Fuel Standards in the US, aiming to use 4 billion gallons of renewable fuel in 2006 and increase its share over time. The revised Renewable Fuel Standard, effective in July 2010, was based on the Energy Independence and Security Act of 2007 and required advanced biofuel producers to achieve a 50% reduction in life-cycle greenhouse gas (GHG) emissions, while standard biofuel producers needed a 20% reduction. The Energy Independence and Security Act set a goal of cutting gasoline use by 20% over the next ten years. The 2008 Biomass Program aimed to reduce gasoline use by 30% by 2030 compared to 2004 levels and convert corn-based to cellulosic ethanol[2].

In line with Bill C-33, Canada's Environmental Protection Act mandates a 5% renewable content in gasoline by 2010 and a 2% in diesel fuel and heating oil by 2012 [3] necessitating 1.9 billion liters of ethanol production and 520 million liters of biodiesel production to meet federal mandates. Argentina's Biofuel Law 26.093, effective in February 2007, mandated a 5% biofuel share for gasoline and diesel starting in January 2010, with pricing structures for ethanol and biodiesel established through Resolutions 1294/2008 and 7/2010, respectively. Brazil's National Program on Biodiesel Production and Usage (PNPB), launched in 2005, required a gradual increase in biodiesel blending with petrol-based diesel, reaching 2% between 2008 and 2012, and 5% from 2013 onwards, with a 4% biodiesel blending share mandated since July 1, 2009 (Colares; 2007).

2.1.2 European biofuel policies

With the introduction of the Directive 2001/77/EC [4], the European Union (EU) started putting biofuel-related goals into practice. The EU set a 12% target for gross national energy consumption and a 22.1% share of electricity to be derived from renewables by 2010. In 2003, the EU introduced the Directive 2003/30/EC; [5] the Biofuel Directive established goals for biofuel penetration of 2.5% by the end of 2005 and 5.75% by the end of 2010. Two significant regulations promoting the

[2] DOE, US Department of Energy, Biomass Multi-Year Program Plan (March 2008), available at http://www1.eere.energy.gov/ biomass/pdfs/biomass program mypp.pdf.

[3] The Government of Canada Biofuels Bill Receives Royal Assent, published in EcoAction on 26 June 2008 and available at http://www.ecoaction.gc.ca/newsnouvelles/20080626-eng.cfm

[4] Directive 2001/77/EC of the EU Parliament and of the Council on the promotion of electricity produced from renewable sources in the internal electricity market, 27.9.2001, 2001.

[5] Directive 2003/30/EC of the European Parliament and of the Council on the promotion of the use of biofuels or other renewable fuels for transport, 8.5.2003, 2003

expanded use of renewable energies that continue through 2020 were passed by the EU Commission in 2009 [6]. According to the Renewable Energy Directive (RED), by 2020, all energy used in the EU must be generated from renewable sources for at least 10% of all fuels used in motor vehicles. Along with the RED, a revised Fuel Quality Directive (FQD) was approved, mandating that by 2020, the EU's road transport fuel mix be 6% less carbon intensive than a baseline made of fossil diesel and gasoline. The FQD and the RED both place requirements on biofuels to meet specific sustainability criteria. These cover the reduced greenhouse gas emissions from using the fuels and the different types of land that could be used to produce biofuels.

2.1.3 Asian biofuel policies

In 2001, China published guidelines for bioethanol gasoline and denatured fuel ethanol for automobiles, followed by the ethanol promotion program in 2002. The National Development and Reform Commission (NDRC) launched the State Scheme of Extensive Pilot Projects on Bioethanol Gasoline for Automobiles (SSEPP) in 2004. In 2007, the NDRC introduced the Medium and Long-Term Development Plan for Renewable Energy, which aimed to increase renewable energy to 10% of total primary energy consumption by 2010 and 15% by 2020, with biofuels playing a significant role. Ethanol production was projected to reach 2 million tonnes by 2010 and 10 million by 2020.

In 2003, the Indian government launched the National Mission on Biodiesel (NMB) and the Ethanol Blended Petrol (EBP) programs, followed by the approval of the National Policy on Biofuels in September 2008(Altenburg et al.; 2009). The policy aimed to blend biodiesel and bioethanol with mineral diesel and gasoline at 20% each by 2017. The government guaranteed a Minimum Support Price (MSP) for biodiesel oil seeds and a Minimum Purchase Price (MPP) for biodiesel and ethanol. Malaysia introduced the National Biofuel Policy (BNP) in 2005, which planned for a 5% biodiesel mandate, and the Biofuel Industries Act of April 2007 to regulate and support the biofuel sector. Indonesia mandated minimum biofuel use levels in October 2008, aiming for a 2.5% biodiesel contribution by 2010 and 20% by 2025, while the percentage of ethanol in gasoline was set to be 3% in 2010 and rise to 15% by 2025 (Dillon et al.; 2008).

[6] Directive 2009/28/EC of the EU Parliament and the Council on the promotion of the use of energy from renewable sources, amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC, 23.4.2009, 2009.

2.1.4 African biofuel policies

Biofuel policies in Africa differ across countries, influenced by factors such as energy security, environmental sustainability, rural development, and economic growth. While some countries have established specific policies and targets to promote biofuel production and usage, others have yet to develop comprehensive strategies. The 2007 biofuels strategy in South Africa aimed to reduce dependence on imported fossil fuels and promote rural development through biofuel production.[7] The strategy targeted a 2% biofuel penetration in the national liquid fuel supply by 2013 and 5% by 2020. Ethiopia launched its Biofuels Development Strategy and Action Plan in 2008, requiring petroleum companies to blend 5% biofuels into gasoline and diesel (Berhanu et al.; 2017).

Several other African countries, such as Nigeria, Ghana, Morocco, Kenya, Tanzania, and Mozambique, have developed biofuel promotion policies. Kenya, for instance, set a target to blend 10% ethanol into gasoline by 2022. Tanzania established a biofuels policy, including a regulatory framework for biofuels and incentives for investment in the sector. Mozambique developed a policy promoting ethanol and biodiesel production from sugarcane, jatropha, and other crops (Ohimain; 2013). Nigeria aimed to increase biofuel usage in transportation to 20% by 2020, and Ghana targeted a 10% increase in biofuel usage in the transport sector by 2020 (Duku et al.; 2011).

2.2 Comovement between vegetable oils and other commodities

Studies primarily employ cointegration analysis and estimate the vector error correction model (VECM) to investigate energy and agricultural commodity price interactions. Peri and Baldi (2010), Saghaian (2010), Campiche et al. (2007), and Ciaian and Kancs (2011a,b) all conclude that energy prices drive feedstock price equilibrium levels. Likewise, Serra et al. (2011); Wixson and Katchova (2012), Mallory et al. (2012), Pokrivčák and Rajčaniová (2011), and Busse et al. (2010) similarly find evidence of long-run relationships between energy and agricultural commodity prices. Zhang et al. (2021) use VECM and directed acyclic graph (DAG) models to explore the role of Shanghai crude oil futures in the international oil market, finding that their pricing power is limited but has begun to have a contemporaneous influence in the Asian oil market.

Another strand of the literature explores the links between key vegetable oil prices using other

[7] Republic of South Africa. (2007). Biofuels Industrial Strategy of the Republic of South Africa.

approaches. Azam et al. (2020), deviating from the common VECM, employ wavelet-based analysis to explore these links from 2003 to 2018. Though overall market integration remains weak, they find significant contagion and interdependence among these oils. Post-2015, Palm oil's interaction with other edible oils declined, while Soybean and Rapeseed oils showed increasing interdependence, with Soybean oil emerging as a potential market leader. Cha and Bae (2011) employ a structural vector auto-regression (SVAR) model to examine how rising international oil prices would affect corn pricing and demand in the US. They find that oil price increases boost short-term corn and bioethanol demand, but corn prices stabilize long-term as corn exports and feedstock demand decline. Similarly, McPhail (2011), Wang and McPhail (2014), and Qiu et al. (2012) also use an SVAR model. McPhail (2011) supports bidirectional causality between crude oil and ethanol prices. Zhang et al. (2010), Mallory et al. (2012), and Qiu et al. (2012) prove that fossil and biofuel market shocks do not spill over to agricultural commodity prices.

Other studies investigate the long-run effects of oil prices on agricultural commodity prices while considering the impact of biofuel production. Based on the estimation of nonlinear, cointegrating regime-switching dynamics, Paris (2018) shows that the development of biofuels has increased the oil price effect on agricultural commodity prices. Conversely, Yu et al. (2006) examine the long-term interdependence of primary edible oils and the interaction between vegetable and crude oil prices using time-series techniques and DAGs. Their study involves Soybean, Sunflower, Rapeseed, Palm oils, and the World's average crude oil price. They discover a long-term cointegration among these five oil prices, with Soybean oil dominating in the long run and crude oil having an insignificant impact on edible oil prices. Esposti (2021) proposes a new approach using a common latent factor hypothesis and a FAVAR-MGARCH model to study the long-run trends of resource and commodity prices. The study finds a minor increase in long-term nominal prices over recent decades, paralleled by stabilizing long-term real prices after a consistent decline.

2.3 Volatility transmission among vegetable oils and other commodities

Studies also examined the connectedness and volatility transmission among crude oil and agricultural commodities. Kang et al. (2019) find that vegetable oils are the most influential price volatility source for other commodities and crude oil. Their study also reveals a bi-directional and asymmetric connectedness between oil and agricultural commodity markets at various frequency bands. Similarly, Naeem et al. (2022) study the nexus between oil shocks and agricultural commodities, documenting stronger intra and weaker inter-connectedness with time-varying spillovers in the short and long run. They provide valuable insights for policymakers and investors. On the other hand, Hasanov et al. (2016) focus on the impact of crude oil price volatility on the price changes of major edible oils, which serve as the main feedstock for the biodiesel industry in the European Union. They find that crude oil price uncertainty significantly affects the price returns of major feedstock edible oils and that the size of the impacts is mainly commodity-specific.

Meanwhile, the influence of external factors on commodity prices and volatility risk has also been a focus in the literature. Guo and Tanaka (2022) use a Time-Varying Parameter Vector Auto-Regression (TVP-VAR) to study the dynamic interplay of African food prices, U.S. biofuel production, global energy and food prices, and financial speculation. They find that U.S. biofuel production and commodity speculation considerably impact African food prices, with global events like the dot-com bubble, global commodity boom, and the COVID-19 pandemic amplifying the interconnection with cross-border factors. Likewise, Yang and Karali (2022) investigate the existence of volatility transmission between soybean and their products, spanning the U.S.-China supply chain. Their study reveals the existence of volatility spillovers between the two markets. In particular, the volatility responses in Chinese soybean product markets to innovation from the U.S. soybean have weakened after 2009. They also study the volatility reactions to two significant economic events: the 2008 financial crisis and the 2018 U.S.-China trade dispute. Evidence supports volatility reactions only during the financial crisis.

Another body of literature explores the price and volatility risk between energy and agricultural commodities, volatility transmission between spot and futures markets, and market integration and volatility drivers. López-Cabrera and Schulz (2016) examine the volatility and correlation risk structure between energy and agricultural commodities in Germany, employing GARCH-DCC and multivariate volatility models to analyze short and long-run links. Malhotra and Sharma (2016) investigate the volatility transmission process between spot and futures markets in India using a bivariate GARCH model, finding that an unexpected increase in futures trading activity destabilizes spot price volatility in three out of four commodities studied. Zhang et al. (2009) study the integration of domestic and foreign markets for major oilseeds and edible oils using the Johansen cointegration test and a GARCH model, discovering that interconnected markets convey volatility from one to another, emphasizing the importance of understanding pricing dynamics for effective policies. Finally, Brümmer et al. (2016) analyze the volatility drivers and spillover effects of oilseeds and vegetable oils markets using a VAR model and a standard GARCH model, finding that spillover effects are evident and volatility drivers are market-specific, implying that policies aimed at lowering volatility must be tailored to the market in question.

While previous studies have made significant strides in understanding the interplay between energy, agricultural commodity prices, and biofuel production, they still need to analyze the effects of biofuel policy implementation on vegetable oil price dynamics. This gap, which this article aims to fill, is a crucial area of exploration given the significant role vegetable oils play in biofuel production and their diverse end-use nature. In addition, this research delves into an area that has often been overlooked: the impact of price changes and biofuel policy implementation on household consumer behaviors. This is a critical issue to understand as it affects individual household decision-making and could have broader implications for economic policy. Hence, by exploring these two areas, our study hopes to contribute significantly to the existing body of knowledge and provide a more nuanced understanding of the dynamics at play.

3 Data and preliminary analyses

We analyze volatility and long-term dynamics of major vegetable oils (Palm, Soybean, Rapeseed, Sunflower) using monthly price data from January 1990 to August 2021 from the Federal Reserve Economic Data (FRED). These benchmark prices, representing the global market, are denoted in nominal U.S. dollars per metric tonne. Additionally, we examine consumer reactions to price shocks and biofuel policy shifts using the monthly consumer confidence indexes of nine representative countries (U.S., China, U.K., Australia, South Africa, France, Germany, Japan, and New Zealand), sourced from the OECD. The indicator gauges future consumption and savings trends based on households' economic expectations and sentiment, with values above or below 100 reflecting positive or negative economic outlooks, respectively.

We begin our analyses by visually examining the time series of the vegetable oil prices, which logarithmic transformations are displayed in Panel A of Figure 1. Interestingly, the figure shows episodes of high vegetable oil prices that have predominantly marked supply-demand imbalances, policy shifts, and global crises. In 2007-2008, a substantial price surge was due to a global food price crisis, triggered by increased biofuel demand, particularly in the U.S. and Europe, which propelled crops such as soy, corn, and palm oil, crucial for vegetable oil production. Another pronounced spike was witnessed in 2011-2012, caused by a mix of biofuel demand, adverse weather conditions affecting yield, and alterations in trade policies. A more recent example was during the COVID-19 pandemic in 2020. Supply chain disruptions due to global lockdowns and changes in consumer behavior and dietary patterns led to significant price escalations.

In the realm of vegetable oil price dynamics, a striking phenomenon emerges in Panel A of Figure 1, where the four major vegetable oil price series exhibit exceptional persistence. Despite occasional brief deviations, these series move synchronously, showcasing remarkable coherence over time. This coherence, accompanied by substantial persistence, prompts us to delve into unit-root tests to discern the presence of non-stationarity. The outcomes of two distinct tests - ADF, and PP - are presented in Table 1 for the entire sample and pre- and post-biofuel subsamples.[8] Corresponding unit-root test results for the logarithmic transformations of country consumer confidence indexes are featured in the right panel of Table 1. Notably, all tests converge to the conclusion that Palm, Soybean, Rapeseed, and Sunflower oil prices and the consumer confidence indexes of seven countries demonstrate non-stationarity. Notably, the PP test does not reject the presence of a unit root for any country's consumer confidence index. The transformation to first-difference series renders them stationary, mirrored by their summary statistics in the remaining cells of Table 1.

Upon considering the full sample, an enlightening comparative analysis of price changes' descriptive statistics unfolds for the four major vegetable oils. Striking parallels emerge, with the most pronounced values evident in Palm and Sunflower oils. For instance, Palm oil's average price change hovers at 0.4%, slightly surpassing the 0.3% registered by the other three major vegetable oils. Indicative of their shared trend, these oils exhibit high volatility, portrayed by their sizable standard deviations and the substantial range between the 5th and 95th percentiles. Specifically, the standard deviation spans from 5.4% for Soybean to 7.2% for Palm and Sunflower oils. While the 5th percentile wavers between -8.3% for Rapeseed oil and -11.6% for Palm oil, the 95th percentile fluctuates from 8.5% for Sunflower oil to a notable 11.8% for Palm oil. Divergent skewness values emerge: negative for Palm and Soybean oils (-0.241 and -0.137, respectively) and positive for

[8] ADF stands for the Dickey and Fuller (1979,1981)'s test, and PP for the Phillips and Perron (1988)'s test.

Rapeseed and Sunflower oils (0.501 and 2.383, respectively). Notably, vegetable oil prices exhibit excess kurtosis, spanning from 1.192 for Soybean oil to an extraordinary 26.931 for Sunflower oil.

Dividing the entire sample into pre- and post-biofuel periods brings forth further insights. In the post-biofuel phase, Palm oil's average price change triples to 0.6%, with an increase in standard deviation from 6.8% to 7.6%. Meanwhile, the post-biofuel to pre-biofuel ratio for Soybean oil's average price change is six, with relatively stable standard deviations of 5.2% and 5.6% across both periods. In contrast, Rapeseed oil maintains a consistent average price change between the two sub-periods but experiences a substantial drop in standard deviation from 6.4% pre-biofuel to 5.0% post-biofuel. For Sunflower oil, post-biofuel average price change witnesses a 50% reduction compared to its pre-biofuel counterpart, while the standard deviation sharply escalates from 5.6% pre-biofuel to 8.6% post-biofuel.

While exploring the landscape of economic indicators, a compelling contrast emerges between the intricate dynamics of vegetable oil prices and the distinct behavior of consumer confidence indexes. Panel B of Figure 1 presents the logarithmic values of these indexes across selected countries, representing diverse geographical regions. This selection provides unique insights into the varying economic contexts of these nations.

Upon visual inspection, a notable absence of any discernible time trend characterizes these country's confidence indexes. This observation gains further support as the virtually zero averages of their first-difference series remain consistent across all considered countries, regardless of the sample period. Significantly, the standard deviations of these consumer confidence indexes remain notably low, oscillating between 0.2% and 0.4% across different sample periods. This starkly contrasts the substantial standard deviations witnessed in the realm of vegetable oil price changes, ranging between 5.0% and 8.6%, thereby suggesting a considerable difference in volatility.

These descriptive statistics vividly illuminate the contrasting nature of volatility between vegetable oil prices and consumer confidence indexes on a global scale. Moreover, a deeper examination of specific countries' consumer reactions unveils interesting trends. For instance, consumer reactions in the US, UK, Japan, and China exhibit negative skewness across all sample periods. However, within this pattern, US and Japan's post-biofuel negative skewness values of -0.881 and -1.127 stand out compared to their pre-biofuel values of -0.234 and -0.269, respectively. Conversely, the UK and China exhibit negative skewness values with higher magnitudes before the biofuel period, which shift to more moderate levels post-biofuel.

Australia and South Africa, on the other hand, display positive consumer confidence index skewness throughout various sample periods, with the latter exhibiting a more consistent skewness value around 0.600 across all periods. Furthermore, an interesting observation arises from the excess kurtosis values: all country consumer indexes, except those of China and France, experience a substantial increase in excess kurtosis during the post-biofuel period.

This comprehensive examination underscores the intriguing interplay between the relatively stable realm of global consumer confidence indexes and the dynamic and volatile landscape of vegetable oil prices. It emphasizes the need to consider these varied economic indicators holistically to understand the broader economic picture comprehensively.

Panel A of Table 2 presents the correlation values between major vegetable oil price changes. Interestingly, all correlation coefficients are positive, indicating that all variables move in the same direction. A standout observation is the correlation between Palm and Soybean oils, which was 62% in the pre-biofuel era but rose to 77% post-biofuel. Conversely, Sunflower oil's price variation consistently ranks the least correlated with other oils across all sample periods. After the biofuel policy implementation, a general strengthening in correlations was observed. However, an exception was found between Sunflower oil and Palm and Soybean oils, where the correlation decreased.

When we shift our focus to the correlation between vegetable oil prices and country consumer confidence indexes, the landscape varies. Before the biofuel policy, these correlations were not globally significant. However, in the post-biofuel era, stark correlations emerged in specific countries: the US, Germany, Japan, and New Zealand. While the first three countries show a positive correlation, New Zealand exhibits a negative one. This discrepancy underscores the inherent heterogeneity in the relationships based on the country.

Further diving into the interpretation and the avenues for subsequent analysis, the correlations paint a picture of a potential long-term link between vegetable oil prices and consumer confidence indexes. Notably, these correlations primarily capture the long-term comovement between the two variables and are silent on their short-term fluctuations. An intriguing exploration lies ahead to gauge the consumer confidence index's instantaneous response to shifts in vegetable oil prices. Given the observed similarities in directional movements across vegetable oil prices, we deemed it prudent to conduct a Principal Component Analysis (PCA). This analysis aimed to unveil shared underlying factors and evaluate the biofuel policy's imprint on these co-movements.

Panel B of Table 2 casts light on the results gleaned from the PCA. The first principal component is dominant for both the comprehensive sample and its post-biofuel counterpart, accounting for 57.0% and 63.0% of the total variance, respectively. Moreover, each type of vegetable oil has a meaningful contribution to this dominant component, with an average loading hovering around 0.5. This suggests that this primary component aptly captures the overall oil price co-movement. However, the pre-biofuel subsample paints a slightly different picture, where the first component encapsulates a lesser 55.8% of the total variance. Yet, when we combine the contributions of the first three principal components, they collectively account for 91.1% of the total variance. This figure is below the 93.5% and 94.9% observed for the comprehensive and post-biofuel samples. Drawing from these patterns, one can infer a correlation between the introduction of the biofuel policy and heightened integration within the vegetable oil market. This heightened integration underscores the notion of one vegetable oil being a potential substitute for another, a trait that seemingly has gained prominence after the biofuel policy's rollout.

4 Long- and short-run relationships among vegetable oil prices

4.1 Cointegration analysis of vegetable oil prices

Engle and Granger (1987) observed that a stationary series could be formed through a linear combination of two or more non-stationary series, a situation termed cointegration. This concept becomes relevant in examining vegetable oil prices, which show simultaneous movement in a uniform direction (see Figure 1). The presence of a unit root in each series further necessitates the investigation of long-run equilibrium relationships. Johansen (1995)'s cointegration test is an optimal empirical analysis tool. We apply this test to the logarithmic prices of the four vegetable oils across our entire sample. This approach is underpinned by a vector autoregressive (VAR) model and leverages the rank of the coefficient matrix. Specifically, our analysis deploys the Trace test, wherein the null hypothesis proposes the number of distinct cointegrating vectors to be less than or equal to r, contesting an alternative hypothesis suggesting more than r vectors.

To ensure thorough testing, we utilize the 1% critical values for the Johansen cointegration Trace test instead of the traditional 5% critical values. This rigorous approach reduces the likelihood of a Type I error, which is falsely rejecting the null hypothesis of no cointegration among the prices. Using the 1% critical values, we can be more confident that the price series are truly cointegrated. Our short time series could result in misleading outcomes, so a stricter critical value provides greater confidence in the cointegration relationships identified. Johansen's test can overestimate the number of cointegrating relationships, particularly in small samples (Reimers; 1992; Cheung and Lai; 1993). However, using the 1% critical value makes the test less susceptible to this bias. Finally, our decision to adopt a 1% critical value demonstrates the robustness of our findings. If the cointegrating relationships hold at this level, it provides strong evidence to support our results.

A positive Trace test outcome, indicating one or more cointegrating vectors, will confirm a long-run equilibrium relationship among the series. For a more nuanced understanding, we further segregate the dataset into pre- and post-biofuel periods, subjecting each to the same cointegration test. Our results (refer to Table 3) reveal fascinating insights. The Trace test statistics surpass critical values for the full sample and the post-biofuel subset, only for the first two null hypotheses, signifying two distinct long-term relationships among vegetable oils, both overall and post-biofuel policy implementation. However, the pre-biofuel subsample, as shown in the middle panel of the table, indicates otherwise. Here, the Trace test statistic of 40.74 falls short of the critical value of 54.68, thus failing to reject the null hypothesis of zero cointegrating vectors. Consequently, it can be inferred that the introduction of the biofuel policy has triggered long-run relationships among vegetable oils, which were absent before its implementation.

Biofuel policies promoting production and use can intertwine agricultural markets, like palm, soybean, rapeseed, and sunflower oils, with energy markets, altering traditional pricing models primarily driven by food-related demand, supply dynamics, and crop-specific production costs. The new shared demand from biofuel production can interlink these oil prices via the substitution effect, where if one oil's price rises, producers may switch to a different oil, thus inflating its demand and price. Moreover, due to their substitutive nature with fossil fuels, biofuel prices can be influenced by the latter's price fluctuations, forming an energy market linkage and establishing a long-term pricing relationship between these oils. Lastly, biofuel policies could foster the cultivation expansion of these oil crops, gradually aligning their prices due to similar production costs, technological evolution, and climate impacts, despite individual oil prices being influenced by other factors. Thus, biofuel policies introduce new shared demand and supply sources, creating potential long-term price relations among these oils.

Early studies exploring long-run relationships have reported negligible or no cointegration among vegetable oil prices. For example, Owen et al. (1996) found no indication of cointegration across five major internationally traded vegetable oils from 1971 to 1993. Similarly, Yu et al. (2006) detected only a single long-run cointegration link among five vegetable oil prices using data from 1999 to 2006. Notably, most biofuel policies were initiated post-2000, leading us to question the 2006 cut-off. To address this and validate our results, we conducted the Johansen cointegration test again, adjusting the cut-off years to 2003 and 2008 respectively. Despite this modification, our findings remain consistently in line with the original conclusions.

4.2 Short-term dynamics of vegetable oil prices

Despite their existence, long-term equilibrium relationships between agricultural oil prices don't remain constant over time, similar to any cointegrated variables. Deviations from this equilibrium frequently occur and are corrected so that price fluctuations are non-divergent, thus affecting the predictability of vegetable oil prices and their short-term dynamics.

The Vector Error-Correction Model (VECM) is an ideal tool for empirically analyzing how short-term equilibrium deviations impact joint price dynamics. We specify this model as follows:

$$\Delta y_t = \lambda_0 + \lambda_1 w_{1,t-1} + \lambda_2 w_{2,t-1} + A_1 \Delta y_{t-1} + \ldots + A_k \Delta y_{t-k} + v_t \tag{1}$$

where $y_t = (\mathrm{LPMO}_t, \mathrm{LSBO}_t, \mathrm{LRSO}_t, \mathrm{LSFO}_t)'$ denotes the vector of log vegetable oil prices, λ_0 is the 4-dimensional vector of intercepts, $w_{1,t-1}$, and $w_{2,t-1}$ are the two error-correction terms or cointegrated residuals whose the corresponding 4-dimensional vectors of adjustment rate parameters are λ_1, and λ_2, respectively. The 4×4 matrices $A_i,\ i = 1, \ldots, k$, are the auto-regressive coefficients, where k is the number of lags, and v_t is the 4×1 vector of error terms.

The two error-correction terms are specified as follows:

$$w_{i,t} = \alpha_{0i} + \alpha_{1i}\mathrm{LPMO}_t + \alpha_{2i}\mathrm{LSBO}_t, + \alpha_{3i}\mathrm{LRSO}_t + \alpha_{4i}\mathrm{LSFO}_t \tag{2}$$

and the coefficient of the target variable in each error-correction term is normalized to one, i.e.,

$\alpha_{11} = \alpha_{22} = 1$, and zero in the other equation, i.e., $\alpha_{12} = \alpha_{21} = 0$. Notice that the duo of leading vegetable oils (Palm, and Soybean) are used as the target variables in the long-run specification of the VECM. Therefore, $w_{1,t}$ measures short-run deviations of Palm oil price from its long-run equilibrium with Rapeseed and Sunflower oil prices. Likewise, $w_{2,t}$ measures short-run equilibrium deviations of Soybean from Rapeseed and Sunflower oil prices. We subsequently analyze fluctuating uncertainty around these vegetable oil short-term equilibrium price deviations and their dynamic correlations. Obviously, the VECM estimation only makes sense for the full sample and the post-biofuel subsample where data evidence long-run relationships among vegetable oil prices.[9]

Table 4 reports VECM results given the specifications (1) and (2). Equation (2) implies that the long-term percentage price increases in Palm and Soybean oils can be represented as weighted sums of their Rapeseed and Sunflower counterparts. These long-run coefficients are displayed in Panel A. In the full sample, Palm oil's percentage price increase is influenced significantly by weights of 0.928 for Rapeseed oil and an insignificant 0.049 for Sunflower oil. Similarly, for Soybean oil's percentage price increase, the weights are statistically insignificant at -0.140 for Rapeseed oil and significant at 1.054 for Sunflower oil. In the post-biofuel subsample, the interpretation remains consistent, but the importance of individual oils shifts. Sunflower oil price significantly impacts Palm oil's equilibrium price, while Rapeseed oil plays a more significant role in determining Soybean oil's price. Formally, the post-biofuel estimates show that for Palm oil's percentage price increase, the weights are insignificant at 0.331 for Rapeseed oil and significant at 0.793 for Sunflower oil. For Soybean oil's percentage price increase, the weights are significant at 0.685 for Rapeseed oil and 0.593 for Sunflower oil. These significant weights demonstrate that vegetable oils can be readily substituted for each other since their prices move together in the long run. Additionally, based on post-biofuel estimates, a high correlation of 0.846 between the two error correction terms further confirms this substitutability, compared to the lower correlation of 0.407 in the full sample.[10] These findings suggest that biofuel policies have reinforced the substitutability of vegetable oils.

The remaining coefficient estimates from the VECM provide valuable insights into the short-run equilibrium price deviations and the dynamics of Palm, Soybean, Rapeseed, and Sunflower oil

[9]We analyze short-run relationships among vegetable oils using a standard VAR model before the implementation of the biofuel policy since the Johansen cointegration test result shows no long-run relationship during the period. Table A1 in the external appendix presents the results of the standard VAR model. The findings show a strong relationship between vegetable oil prices in a given period and one period before.

[10]See Table A2 in the external appendix.

prices. When a deviation occurs at a given period, the subsequent price movements indicate a tendency to revert to equilibrium. In our full sample estimates, we find that if Palm oil is currently trading above its equilibrium value, as determined by Rapeseed and Sunflower oils, denoted by a positive value of w_1, approximately 8.5% of this price gap negatively impacts the expected price change of Palm oil in the next period. This contribution directly leads to adjusting Palm oil's price towards its long-term equilibrium value.

Similarly, if Soybean oil is above its equilibrium value based on Rapeseed and Sunflower oils, denoted by a positive value of w_2, then around 3.3% and 9.2% of this gap positively impact the expected price changes of Palm and Sunflower oils in the next period, respectively. These indirect effects help bring the price of Soybean oil closer to its long-term equilibrium value.

The patterns remain consistent when examining the post-biofuel subsample estimates. In this case, approximately 9.1% and 10.2% of Palm oil's current short-term equilibrium price deviations significantly impact the expected price changes of Soybean and Sunflower oils in the next period, respectively, further contributing to the partial restoration of Palm oil's price disequilibrium. Additionally, 16.1% of the current short-term equilibrium price deviations of Soybean oil significantly impact the expected price change of Palm oil in the next period, indirectly contributing to partially restoring Soybean oil's price disequilibrium.

These indirect effects, where the movements of other agricultural commodity prices participate in correcting each other's disequilibrium, further support the argument of substitutability among vegetable oils. Notably, the impact of biofuel policies on vegetable oil prices is also evident through the greater predictability of price changes observed in the post-biofuel period. For instance, compared to the total sample, the R-squared values increase from approximately 17.5% to 24% and 26% for Rapeseed and Sunflower oils, respectively.

It is important to highlight that the price changes of Palm, Soybean, and Sunflower oils are positively predicted by their previous values, and these coefficients are statistically significant at the 1% level for both sample periods. Additionally, the previous price change of Soybean oil positively predicts the current price of Rapeseed oil, which is consistent with the pre-biofuel results.

Our approach aligns with similar studies utilizing the VECM to investigate various agricultural commodities' short-run and long-run dynamics, including vegetable and energy oils. However, it's important to acknowledge that the results are specific to the asset menu and the sample period under consideration (López-Cabrera and Schulz; 2016; Lajdová et al.; 2017; Siami-Namini; 2019).

Overall, the VECM analysis provides valuable insights into three key aspects: the interconnections between vegetable oil prices, the mechanisms involved in the recovery of long-term equilibrium from short-term deviations, and the influence of biofuel policies on these market dynamics.

In our study, we sought to measure how each of the four major vegetable oil markets impacts the others. We used the Diebold and Yilmaz method to quantify the spillover effects, examining how shocks in each vegetable oil market predict changes in the others over 100 months. Our analysis was carried out for the entire sample and subsamples before and after implementing biofuel policies.

Our findings, outlined in Panel A of Table 5, reveal a strong spillover effect from Palm oil to other vegetable oil markets. In the full sample, the shocks in the Palm oil market accounted for a significant 104.31% of the total 212.27% forecast error variance coming from all other vegetable oil markets. The impact of Palm oil shocks became even more pronounced in the period following the implementation of biofuel policies, contributing 204.76% out of 277.88%, a marked increase from the pre-biofuel period, where Palm oil's contribution was 73.57% out of 104.91%.

Moreover, we observed an increase in the sensitivity of Soybean, Rapeseed, and Sunflower oil markets to shocks from other vegetable oils in the post-biofuel policy period. In the full sample, the contribution of other vegetable oils to the forecast error variance was 40.37% for Soybean, 55.24% for Rapeseed, and 80.24% for Sunflower. However, in the post-biofuel period, these values more than doubled to 88.22%, 91.86%, and 85.69%, respectively, compared to their pre-biofuel contributions of 41.58%, 20.78%, and 38.48%.

Our study unveils significant economic implications, notably the heightened comovement, and substitutability among Palm, Soybean, Rapeseed, and Sunflower oil prices, largely driven by the implementation of biofuel policies. This close interrelation suggests that shocks in one market could quickly proliferate through others (Mallory et al. 2012; Busse et al. 2010), emphasizing the necessity for coordinated risk management strategies. Given Palm oil's dominance in the market, its price volatility could notably influence other vegetable oils, thus affecting the overall market stability. Therefore, policymakers should consider these market interdependencies and the impact of biofuel policies on vegetable oil price dynamics when formulating future regulations and interventions.

5 Volatility analysis of vegetable oils

To analyze the volatility of vegetable oils, we fit an exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model to each cointegrated residual from equation (2). Figure 2 displays the plots of cointegrated residuals ($w_{1,t}$, and $w_{2,t}$) and evidence periods of high and low volatility. Formally, we specify the following AR(1)-EGARCH(1,1) for the cointegrated residuals:

$$\begin{aligned} w_{i,t} &= \phi_{0i} + \phi_{1i} w_{1i,t-1} + u_{i,t} \\ u_{i,t} &= \sigma_{i,t}\epsilon_{i,t} \quad \text{with} \quad \epsilon_{i,t} \sim \mathcal{N}(0,1) \\ \ln \sigma^2_{i,t} &= \omega_i + \alpha_i \left(\left|\epsilon_{i,t-1}\right| - \mathbb{E}\left[\left|\epsilon_{i,t-1}\right|\right] \right) + \gamma_i \epsilon_{i,t-1} + \beta_i \ln \sigma^2_{i,t-1} \end{aligned} \tag{3}$$

where the conditional variance recursion is due to Nelson (1991). The parameters α_i and β_i are the ARCH and GARCH coefficients, respectively, and the parameter γ_i captures the leverage effect. Positive values of γ_i would imply that negative short-term price deviations increase the conditional volatility by a larger magnitude than positive innovations.

The EGARCH specification (3) analyzes how large unexpected short-term vegetable oil equilibrium price deviations are, and if the size of these deviations varies through time. In addition, we also study how correlated are these deviations and if these correlations are time-varying. Unlike traditional approaches used in the literature, we estimate a multivariate volatility model for the cointegrated residuals that combines the above AR(1)-EGARCH(1,1) specification with a dynamic conditional correlation (DCC) model, accounting for asymmetric behavior (i.e., leverage effects) both at univariate and multivariate levels. Following Engle (2002) and Cappiello et al. (2006), we specify the DCC as:

$$\begin{aligned} \rho_t &= J_t Q_t J_t \\ Q_t &= (1-\theta_1-\theta_2)\bar{Q} + \theta_1 \epsilon_{t-1}\epsilon'_{t-1} + \theta_2 Q_{t-1} + \theta_3 \left(\eta_{t-1}\eta'_{t-1} - \mathbb{E}\left[\eta_{t-1}\eta'_{t-1}\right]\right) \end{aligned} \tag{4}$$

where $Q_t = \left(q_{ij,t}\right)$ is a 2×2 positive-definite matrix, $J_t = \operatorname{diag}\left(\frac{1}{\sqrt{q_{11,t}}}, \frac{1}{\sqrt{q_{22,t}}}\right)$ is a diagonal matrix, $\epsilon_t = \left(\epsilon_{1,t}, \epsilon_{2,t}\right)'$ is the vector of standardized innovations in cointegrated residuals, $\bar{Q}$ denotes an unconditional covariance matrix, and the parameters θ_1 and θ_2 are the correlation persistence parameters satisfying $0 < \theta_1 + \theta_2 < 1$. Likewise, we have $\eta_t = \left(\eta_{1,t}, \eta_{2,t}\right)'$ where $\eta_{i,t} = \epsilon_{i,t}\mathbf{1}\left(\epsilon_{i,t} < 0\right)$, and where $\mathbf{1}(\cdot)$ denotes the indicator function.[11]

Applying the GARCH-DCC modeling approach to the two cointegrated residuals rather than the four original vegetable oil price residuals allows a more nuanced understanding of the volatility dynamics in vegetable oil markets. The cointegrated residuals represent the long-term deviations from equilibrium relationships between Palm, Soybean, Rapeseed, and Sunflower oil prices, encapsulating significant economic interactions. Employing GARCH DCC for these residuals reduces the model's complexity by lessening the number of parameters needed and effectively captures the time-varying volatility and correlations inherent in these deviations. The GARCH component illuminates how these deviations' volatility evolves, mainly how it responds to market shocks. Concurrently, the DCC element dynamically tracks the correlations between these residuals, which is crucial for recognizing interdependencies during market turbulence. This dual-faceted model provides a more precise risk management tool, benefiting trading strategies and procurement decisions by identifying periods of heightened price co-movements and volatility.

Table 6 presents the outcomes of the GARCH-DCC model estimation, offering key insights into the short-term dynamics, volatility, and correlation patterns of the vegetable oil markets. The autoregressive parameters for all cointegrated residuals, in both the complete and the post-biofuel periods, are both significant and high (0.937 for $w_{1,t}$ and 0.929 for $w_{2,t}$ for the full sample; and 0.892 and 0.947 for $w_{1,t}$ and $w_{2,t}$ respectively for the post-biofuel subsample). This suggests that while short-term deviations from the long-term equilibrium price of vegetable oils return to the mean, they persist over an extended period before realigning with the long-term equilibrium. This may reflect the time the market takes to adjust to these deviations, potentially due to the spread of information or biases in market participant behavior.

Both sample sets exhibit statistically significant ARCH coefficients, indicating an intensive response of volatility to unexpected short-term deviations in vegetable oil equilibrium prices. The response is more pronounced for the post-biofuel and Soybean oil price deviations, suggesting that unanticipated shifts in vegetable oil prices substantially influence future volatility. This results in a heightened risk and unpredictability in the market, particularly evident in the post-biofuel period.

[11] Cappiello et al. (2006) point out a significant flaw in the original GARCH-DCC approach of Engle (2002): the conditional correlation dynamics ignores asymmetric effects. This also means that while the original DCC model considers the influence of previous shocks on future conditional volatility and correlation, it is unable to distinguish between positive and negative shocks. Including the last term in the right-hand-side of the recursion in equation (4) accounts for these asymmetric effects.

Furthermore, the enduring impact of volatility shocks on the vegetable oil market, as implied by the high GARCH coefficients in both sample sets (0.772 for $w_{1,t}$ and 0.914 for $w_{2,t}$ for the full sample; and 0.897 for $w_{1,t}$ and 0.860 for $w_{2,t}$ for the post-biofuel subsample), suggests that market participants may experience extended periods of risk and uncertainty. This has critical implications for decision-making and risk management strategies for market actors, policymakers, and investors.

Additionally, the significant and positive ARCH-like coefficient in the conditional correlation dynamics for both samples (0.265 for the full sample and 0.736 for the post-biofuel subsample) signifies that the conditional correlation, akin to conditional variance, responds significantly to unexpected short-run vegetable oil equilibrium price deviations. This demonstrates that price deviations influence the correlation among different vegetable oil prices. Furthermore, the significant leverage coefficient, which exhibits contrasting behavior in both samples (positive for the full sample and negative for the post-biofuel subsample), suggests a fundamental shift in the time-varying correlations among vegetable oil price shocks due to biofuel policies. This shift in correlation patterns could result from altered supply and demand dynamics instigated by these policies, underscoring the need to carefully evaluate these policies' impact on market interconnectedness and risk exposure by market participants and policymakers.

Our GARCH-DCC model results illuminate the intricacies of short-term price deviations, volatility, and correlation patterns in the vegetable oil market, particularly in light of biofuel policies. These findings underscore the need to monitor unexpected price movements and consider the potential risks and uncertainties associated with prolonged market adjustments. Market actors, policymakers, and investors should leverage these insights for informed decision-making, devising effective risk management strategies, and maintaining market stability amidst evolving economic circumstances and policy interventions (Brümmer et al.; 2016; López-Cabrera and Schulz; 2016).

6 Household consumers' reactions to vegetable oil price shocks

As we venture further into an era marked by energy transition and environmental consciousness, it is vital to consider the broader implications of these shifts on various market sectors. Remarkably, given its dual role in the food and burgeoning biofuel industries, the vegetable oil industry provides a compelling case for analysis. To further enrich our understanding of this complex market, examining consumer responses to vegetable oil price shocks is critical, especially in major importing and exporting countries. This analysis allows us to explore how these reactions could influence or be influenced by the transition towards renewable energy sources and the subsequent post-biofuel policies. While our research has delved into the long-term relationships, volatility, and correlation dynamics among vegetable oils, incorporating consumer reactions adds a crucial, market-facing dimension. By investigating how consumers respond to price shocks in these key countries, we can illuminate how household behaviors are shaped by and shape the broader energy transition. This added perspective deepens our understanding of the vegetable oil market dynamics and informs stakeholders, policymakers, and consumers as they navigate the challenges and opportunities presented by this transformative period.

Our investigation starts by measuring the extent to which shocks to each of the four major vegetable oils contribute to the forecast error variance of the consumer confidence index in various countries. Utilizing Diebold and Yilmaz's methodology for measuring spillovers, we quantify the percentage contribution of shocks from each vegetable oil to innovations in the consumer confidence indexes of nine countries over an extended duration of 100 months. We trace these vegetable oil shocks back to the VECM, as defined in equation (1) for the full sample and post-biofuel subsample, and the standard VAR model for the pre-biofuel subsample.

Our results in Panel B of Table 5 indicate a pronounced impact of vegetable oil shocks on consumer confidence indexes, especially in the post-biofuel period, across all surveyed countries. We observe varying magnitudes of change when comparing the spillover ratios in the post- to the pre-biofuel subsample. The spillover ratio for the United States, the United Kingdom, Germany, and Japan approximately doubled. For China, Australia, and New Zealand, the ratio increases fivefold. And for South Africa and France, the ratio surges eightfold and ninefold, respectively.

Interestingly, we observe shifts in the sources of these spillovers across different periods and countries. In the pre-biofuel period, Soybean oil shocks had the most significant spillover effects on the consumer confidence indexes of the US and China. However, in the post-biofuel period, Palm oil emerged as the primary source of these spillovers. In the case of the UK and New Zealand, Soybean oil displayed the highest post-biofuel spillovers, supplanting Rapeseed and Sunflower oils which dominated the pre-biofuel period, respectively.

These findings vividly illustrate the profound alterations brought about by implementing biofuel policies. They underscore the considerable interplay between vegetable oil markets and broader economic sentiment and how this relationship has been affected by shifts in energy policy. These insights are essential for understanding how changes in the vegetable oil markets influence consumer confidence across various countries, thereby providing a valuable context for evaluating the implications of biofuel policies.

To deepen our analysis, we present the results of the instantaneous (one-month) responses of consumer confidence indexes to vegetable oil price shocks using a structural VAR model. We estimate structural coefficients as specified in equation (5) for the full sample and the pre- and post-biofuel subsamples. We expect consumers to be highly sensitive to uncertainties related to vegetable oil prices after the implementation of the biofuel policy, due to the increased demand for vegetable oil by biofuel producers, which is associated with price and volatility increases. Let's denote the structural residuals of the VAR model by ε_t. They can be obtained from the reduced form residuals u_t by the following linear transformation:

$$\begin{bmatrix} u_{\mathrm{LPMO}} \\ u_{\mathrm{LSBO}} \\ u_{\mathrm{LRSO}} \\ u_{\mathrm{LSFO}} \\ u_{\mathrm{LCCI}} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \begin{bmatrix} \varepsilon_{\mathrm{LPMO}} \\ \varepsilon_{\mathrm{LSBO}} \\ \varepsilon_{\mathrm{LRSO}} \\ \varepsilon_{\mathrm{LSFO}} \\ \varepsilon_{\mathrm{LCCI}} \end{bmatrix} \tag{5}$$

where u_{LPMO}, u_{LSBO}, u_{LRSO}, and u_{LSFO} are reduced-form shocks for Palm, Soybean, Rapeseed, and Sunflower oil log price changes, respectively, and u_{LCCI} represents the reduced-form shock for changes in a given country log consumers' confidence index. Parameters a_{ij} are the instantaneous effects of the structural shocks on the observed variables, or alternatively, they measure the instantaneous responses of the observed variables to structural shocks. However, we are mostly interested in capturing the behavior of consumers' confidence indexes to structural shocks related to vegetable oil price changes, i.e., the parameters $a_{5j},\ j \in \{1, 2, 3, 4\}$. In the conventional structural VAR analysis, one has to first identify the shocks based on certain economic assumptions. The standard approach is to impose restrictions on the matrix of structural coefficients to pin down the economic shocks of interest. In our setup, we employ the approach of Blanchard and Quah (1988) who propose an alternative identification method using restrictions on the long-run properties of the accumulated impulse responses.

The top panel of Table 7 displays estimates of the instantaneous response of country consumer confidence indexes to price shocks in Palm, Soybean, Rapeseed, and Sunflower oils. Our analysis covers the complete dataset, pre-biofuel policy, and post-biofuel policy eras. The results offer captivating insights into the role of biofuel policies in mediating the relationship between oil prices and consumer sentiment. In the era before biofuel policy adoption, the analysis shows muted effects of vegetable oil price shocks on national consumer confidence, except for a notable exception: Germany's consumer confidence demonstrates a subtle, yet significant, decline in response to Sunflower oil price fluctuations. Such findings highlight the diverse reactions that manifest across different scenarios. However, in the post-biofuel policy timeframe, vegetable oil price shifts significantly influence consumer confidence in all the nations examined.[12]

The influence of the post-biofuel policy era is clear upon evaluating the complete dataset. Excluding China, Germany, and South Africa, there is a uniform decline in consumer sentiment in response to major vegetable oil price hikes, backed by statistically significant negative coefficients. In contrast, China and Germany show a surge in consumer sentiment in response to these price shocks, hinting at the intricate factors at play. South Africa also presents a nuanced scenario, with Palm oil prices boosting consumer confidence and Sunflower oil doing the opposite. Factoring in biofuel policy markers in the bottom panel of Table 7 confirms our critical observation: the advent and adoption of biofuel policies not only influence but also magnify the repercussions of vegetable oil price shocks on consumer confidence across all surveyed nations. Our study underscores the nuanced dynamics between biofuel regulations, vegetable oil prices, and consumer sentiment, emphasizing the need for policymakers and industry stakeholders to grasp these interrelations fully.

[12]Further analyses reveal nuanced differences in consumer responses to positive and negative vegetable oil price shocks post-biofuel implementation. For a detailed breakdown, see Table A3 in the external appendix. China and Germany's cases are very instructive. Recall both countries display a positive relationship between consumer sentiment and vegetable oil price shocks. However, in comparing the consumer reactions to vegetable oil price changes in China and Germany, it's evident that Chinese consumers tend to remain unaffected by positive shocks (increases in vegetable oil prices) but are notably sensitive to negative shocks, particularly sharp decreases in vegetable oil prices, which dampen their consumer sentiment. On the other hand, German consumers asymmetrically display sensitivity to both positive and negative shocks associated with vegetable oil price fluctuations. They experience increased consumer sentiment with price hikes and a more pronounced decrease with price drops. These distinctions may stem from cultural, economic, and historical differences between the two countries, with Germany's mature economy possibly making its consumers more attuned to price changes, whereas China's consumers may be less accustomed to such fluctuations. The variability in response across nations underscores the importance of understanding the specific contexts of each country when considering energy transition strategies. This further emphasizes the delicate balance between pursuing sustainable energy and ensuring food security.

7 Conclusion and policy implications

The transition towards biofuels since the early 2000s has led to a notable increase in the utilization of food crops for energy production. This move was primarily motivated by global endeavors to shield economies from oil price volatility and decrease dependence on external energy sources. The present research thoroughly examines the economic dynamics of this shift in the global vegetable oil markets, focusing on Palm, Soybean, Rapeseed, and Sunflower oils.

A significant observation from our study is the emergence of a long-term relationship among vegetable oil prices in the wake of biofuel policy enactments. Such co-movement in prices holds profound implications for future policy directions. As countries strategize their energy transitions, these observed long-term trends in vegetable oil prices cannot be overlooked. Policymakers are encouraged to reflect on these patterns when framing future energy transition policies, particularly those promoting biofuels. An all-encompassing strategy should consider the potential repercussions on vegetable oil prices, global agricultural trends, and food security. Moreover, as the biofuel demand burgeons, there's a pressing need to simultaneously address the inevitable strain on agricultural lands and advocate sustainable agricultural practices, which could help mitigate the environmental ramifications associated with increased farming (Mahmudul et al.; 2022).

Another consequential finding pertains to household consumers' heightened sensitivity to vegetable oil price fluctuations. While advocating for biofuel production, policymakers must judiciously weigh the associated benefits against potential adverse effects on food prices, availability, and overall food security. A potential pathway to alleviate some of these concerns might involve the promotion of advanced biofuels that are not derived from food crops. Further diversifying into other renewable energy sources like solar and wind could significantly offset the burgeoning pressure on global food markets, ensuring a more harmonious energy-food balance (Das and Gundimeda; 2022).

Due to their increasing use as biofuel feedstocks, the surge in demand for vegetable oils poses another challenge by putting additional strain on global supply chains. Policymakers and food crop producers are thus urged to collaborate to fortify agricultural production capacities. Essential interventions in this domain might encompass substantial R&D investments to bolster crop yields, foster sustainable farming practices, and ensure agricultural systems' resilience against potential disruptions, such as the vagaries of climate change (Zahraee et al.; 2022).

Biofuel policies have inadvertently injected a degree of volatility in vegetable oil markets. This instability, our study finds, resonates across producers, consumers, and investors. Such market fluctuations necessitate proactive policy interventions. Policymakers are thus prompted to devise strategies to curb extreme price swings, an endeavor that could benefit from mechanisms like strategic reserves or direct market interventions. A parallel strategy encouraging diverse biofuel feedstocks can further ease the pressure on the vegetable oil market, ensuring its stability and sustained growth (Cheng et al.; 2023).

Lastly, albeit environmentally motivated, the pivot towards biofuels has triggered unintended consequences. A noticeable rise in food prices can be attributed to this shift, which, in turn, has exacerbated hunger and malnutrition in regions already grappling with these challenges (Martínez-Jaramillo et al.; 2019). Policymakers must adopt a nuanced approach, tailoring interventions catering to country-specific challenges and vulnerabilities. Potential solutions could include stabilizing prices, efforts to diversify energy sources, or enhancements to existing social safety nets. Constant monitoring and evaluating biofuel policies' effects on consumer behavior across different countries are paramount, offering insights that can inform and refine future policy directions.

To encapsulate, biofuel policies, though environmentally well-intentioned, have inadvertently introduced complexities in the agricultural sector and influenced consumer behaviors and sentiments. As the world progresses, striking a judicious balance between energy transitions and global food security implications remains an imperative.

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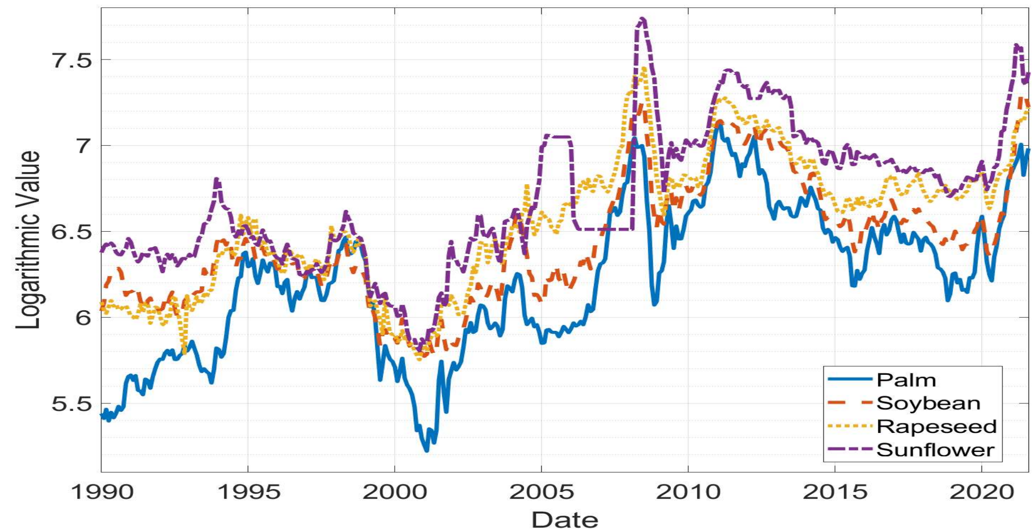
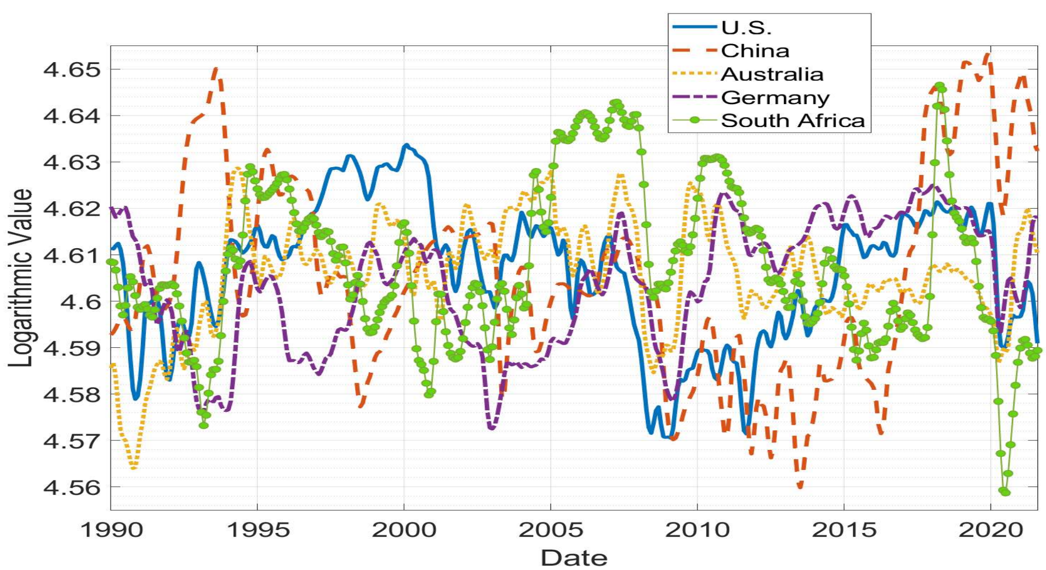
A. Vegetable oil prices



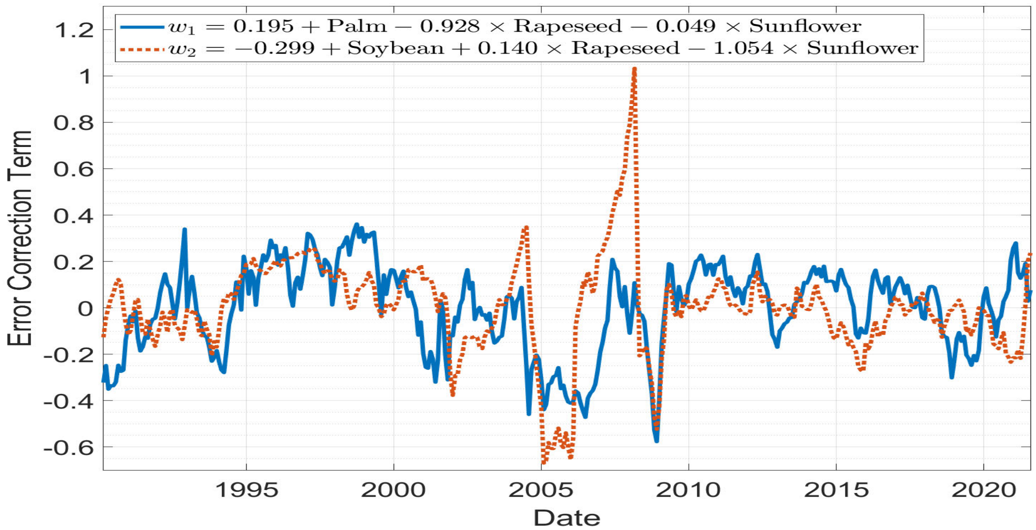
B. Country consumer confidence indexes



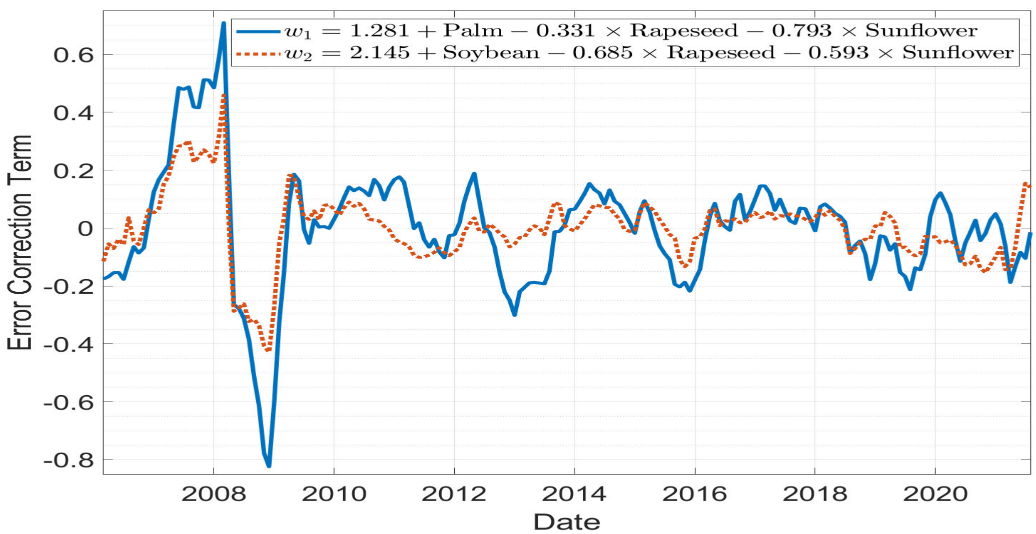
Panel **A** plots logarithmic values of the four major vegetable oil prices from January 1990 to August 2021. Panel **B** plots logarithmic values of the selected country consumer confidence indexes over the same period.

Figure 1: Evolution of major vegetable oil prices and country consumer confidence indexes

A. Full sample



B. Post-biofuel subsample



Panel **A** plots the short-term equilibrium deviations major vegetable oil prices for the full sample (1990 to 2021) analysis. Panel **B** displays similar plots for the post-biofuel subsample (2006 to 2021).

Figure 2: Evolution of short-term equilibrium deviations of major vegetable oil prices

Table 1: Unit-root test and descriptive statistics for vegetable oil prices and country consumer confidence indexes

	Vegetable oil prices				Country consumers confidence indexes								
	Palm	Soybean	Rapeseed	Sunflower	USA	China	Australia	UK	France	Germany	Japan	SA	NZ
							Full sample						
ADF (Level)	0.129	0.461	0.689	0.186	0.267	0.254	0.000	0.022	0.017	0.101	0.008	0.015	0.000
ADF (Diff)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PP (Level)	0.274	0.506	0.592	0.293	0.214	0.124	0.008	0.065	0.058	0.100	0.026	0.045	0.032
PP (Diff)	0.000	0.000	0.000	0.000	0.001	0.002	0.000	0.000	0.000	0.002	0.019	0.007	0.049
Mean	0.004	0.003	0.003	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Std	0.072	0.054	0.058	0.072	0.002	0.003	0.003	0.003	0.003	0.002	0.002	0.003	0.002
5%	−0.116	−0.085	−0.083	−0.089	−0.005	−0.006	−0.004	−0.005	−0.004	−0.003	−0.003	−0.005	−0.003
50%	0.007	0.004	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
95%	0.118	0.097	0.098	0.085	0.004	0.005	0.004	0.005	0.004	0.003	0.003	0.006	0.004
Min	−0.316	−0.253	−0.193	−0.422	−0.011	−0.016	−0.008	−0.016	−0.009	−0.008	−0.014	−0.011	−0.007
Max	0.290	0.151	0.337	0.661	0.008	0.010	0.009	0.013	0.009	0.007	0.007	0.016	0.007
Skew	−0.241	−0.137	0.501	2.383	−0.548	−0.595	0.269	−0.436	−0.193	−0.077	−1.025	0.612	0.096
Kurt	1.762	1.198	4.005	26.931	1.960	1.585	0.833	3.274	0.691	2.076	6.299	3.035	1.039
							Pre-biofuel subsample						
ADF (Level)	0.151	0.145	0.517	0.510	0.252	0.093	0.052	0.125	0.119	0.017	0.139	0.007	0.172
ADF (Diff)	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.008
PP (Level)	0.776	0.701	0.860	0.878	0.630	0.716	0.812	0.820	0.507	0.528	0.648	0.758	0.815
PP (Diff)	0.000	0.000	0.000	0.000	0.007	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.001
Mean	0.002	0.001	0.003	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Std	0.068	0.052	0.064	0.056	0.003	0.003	0.003	0.003	0.002	0.002	0.002	0.003	0.002
5%	−0.114	−0.085	−0.102	−0.085	−0.005	−0.006	−0.004	−0.005	−0.004	−0.004	−0.003	−0.004	−0.003
50%	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
95%	0.114	0.093	0.106	0.092	0.004	0.005	0.005	0.005	0.003	0.003	0.003	0.006	0.004
Min	−0.186	−0.131	−0.193	−0.169	−0.008	−0.016	−0.007	−0.010	−0.008	−0.007	−0.005	−0.008	−0.007
Max	0.290	0.151	0.337	0.269	0.008	0.007	0.006	0.006	0.006	0.007	0.004	0.011	0.006
Skew	0.221	0.275	0.735	0.827	−0.234	−1.208	0.084	−0.790	−0.623	0.074	−0.269	0.599	−0.124
Kurt	1.568	0.241	3.941	3.058	1.399	3.673	−0.076	1.903	0.881	1.733	−0.144	0.787	0.779
							Post-biofuel subsample						
ADF (Level)	0.175	0.240	0.428	0.116	0.699	0.644	0.000	0.174	0.159	0.196	0.036	0.023	0.015
ADF (Diff)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.007	0.006
PP (Level)	0.253	0.442	0.381	0.311	0.880	0.601	0.074	0.409	0.346	0.369	0.356	0.189	0.138
PP (Diff)	0.000	0.000	0.000	0.000	0.018	0.005	0.000	0.069	0.023	0.007	0.050	0.047	0.023
Mean	0.006	0.006	0.003	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Std	0.076	0.056	0.050	0.086	0.002	0.004	0.003	0.004	0.003	0.002	0.003	0.003	0.002
5%	−0.129	−0.086	−0.068	−0.094	−0.005	−0.006	−0.004	−0.005	−0.005	−0.003	−0.004	−0.006	−0.003
50%	0.009	0.008	0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
95%	0.127	0.102	0.078	0.078	0.004	0.006	0.004	0.006	0.005	0.004	0.004	0.004	0.004
Min	−0.316	−0.253	−0.168	−0.422	−0.011	−0.009	−0.008	−0.016	−0.009	−0.008	−0.014	−0.011	−0.006
Max	0.218	0.144	0.193	0.661	0.006	0.010	0.009	0.013	0.009	0.005	0.007	0.016	0.007
Skew	−0.597	−0.479	−0.045	2.638	−0.881	−0.154	0.482	−0.240	−0.039	−0.231	−1.127	0.659	0.340
Kurt	1.865	1.976	2.546	26.123	2.553	0.072	1.993	3.202	0.254	2.571	5.988	4.694	1.393

For the full sample and the pre- and post-biofuel subsamples, the table presents the unit-root test results for logarithmic vegetable oil prices and country consumer confidence indexes as well as their first-differences. ADF stands for the Dickey and Fuller (1979,1981)'s unit-root test, and PP for the Phillips and Perron (1988)'s test. Both tests present p-values for levels and first-differences. The unit-root test results are followed by the descriptive statistics. The mean, standard deviation, 5th, 50th, and 95th percentiles, minimum, maximum, skewness and excess kurtosis are computed for each first-difference series.

Table 2: Vegetable oil price correlations and principal component analysis

A: Correlations

	Full sample				Pre-biofuel subsample				Post-biofuel subsample			
	Palm	Soybean	Rapeseed	Sunflower	Palm	Soybean	Rapeseed	Sunflower	Palm	Soybean	Rapeseed	Sunflower
Soybean	0.705***				0.623***				0.768***			
	(0.000)				(0.000)				(0.000)			
Rapeseed	0.352***	0.412***			0.208***	0.210***			0.533***	0.671***		
	(0.000)	(0.000)			(0.004)	(0.004)			(0.000)	(0.000)		
Sunflower	0.328***	0.398***	0.319***		0.464***	0.550***	0.280***		0.253***	0.319***	0.389***	
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.001)	(0.000)	(0.000)	
With consumers confidence indexes												
USA	0.095*	0.140***	0.034	−0.031	0.010	0.135*	0.008	0.020	0.177**	0.144**	0.069	−0.063
	(0.064)	(0.006)	(0.507)	(0.549)	(0.886)	(0.063)	(0.916)	(0.784)	(0.016)	(0.049)	(0.351)	(0.394)
China	0.039	0.041	0.010	0.036	−0.032	−0.039	−0.085	−0.012	0.098	0.106	0.121*	0.066
	(0.444)	(0.431)	(0.849)	(0.482)	(0.655)	(0.592)	(0.244)	(0.871)	(0.182)	(0.149)	(0.098)	(0.372)
Australia	0.028	−0.052	−0.051	−0.091*	0.044	−0.070	−0.046	−0.012	0.019	−0.038	−0.062	−0.145*
	(0.586)	(0.311)	(0.321)	(0.076)	(0.548)	(0.338)	(0.531)	(0.869)	(0.800)	(0.603)	(0.396)	(0.048)
UK	0.054	0.063	0.012	−0.091*	0.010	−0.015	−0.035	0.042	0.085	0.119	0.060	−0.157*
	(0.295)	(0.222)	(0.815)	(0.078)	(0.895)	(0.840)	(0.630)	(0.562)	(0.247)	(0.104)	(0.413)	(0.032)
France	0.047	0.057	−0.002	−0.068	−0.007	−0.028	−0.056	−0.003	0.082	0.111	0.050	−0.098
	(0.358)	(0.272)	(0.968)	(0.184)	(0.923)	(0.702)	(0.441)	(0.963)	(0.263)	(0.130)	(0.499)	(0.184)
Germany	0.129**	0.092*	0.102**	−0.016	−0.020	−0.122*	0.020	−0.088	0.257***	0.283***	0.211***	0.037
	(0.012)	(0.073)	(0.046)	(0.757)	(0.787)	(0.094)	(0.787)	(0.226)	(0.000)	(0.000)	(0.004)	(0.613)
Japan	0.105**	0.067	0.076	−0.073	−0.050	−0.074	0.004	−0.150**	0.205***	0.157**	0.145**	−0.038
	(0.042)	(0.191)	(0.142)	(0.154)	(0.489)	(0.311)	(0.954)	(0.039)	(0.005)	(0.032)	(0.048)	(0.606)
SA	0.037	0.008	0.002	−0.091*	−0.047	0.013	0.069	−0.014	0.115	0.008	−0.081	−0.140*
	(0.468)	(0.880)	(0.976)	(0.077)	(0.519)	(0.860)	(0.340)	(0.847)	(0.116)	(0.911)	(0.268)	(0.056)
NZ	−0.133**	−0.085	−0.109**	−0.124**	−0.100	−0.029	−0.094	−0.042	−0.164**	−0.136*	−0.130*	−0.191***
	(0.010)	(0.100)	(0.034)	(0.016)	(0.170)	(0.691)	(0.194)	(0.568)	(0.025)	(0.064)	(0.076)	(0.009)

B: Principal component analysis

Factor	Loading				Proportion	Loading				Proportion	Loading				Proportion
	Palm	Soybean	Rapeseed	Sunflower		Palm	Soybean	Rapeseed	Sunflower		Palm	Soybean	Rapeseed	Sunflower	
PC1	0.545	0.573	0.440	0.426	0.570	0.545	0.569	0.311	0.531	0.558	0.530	0.571	0.525	0.342	0.630
PC2	−0.503	−0.344	0.421	0.671	0.188	0.253	0.257	−0.933	0.011	0.220	−0.358	−0.249	0.046	0.899	0.208
PC3	−0.089	−0.075	0.791	−0.601	0.170	0.547	0.134	0.176	−0.807	0.133	0.523	0.089	−0.802	0.274	0.111
PC4	0.665	−0.740	0.065	0.078	0.072	0.582	−0.770	−0.051	0.256	0.089	0.564	−0.777	0.280	−0.005	0.051

For the full sample and the pre- and post-biofuel subsamples, Panel A of the table presents the correlations among vegetable oil prices and with country consumer confidence indexes. Panel B presents the results of the principal component analysis on Palm, Soybean, Rapeseed, and Sunflower oil price changes. Factor loadings on the principal components and the proportion of total variance they explain are shown for each time period. The acronyms PC1, PC2, PC3, and PC4 denote the first, second, third, and fourth principal components, respectively. p-values are given in parantheses, and the asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Johansen cointegration test on vegetable oil price levels

Nb of CE(s)	Eigenvalue	Trace Statistic	Critical Value	Prob
		Full sample		
None *	0.0786	72.5253	54.6815	0.0001
At most 1 *	0.0631	41.8386	35.4582	0.0013
At most 2	0.0363	17.4121	19.9371	0.0254
At most 3	0.0094	3.5394	6.6349	0.0599
		Pre-biofuel subsample		
None	0.1139	40.7403	54.6815	0.1971
At most 1	0.0615	18.1328	35.4582	0.5563
At most 2	0.0329	6.2656	19.9371	0.6641
At most 3	0.0000	0.0026	6.6349	0.9572
		Post-biofuel subsample		
None *	0.1568	68.8045	54.6815	0.0002
At most 1 *	0.1061	37.5982	35.4582	0.0052
At most 2	0.0567	17.0687	19.9371	0.0287
At most 3	0.0343	6.3782	6.6349	0.0115

The table presents the Johansen cointegration test results for vegetable oil logarithmic price levels. The test is based on the Trace statistic. The number of cointegration equations (null hypothesis), eigenvalue, test-statistic, critical value, and probability value are shown for the full sample, the subsample before implementation of the biofuel policy, and the post-biofuel subsample. “None”, “At most 1”, “At most 2”, and “At most 3” are the null hypotheses specifying the number of cointegrating equations. The asterisk * denotes rejection of the null hypothesis.

Table 4: VECM results of vegetable oils both for the post-biofuel subsample and for full sample

	Full sample				Post-biofuel subsample			
	Long-run coefficients							
		$w_{1,t}$	$w_{2,t}$			$w_{1,t}$	$w_{2,t}$	
Constant		0.195	−0.299			1.281	2.145***	
		(0.238)	(0.462)			(1.140)	(3.103)	
ΔLPMO$_t$		1.000	0.000			1.000	0.000	
		(0.000)	(0.000)			(0.000)	(0.000)	
ΔLSBO$_t$		0.000	1.000			0.000	1.000	
		(0.000)	(0.000)			(0.000)	(0.000)	
ΔLRSO$_t$		−0.928***	0.140			−0.331	−0.685***	
		(4.532)	(0.683)			(1.471)	(5.032)	
ΔLSFO$_t$		−0.049	−1.054***			−0.793***	−0.593***	
		(0.247)	(5.303)			(5.061)	(6.251)	
	Short-run coefficients							
	ΔLPMO$_t$	ΔLSBO$_t$	ΔLRSO$_t$	ΔLSFO$_t$	ΔLPMO$_t$	ΔLSBO$_t$	ΔLRSO$_t$	ΔLSFO$_t$
$w_{1,t-1}$	−0.085***	−0.013	0.011	−0.033	−0.058	0.091**	0.040	0.102*
	(4.049)	(0.806)	(0.688)	(1.638)	(1.076)	(2.326)	(1.211)	(1.938)
$w_{2,t-1}$	0.033*	−0.002	0.010	0.092***	0.161*	−0.096	0.061	0.042
	(1.772)	(0.112)	(0.715)	(4.992)	(1.836)	(1.504)	(1.121)	(0.485)
ΔLPMO$_{t-1}$	0.334***	0.039	0.066	−0.027	0.329***	0.063	−0.036	−0.035
	(4.842)	(0.740)	(1.227)	(0.401)	(2.974)	(0.780)	(0.531)	(0.321)
ΔLSBO$_{t-1}$	0.095	0.346***	0.405***	0.037	0.108	0.283**	0.230**	0.025
	(0.979)	(4.690)	(5.377)	(0.393)	(0.632)	(2.252)	(2.172)	(0.147)
ΔLRSO$_{t-1}$	−0.206***	−0.082	−0.093*	−0.052	−0.123	0.002	0.135	0.093
	(3.000)	(1.560)	(1.743)	(0.779)	(0.820)	(0.014)	(1.459)	(0.631)
ΔLSFO$_{t-1}$	−0.021	−0.027	0.011	0.394***	−0.064	−0.062	−0.011	0.334***
	(0.393)	(0.662)	(0.258)	(7.471)	(0.925)	(1.223)	(0.265)	(4.921)
Constant	0.003	0.002	0.002	0.002	0.004	0.004	0.001	0.004
	(0.920)	(0.770)	(0.654)	(0.532)	(0.682)	(0.932)	(0.439)	(0.724)
Adj. R^2	0.126	0.101	0.174	0.176	0.135	0.160	0.240	0.257

The table presents VECM coefficient estimates for vegetable oil price dynamics for the full sample and the post-biofuel subsample. The variables $w_{1,t}$, and $w_{2,t}$ are the cointegrated residuals characterizing the long-run vegetable oil price dynamics. The top panel shows coefficients of the long-run equilibrium dynamics (see equation (2)). The variables ΔLPMO$_t$, ΔLSBO$_t$, ΔLRSO$_t$, and ΔLSFO$_t$ denote changes of Palm, Soybean, Rapeseed, and Sunflower oil prices, respectively. The bottom panel shows coefficients of the short-run equilibrium dynamics (see equation (1)). The lag selection is based on the Schwarz Information Criterium. In parentheses are the t-statistic absolute values, while the R^2 is adjusted. The asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Spillovers among vegetable oils and between vegetable oils and consumer confidence indexes

A. Diebold and Yilmaz spillovers among vegetable oils

Full Sample

	LPMO	LSBO	LRSO	LSFO	From Others
Palm	63.57	13.09	21.35	1.99	36.43
Soybean	39.48	59.63	0.50	0.38	40.37
Rapeseed	35.76	18.63	44.76	0.85	55.24
Sunflower	29.07	47.88	3.29	19.76	80.24
To others	104.31	79.60	25.15	3.22	212.27
Incl. own	167.88	139.23	69.91	22.98	53.07

Pre-biofuel subsample

	LPMO	LSBO	LRSO	LSFO	From Others
Palm	95.93	0.24	1.79	2.03	4.07
Soybean	39.26	58.42	2.31	0.01	41.58
Rapeseed	13.33	7.39	79.22	0.06	20.78
Sunflower	20.99	12.47	5.02	61.52	38.48
To others	73.57	20.11	9.12	2.10	104.91
Incl. own	169.51	78.53	88.34	63.62	26.23

Post-biofuel subsample

	LPMO	LSBO	LRSO	LSFO	From Others
Palm	87.89	4.65	4.78	2.68	12.11
Soybean	80.08	11.78	0.59	7.55	88.22
Rapeseed	51.04	13.68	8.14	27.14	91.86
Sunflower	73.64	2.60	9.45	14.31	85.69
To others	204.76	20.93	14.82	37.37	277.88
Incl. own	292.65	32.71	22.96	51.68	69.47

B. Spillovers between vegetable oils and consumer confidence indexes

Full Sample

Country	CCI	LPMO	LSBO	LRSO	LSFO	From Others
USA	90.72	1.33	7.72	0.03	0.20	9.28
China	94.42	1.71	1.38	2.42	0.07	5.58
Australia	98.32	0.05	0.23	0.66	0.73	1.68
UK	94.09	0.61	2.92	1.64	0.74	5.91
France	97.74	1.01	0.59	0.00	0.66	2.26
Germany	97.36	0.23	1.53	0.31	0.56	2.64
Japan	96.25	0.67	0.73	1.25	1.10	3.75
SA	98.56	0.64	0.32	0.17	0.30	1.44
NZ	97.69	0.12	0.35	1.35	0.49	2.31

Pre-biofuel subsample

Country	CCI	LPMO	LSBO	LRSO	LSFO	From Others
USA	92.76	0.49	6.28	0.28	0.18	7.24
China	98.75	0.07	0.80	0.26	0.12	1.25
Australia	99.01	0.06	0.01	0.05	0.87	0.99
UK	95.95	0.31	0.28	3.04	0.43	4.05
France	98.78	0.73	0.07	0.20	0.22	1.22
Germany	98.01	0.08	0.12	0.52	1.27	1.99
Japan	96.78	0.83	0.61	0.73	1.05	3.22
SA	99.38	0.21	0.20	0.17	0.03	0.62
NZ	98.21	0.12	0.74	0.06	0.88	1.79

Post-biofuel subsample

Country	CCI	LPMO	LSBO	LRSO	LSFO	From Others
USA	85.07	8.38	5.31	1.19	0.05	14.93
China	93.29	3.29	1.88	0.06	1.47	6.71
Australia	94.82	0.12	0.11	4.48	0.47	5.18
UK	90.28	0.59	6.08	2.65	0.41	9.72
France	88.90	7.80	2.56	0.60	0.15	11.10
Germany	96.16	0.21	0.56	0.12	2.95	3.84
Japan	92.87	2.16	0.82	2.90	1.25	7.13
SA	94.76	0.45	0.71	0.17	3.92	5.24
NZ	90.17	4.26	4.60	0.53	0.44	9.83

Panel A presents results of the Diebold and Yilmaz spillovers among vegetable oils. The spillover coefficients of the pre-biofuel subsample are computed using the forecast error variance decomposition from the standard VAR model as presented in Table A1 while the spillover coefficients of the full sample and the post-biofuel subsample are computed using the forecast error variance decomposition of the VECM as presented in Table 4. Panel B presents the results of the Diebold and Yilmaz spillovers between vegetable oils and country consumer confidence indexes. The spillover coefficients of the full sample and the subsamples are computed using the forecast error variance decomposition of the SVAR model as presented in Table 7. All the forecast error variance decomposition are computed for a 100-month horizon.

Table 6: Asymmetric AR-EGARCH-DCC model estimation on vegetable oil cointegrated residuals

	ϕ_0	ϕ_1	ω	α	γ	β
	Full sample					
$w_{1,t}$	0.026	0.937***	−1.603**	0.462***	−0.014	0.772***
	(0.631)	(0.000)	(0.010)	(0.000)	(0.806)	(0.000)
$w_{2,t}$	0.108**	0.929***	−0.927***	0.569***	−0.014	0.914***
	(0.031)	(0.000)	(0.001)	(0.000)	(0.804)	(0.000)
Correlation	θ_1	θ_2	θ_3			
Dynamics	0.265***	0.527***	0.108***			
	(0.000)	(0.000)	(0.000)			
	Post-biofuel subsample					
$w_{1,t}$	0.046	0.892***	−0.942**	0.474***	0.052	0.897***
	(0.303)	(0.000)	(0.018)	(0.001)	(0.372)	(0.000)
$w_{2,t}$	0.051	0.947***	−1.416***	0.692***	0.126	0.860***
	(0.360)	(0.000)	(0.000)	(0.000)	(0.180)	(0.000)
Correlation	θ_1	θ_2	θ_3			
Dynamics	0.736***	0.084	−0.059**			
	(0.000)	(0.133)	(0.016)			

The table reports coefficient estimates of the asymmetric AR(1)-EGARCH(1,1)-DCC model on vegetable oil cointegrated residuals as specified in equations (3) and (4). The variables $w_{1,t}$, and $w_{2,t}$ are the cointegrated residuals generated from equation (2). The parameters ϕ_0 and ϕ_1 are the constant term and the auto-regressive coefficient in the AR(1) specification. The parameters ω, α, β, and γ are respectively the constant, ARCH, GARCH, and leverage coefficients. The parameters θ_1 and θ_2 are the short-run and long-run volatility correlation persistence coefficients, while θ_3 captures the asymmetric effect in the condition correlation. The asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Structural VAR estimation on vegetable oil prices and country consumer confidence indexes

(a) Subsample analysis

	Full sample				Pre-biofuel subsample				Post-biofuel subsample			
	LPMO	LSBO	LRSO	LSFO	LPMO	LSBO	LRSO	LSFO	LPMO	LSBO	LRSO	LSFO
USA	−0.001	−0.008***	−0.010***	−0.027***	0.001	0.003*	−0.001	0.000	−0.014*	−0.025***	−0.027***	−0.036***
	(0.876)	(0.061)	(0.007)	(0.000)	(0.484)	(0.095)	(0.520)	(0.992)	(0.080)	(0.001)	(0.000)	(0.000)
China	0.006	0.017***	0.010***	0.022***	0.001	0.000	0.003*	0.001	0.027***	0.026***	0.023***	0.027***
	(0.204)	(0.000)	(0.004)	(0.000)	(0.749)	(0.951)	(0.094)	(0.620)	(0.001)	(0.001)	(0.000)	(0.004)
Australia	0.005	0.002	−0.002	−0.018***	0.001	0.001	0.000	−0.002	0.011	0.006	−0.008	−0.022*
	(0.279)	(0.536)	(0.528)	(0.000)	(0.676)	(0.668)	(0.924)	(0.326)	(0.156)	(0.392)	(0.239)	(0.018)
UK	0.000	−0.004	−0.009***	−0.027***	−0.002	0.001	−0.002	0.001	0.014*	0.013*	−0.002	−0.031***
	(0.921)	(0.355)	(0.010)	(0.000)	(0.335)	(0.336)	(0.224)	(0.364)	(0.078)	(0.088)	(0.811)	(0.001)
France	0.002	−0.002	−0.003	−0.021***	−0.001	−0.002	0.001	−0.002	−0.002	−0.008	−0.015**	−0.032***
	(0.601)	(0.595)	(0.391)	(0.000)	(0.626)	(0.280)	(0.696)	(0.292)	(0.817)	(0.275)	(0.021)	(0.001)
Germany	0.023***	0.019***	0.011***	−0.007	0.001	−0.001	−0.001	−0.007***	0.042***	0.039***	0.025***	0.008
	(0.000)	(0.000)	(0.002)	(0.169)	(0.770)	(0.710)	(0.623)	(0.000)	(0.000)	(0.000)	(0.000)	(0.386)
Japan	−0.002	−0.004	−0.011***	−0.028***	0.002	0.001	0.003	0.003*	0.000	−0.003	−0.016**	−0.034***
	(0.577)	(0.352)	(0.002)	(0.000)	(0.385)	(0.725)	(0.136)	(0.050)	(0.979)	(0.660)	(0.012)	(0.000)
SA	0.019***	0.005	−0.003	−0.012**	0.003	0.001	−0.003	0.000	0.033***	0.024***	0.012*	−0.014
	(0.000)	(0.204)	(0.454)	(0.018)	(0.142)	(0.682)	(0.152)	(0.932)	(0.000)	(0.001)	(0.068)	(0.143)
NZ	−0.016***	−0.009**	−0.009**	−0.010**	−0.006	−0.001	−0.001	−0.002	−0.026***	−0.033***	−0.031***	−0.049***
	(0.000)	(0.020)	(0.011)	(0.044)	(0.002)	(0.505)	(0.472)	(0.163)	(0.001)	(0.000)	(0.000)	(0.000)

(b) Full sample analysis considering country biofuel policy dummies

	LPMO	LSBO	LRSO	LSFO	$D_{it}\times$ LPMO	$D_{it}\times$ LSBO	$D_{it}\times$ LRSO	$D_{it}\times$ LSFO
USA	−0.005	−0.012***	−0.013***	−0.033***	−0.007**	−0.009***	−0.012***	−0.017***
	(0.302)	(0.003)	(0.000)	(0.000)	(0.011)	(0.000)	(0.000)	(0.000)
China	0.009*	0.020***	0.013***	0.023***	0.012***	0.012***	0.012***	0.016***
	(0.052)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Australia	0.003	−0.001	−0.005	−0.023***	−0.006**	−0.006**	−0.008***	−0.015***
	(0.526)	(0.835)	(0.175)	(0.000)	(0.041)	(0.013)	(0.000)	(0.000)
UK	0.000	−0.006	−0.012***	−0.029***	−0.004	−0.007***	−0.013***	−0.021***
	(0.988)	(0.180)	(0.001)	(0.000)	(0.160)	(0.006)	(0.000)	(0.000)
France	−0.004	−0.007*	−0.009**	−0.024***	−0.013***	−0.013***	−0.012***	−0.019***
	(0.374)	(0.067)	(0.012)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Germany	0.019***	0.016***	0.008**	−0.008	0.004	0.005**	0.005*	0.001
	(0.000)	(0.000)	(0.028)	(0.141)	(0.210)	(0.033)	(0.052)	(0.732)
Japan	−0.004	−0.008*	−0.015***	−0.033***	−0.005*	−0.005**	−0.013***	−0.019***
	(0.419)	(0.051)	(0.000)	(0.000)	(0.079)	(0.029)	(0.000)	(0.000)
SA	0.019***	0.005	−0.003	−0.013***	0.007**	0.003	−0.002	−0.012***
	(0.000)	(0.252)	(0.491)	(0.009)	(0.014)	(0.226)	(0.322)	(0.000)
NZ	−0.022***	−0.015***	−0.016***	−0.018***	−0.010***	−0.016***	−0.017***	−0.026***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)

The top panel of the table displays the results of the structural VAR model estimation on vegetable oils and consumer confidence indexes, as specified in equation (5), for the full sample and the pre- and post-biofuel subsamples. The reported parameter estimates measure the instantaneous response of country consumer confidence indexes to vegetable oil price shocks. The values in parentheses are the corresponding p-values. The lag length is determined by the Schwarz information criterium. The asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The bottom panel reports the results considering a dummy variable, $D_{it} = 1$ if country i has a biofuel policy in effect at time t, and 0 otherwise.

EXTERNAL APPENDIX

for

"Biofuel Policies and Their Ripple Effects: An Analysis of Vegetable Oil Price Dynamics and Global Consumer Responses"

This supplemental appendix provides additional tables that complement the analysis presented in the main text including using alternative empirical approaches for robustness checks.

Table A1: Standard VAR model estimation on vegetable oil prices for the pre-biofuel subsample

	$\Delta\mathrm{LPMO}_t$	$\Delta\mathrm{LSBO}_t$	$\Delta\mathrm{LRSO}_t$	$\Delta\mathrm{LSFO}_t$
$\Delta\mathrm{LPMO}_{t-1}$	0.227^{**}	-0.033	0.134^{*}	-0.147^{**}
	(2.474)	(0.473)	(1.675)	(1.995)
$\Delta\mathrm{LSBO}_{t-1}$	-0.087	0.311^{***}	0.459^{***}	-0.009
	(0.679)	(3.202)	(4.090)	(0.083)
$\Delta\mathrm{LRSO}_{t-1}$	-0.206^{***}	-0.141^{**}	-0.170^{**}	-0.103
	(2.649)	(2.406)	(2.503)	(1.639)
$\Delta\mathrm{LSFO}_{t-1}$	0.204^{*}	0.010	0.013	0.392^{***}
	(1.916)	(0.119)	(0.144)	(4.576)
Constant	0.002	0.001	0.003	0.003
	(0.419)	(0.147)	(0.691)	(0.690)
Adj. R^2	0.075	0.076	0.203	0.097

The table reports results of the standard VAR model estimation on vegetable oils for the subsample before the implementation of the biofuel policy. The variables ΔLPMO, ΔLSBO, ΔLRSO, and ΔLSFO represent Palm, Soybean, Rapeseed, and Sunflower oil price changes, respectively. The coefficient C denotes the constant term in the VAR equations. The lag length of 2 is determined by the Schwarz information criterium. The values in parenthesis represent the standard errors. The asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A2: Descriptive statistics and correlations of cointegrating residuals

	Full Sample				Post-biofuel subsample			
	$w_{1,t}$	Prob	$w_{2,t}$	Prob	$w_{1,t}$	Prob	$w_{2,t}$	Prob
A. Descriptive Statistics								
Mean	0.000		0.000		0.000		0.000	
Std	0.186		0.207		0.205		0.120	
5%	−0.356		−0.335		−0.293		−0.224	
Median	0.034		0.007		0.122		0.717	
95%	0.270		0.253		0.417		0.239	
Skew	−0.567		0.144		−0.258		−0.131	
Kurt	−0.211		4.309		0.349		0.288	
Min	−0.578		−0.670		−0.824		−0.429	
Max	0.362		1.034		0.709		0.459	
B. Correlations								
Palm	−0.108**	0.036	0.033	0.521	0.189**	0.010	0.246***	0.001
Soybean	0.019	0.717	0.025	0.622	0.297***	0.000	0.205***	0.005
Rapeseed	0.131**	0.011	0.107**	0.037	0.423***	0.000	0.389***	0.000
Sunflower	0.044	0.391	0.203***	0.000	0.386***	0.000	0.275***	0.000
$w_{1,t}$	1.000		0.407***	0.000	1.000		0.846***	0.000

Panel A reports results of the descriptive statistics of cointegrating residuals while Panel B presents their correlations with vegetable oil prices. The variables $w_{1,t}$ and $w_{2,t}$ are the cointegrated residuals generated from equation (2). The asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Structural VAR results: disentangling the effects of positive and negative shocks

	FS Positive				FS Negative			
	LPMO	LSBO	LRSO	LSFO	LPMO	LSBO	LRSO	LSFO
USA	−0.004	−0.004	−0.005**	−0.015***	0.002	−0.004*	−0.006***	−0.013***
	(0.135)	(0.105)	(0.028)	(0.000)	(0.552)	(0.099)	(0.009)	(0.000)
China	−0.002	0.004	0.002	0.000	0.007**	0.012***	0.007***	0.021***
	(0.480)	(0.104)	(0.353)	(0.925)	(0.019)	(0.000)	(0.002)	(0.000)
Australia	0.009***	0.006***	0.000	−0.009**	−0.005*	−0.003	−0.002	−0.008***
	(0.000)	(0.009)	(0.971)	(0.018)	(0.081)	(0.162)	(0.429)	(0.005)
UK	−0.002	−0.005**	−0.011***	−0.021***	0.003	0.002	0.002	−0.006**
	(0.309)	(0.026)	(0.000)	(0.000)	(0.313)	(0.413)	(0.363)	(0.023)
France	0.000	0.000	−0.002	−0.015***	0.002	−0.002	0.000	−0.007**
	(0.948)	(0.993)	(0.302)	(0.000)	(0.493)	(0.379)	(0.927)	(0.014)
Germany	0.005*	0.008***	−0.002	−0.004	0.021***	0.011***	0.014***	−0.002
	(0.058)	(0.001)	(0.313)	(0.303)	(0.000)	(0.000)	(0.000)	(0.547)
Japan	0.000	0.002	−0.007***	−0.010**	−0.004	−0.007**	−0.005**	−0.019***
	(0.966)	(0.312)	(0.001)	(0.012)	(0.165)	(0.006)	(0.042)	(0.000)
SA	0.006*	0.005*	−0.003	−0.009**	0.015***	0.003	0.002	0.001
	(0.015)	(0.055)	(0.138)	(0.015)	(0.000)	(0.248)	(0.442)	(0.796)
NZ	−0.006**	−0.001	−0.002	−0.004	−0.010***	−0.008***	−0.009***	−0.006**
	(0.023)	(0.680)	(0.473)	(0.226)	(0.001)	(0.001)	(0.000)	(0.032)

	PBS Positive				PBS Negative			
	LPMO	LSBO	LRSO	LSFO	LPMO	LSBO	LRSO	LSFO
USA	0.015***	0.010***	−0.001	−0.037***	0.021***	0.009*	0.006**	−0.002
	(0.000)	(0.003)	(0.796)	(0.000)	(0.000)	(0.008)	(0.050)	(0.626)
China	0.003	−0.002	−0.007**	−0.008	0.031***	0.028***	0.028***	0.027***
	(0.402)	(0.514)	(0.019)	(0.292)	(0.000)	(0.000)	(0.000)	(0.000)
Australia	0.020***	0.008**	−0.002	−0.023***	−0.007	−0.006	−0.001	−0.013***
	(0.000)	(0.015)	(0.465)	(0.002)	(0.199)	(0.107)	(0.861)	(0.004)
UK	0.009**	0.018***	−0.002	−0.036***	0.014***	0.006	0.009***	−0.014***
	(0.028)	(0.000)	(0.582)	(0.000)	(0.007)	(0.119)	(0.006)	(0.004)
France	0.015***	0.015***	0.000	−0.020**	0.010*	0.005	0.004	−0.015***
	(0.000)	(0.000)	(0.978)	(0.011)	(0.066)	(0.228)	(0.199)	(0.001)
Germany	0.028***	0.021***	0.006**	−0.006	0.039***	0.032***	0.027***	0.002
	(0.000)	(0.000)	(0.037)	(0.455)	(0.000)	(0.000)	(0.000)	(0.668)
Japan	0.023***	0.010**	0.001	−0.014*	0.020***	0.013***	0.013***	−0.008*
	(0.000)	(0.004)	(0.730)	(0.072)	(0.000)	(0.001)	(0.000)	(0.097)
SA	0.015***	0.002	−0.009***	−0.047***	0.018***	0.002	−0.006*	−0.004
	(0.000)	(0.515)	(0.002)	(0.000)	(0.000)	(0.612)	(0.056)	(0.360)
NZ	−0.007*	−0.009***	−0.014***	−0.063***	−0.037***	−0.022***	−0.013***	−0.003
	(0.099)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.454)

This table reports the results of the structural VAR model for the full sample (FS) and post-biofuel subsample (PBS) as specified in equation (5) considering positive and negative shocks. The Schwarz information criteria determine the lag length. The values between parenthesis represent the p-values. The asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.