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Nonlinear Effects of Oil Prices on Consumer Prices: A Comparative Study of Net Oil Consuming and Producing Countries

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In this paper, we implement a number of modified causality tests, including linear models, and nonlinear nonparametric Hiemstra–Jones and parametric Mackey–Glass models, to compare the causal relationships between changes in oil prices and consumer prices across large net oil consuming and producing countries. Our findings indicate that despite the inconclusive results in the extant literature, oil prices affect consumer prices mostly (non)linearly in net oil-consuming (-producing) countries through country-specific mechanisms. Moreover, the nonlinear causations are largely asymmetric.

Keywords: oil prices, consumer prices, oil consuming/producing countries, panel linear causality, nonlinear causality

JEL Classification: C14, E21, E31, Q43

1 Introduction

Study of the effects of oil price movements on economies dates back at least to the 1970s with the advent of global oil price shocks–recessions. Through the first generation of studies, researchers mainly analyzed the macroeconomic aspects of the oil price shocks, including their effect on major macroeconomic variables such as GDP, inflation and interest rates. The inflationary effects of global oil price shocks on recessions in particular have been a major subject of discussion, the preface to which is the 1973 recession and its possible relation to the first OPEC embargo.

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Some proven hypotheses suggest that if consumers expect that oil price increases are transitory, they save less and borrow more. Thus, increasing demand leads to an increasing price level (the real balance effect). Monetary tightening in response will then contract GDP followed by recession (Cologni and Manera, 2008). However, others argue that there is insufficient evidence to support the argument for the inflationary effects of oil price shocks (see Bohi, 1989; Bohi, 1991; Keane and Prasad, 1996 and Rotemberg and Woodford, 1996). Such mixed outcomes motivate us to consider the consumer price index (*CPI*) as an indicator of the response of the consumer cost of living to global oil price movements.

Possible reasons for the mixed evidence on this relationship to date are the various methods of estimation, differences in the identification of the oil price shocks, and changes in sample selection. In addition, it is possible that different countries depending on their pattern of oil use will also display differences. For instance, while an increase in oil prices is costly in oil-importing countries, oil-exporting countries may benefit from the associated income effects. Thus, the question we have in mind is whether the effects of oil price variations on consumer costs of living are the same in net oil consuming and net oil producing countries.

In this paper, we aim to respond to this question by applying the most powerful nonlinear parametric and nonparametric models available. We identify countries as net oil consuming and net oil producing rather than simply oil importing and oil exporting. In this way anything affecting net oil production or consumption will also influence the ability to export or import oil. Additionally, by defining countries as net oil consuming and producing, we are able to collect the highest frequency of data available. As a result, we expect to extend our findings to other oil consuming and producing countries not included in the analysis because of data limitations. Implementing both linear and nonlinear estimation methods using panel data and time series also enhances the validity of our findings.

Our study differs in some respects from previous work in the area. First, as discussed, we use the categorization of net oil consumption and net oil production. This enables us to expand our sample beyond oil export and imports, which can be a rather simple approach to the impact of oil on economies and consumers. Second, we collect the highest frequency of data available, which enables us to obtain findings that are more precise. Finally, we run several econometric methods, which reveal any possible causality between global oil prices and consumer prices. While most similar studies employ linear causality tests using time series, we estimate panel linear causality models. These yield the least bias in the estimated results. Additionally, estimation of nonlinear models enables us consider any nonlinear relationships between the variables.

The remainder of this paper is structured as follows. Section 2 reviews the literature background and Section 3 describes our data set. Sections 4 and 5 detail the estimation method and estimation results, respectively. Section 6 provides some concluding remarks and policy recommendations.

2 Background

While some studies consider that oil prices influence other prices directly, others assume that such effects are indirect. A review of the existing literature reveals that other than these direct and indirect mechanisms, oil price shocks affect economies through both aggregate and disaggregate channels. In a seminal study, Jones and Kaul (1996) note that the aggregate channel includes those studies, which investigate traditional supply shocks and demand adjustments theoretically or by generally regressing GDP on oil price and other variables empirically. One of the main findings of these aggregate level studies is the significant effects of oil price shocks on economic activity (see Hamilton, 1983, 1996, 2003; Gisser and Goodwin, 1986; Mork, 1989; Hooker, 1999; Burbidge and Harrison, 1984; Mork *et al,*. 1994; Jiménez-Rodríguez and Sánchez, 2005, 2009 and Kilian, 2008). In contrast, disaggregate level studies mainly focus on the impact of oil price shocks on individual markets, sectors and industries.

At the aggregate level, some studies support the existence of the significant effects of oil price changes on consumer price indexes. For instance, Burbidge and Harrison (1984) assess the dynamic relationship between oil prices and six other economic variables, including the aggregate price level, for five developed countries. Applying a vector auto regressive (VAR) model to a monthly data set covering the period January 1961 to June 1982, they find that oil prices have significant effects on both US and Canadian aggregate prices. However, such effects are found to be considerably weaker in Germany, Japan, and the UK. Likewise, using annual data over the period 1970 to 2006, Greenidge and DaCosta (2009) show that oil price changes exert significant effects on the inflation rate of four Caribbean countries (Barbados, Jamaica, Guyana, and Trinidad and Tobago). Finally, Cunado and Perez de Gracia (2005) prove that oil price shocks have rather significant influences on the inflation rate. Using quarterly data 1975Q1 to 2002Q2 for a group of six Asian countries—Japan, Singapore, South Korea, Malaysia, Thailand and Philippines—in a bivariate VAR framework, they conclude that such influences are even stronger when the oil price is in the local currency.

In contrast to the results of these studies, there is substantial evidence that oil price changes have only neutral or no effect on consumer prices (Hooker, 2002; LeBlanc and Chinn, 2004; Barsky and Kilian, 2004; Gregorio *et al.,* 2007; Bachmeier *et al.,* 2008 and Chen, 2009). Employing quarterly data in a Philips curve framework, Hooker (2002) shows that the inflationary effects of increasing oil prices have declined or even disappeared since 1980. Using a similar framework, LeBlanc and Chinn (2004) employ quarterly data for five developed countries over the period 1980 to 2001 to argue that the effects of oil prices on inflation across all the sample countries are only moderate, while Barsky and Kilian (2004) suggest that the effects of oil price shocks on inflation are not as significant as claimed. Employing US inflation rates from 1971 to 2004, they note that oil price shocks several spikes in US inflation rates.

Additionally, inflation in consumer prices does not follow major oil shocks. Likewise, Gregario *et al.* (2007) and Chen (2009) identify only minor effects of oil price shocks on the inflation rate, in most of 39 developing and developed sample countries in the former and 19 industrialized countries in the latter. Finally, using US data from the late 1940s to 2004, Bachmeier *et al.* (2008) suggest that oil price changes do not have predictive power over either future inflation or output.

Disaggregate level studies present findings concerning the possible channels that transfer the effects of oil price shocks to aggregate price levels, although the main emphasis is on disaggregate price levels. A review of the literature reveals little evidence these ever transfer to aggregate consumer prices. For instance, Zhang *et al.* (2010) conclude that the long-term relationship between energy prices—ethanol, gasoline, and oil—and a group of global commodities—corn, rice, soybeans, sugar, and wheat—is not evident in China. They also find that, at least in the short term, there is no causal relationship between energy prices and agricultural prices. In a similar study, Nazlioglu and Soytas (2011) find that oil prices have no significant effects on agricultural production.

Elsewhere, Baffes (2007), Harri and Nalley (2009) and Chen *et al.* (2010) prove that movements in oil prices display a close relationship with tradable agricultural commodities, while Panagiotidis and Rutledge (2007) show that oil price shocks in the UK could exert linear short-term effects on gas prices. In other work, Alghalith (2010) and Ibrahim and Said (2012) evidence a significant linkage between oil price movements and general food prices. Most recently, Ibrahim and Chancharoenchai (2013) find that there are long-term relationships between oil prices, aggregate consumer price indexes, and sets of disaggregate price indices. Employing quarterly Thai data from 1993Q1–2010Q2, Ibrahim and Chancharoenchai (2013) note that aggregate consumer prices, nonfood and beverage prices, and housing and furnishing prices asymmetrically adjust their long-term equilibrium with oil price movements. They also show that oil price changes exert short-term effects on the inflation rates of all types of commodities.

In sum, recent studies mainly address the oil price and consumer price relationship in either the US or Canada. Within the limited number of other studies, there is no comparative study of net oil consuming and producing countries. Further, the disaggregate level studies tend to concentrate on certain narrow groups of commodities. Finally, despite the importance of considering the effects of global oil price changes on consumer cost of living, there is no evidence of possible nonlinear causation between the two variables. Accordingly, this analysis sheds light on these issues using the most powerful nonlinear models, panel linear models, and selected groups of net oil consuming and producing countries.

3 Data Description and Overview

Our data set consists of oil prices (*OP*) and consumer price indexes (*CPI*) in selected net oil consuming and producing countries during the period January 1986–August 2013. The sample selection criterion is the net oil production (consumption) share of GDP. Based on this criterion for a large number of oil exporting and oil importing countries and given data availability, we designate the US, Brazil, Denmark, Italy, Germany, Netherlands and Sweden as net oil consuming countries and Canada, Mexico and Norway as net oil producing countries.

As a proxy for consumer cost of living, we employ consumer price indexes collected from the Organization for Economic Co-operation and Development (OECD). In addition, as a proxy for the global oil price (*OP*), we use the monthly oil price for West Texas Intermediate (WTI) crude oil. The WTI has widely been used in the literature as a benchmark for oil pricing. Moreover, it is highly correlated with the prices for the other major categories of crude oil, namely Brent and Dubai (Wang et al, 2013). We collect WTI statistics from the World Bank website. Then, using monthly US *CPI* from the OECD website, we calculate inflation-adjusted real oil prices. Finally, we index all data by their monthly-averaged 2010 values.

Table 1 presents some statistics. As shown, the average *CPI* ranges between 40.4 equivalents for Mexico to 70.9 equivalents for Germany. We also plot the time variation of growth rates of *OP* and *CPI* in Fig. 1.

Table 1: Selected statistics

Countries	Mean		SD	
	Level	Difference	Level	Difference
CPI				
Brazil	65.6484	0.4723	31.1679	0.7451
Denmark	62.8376	0.1757	27.5755	0.2762
Germany	70.9101	0.14282	21.3249	0.2325
Italy	56.4595	0.19464	32.8547	0.1520
Netherlands	68.1223	0.16003	22.6615	0.3144
Sweden	64.0492	0.17284	30.2663	0.3476
US	61.2652	0.17189	26.9451	0.2439
Canada	64.0492	0.16883	27.2263	0.2583
Norway	61.0389	0.17342	28.5041	0.3112
Mexico	40.4424	0.25203	38.5547	0.3052
OP	59.2783	0.2042	31.78851	5.5322

This table provides statistics for the period January 1986–August 2013. Both the consumer price indexes (*CPI*) and the oil price (*OP*) are monthly price and indexed to the constant inflation-adjusted year (2010).

Source: OECD, World Bank.

Because of small fluctuations in *CPI* compared with *OP* levels, we plot the growth rates of the variables to highlight such fluctuations. As depicted in Fig 1, it is difficult to identify visually any relationship between the two time series, with the possible exception of the US where consumer prices appear to lag oil prices.

Fig 1. Growth rates of global oil and national consumer prices.CPI × 10.

—— Growth rate of consumer price index - - - Growth rate of global oil price

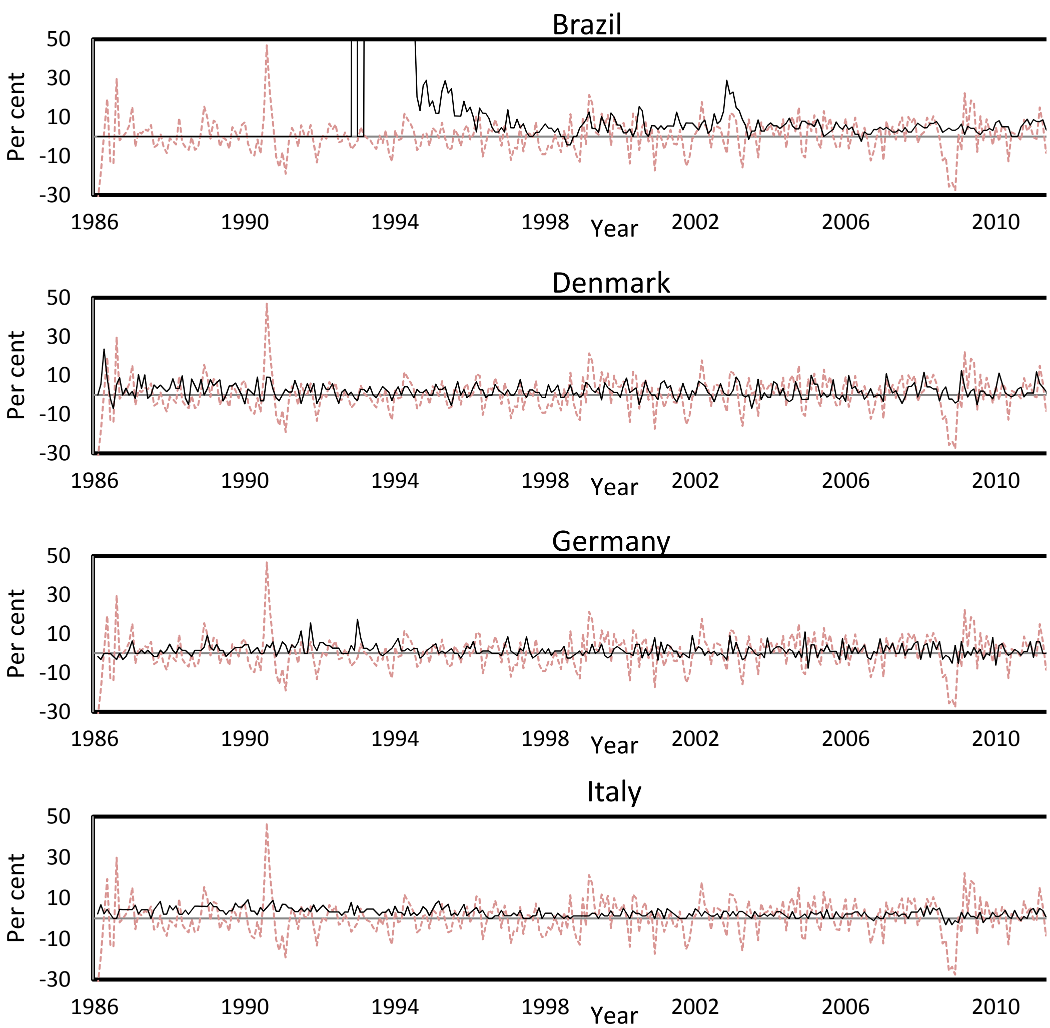


Figure 1 continued

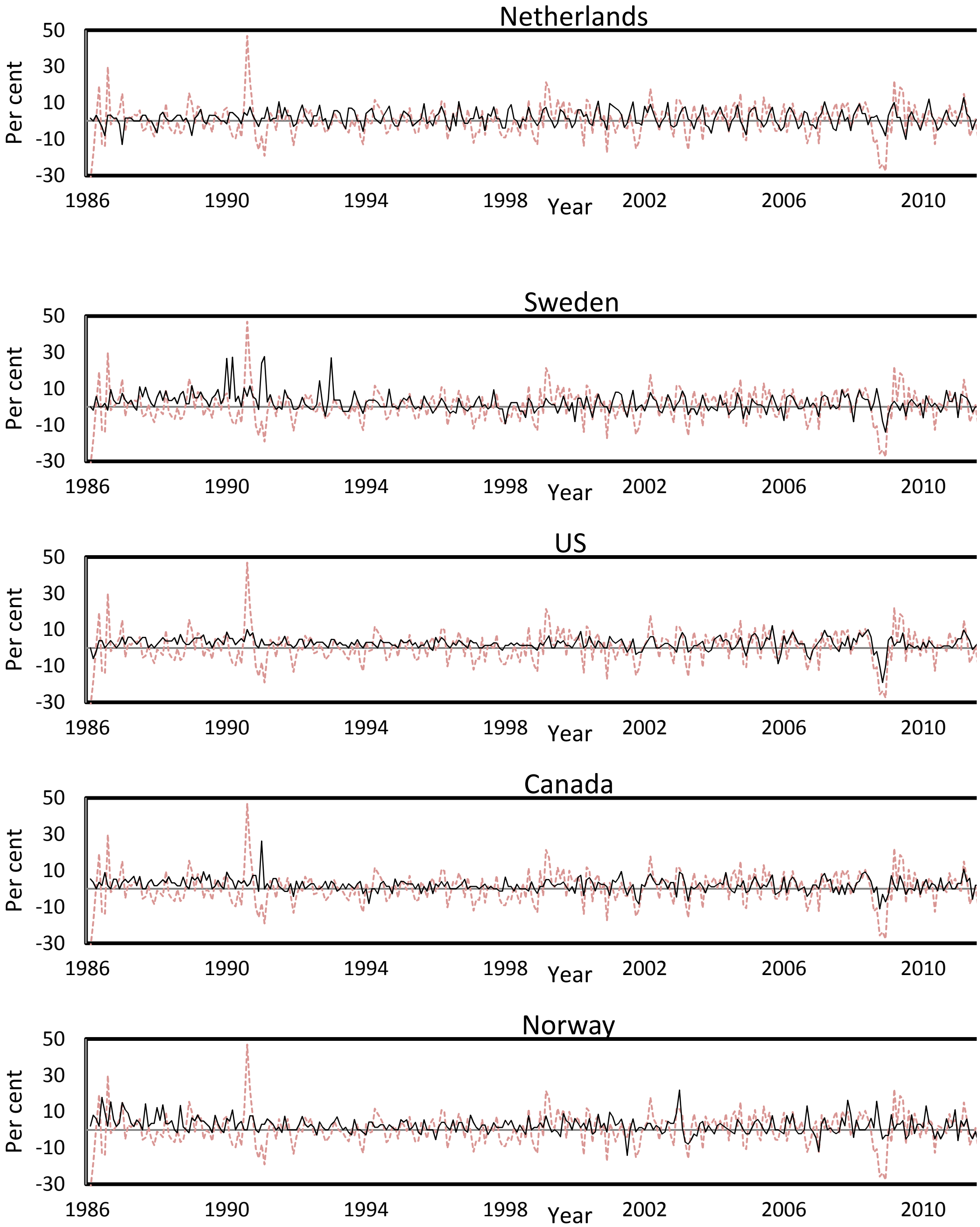
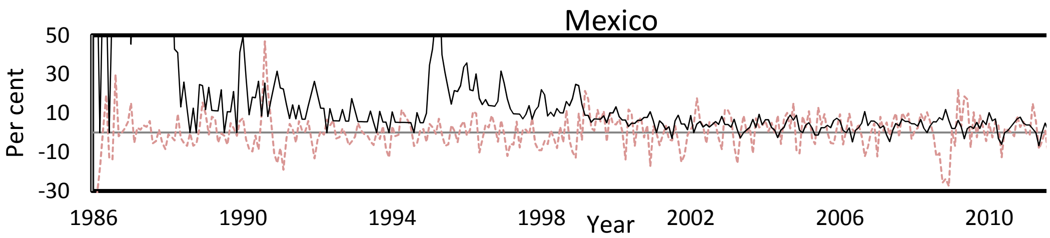


Figure 1 continued



Our preliminary investigation suggests a linear correlation between *OP* and *CPI*. The correlation coefficients reported in Table 2 vary between 0.62 equivalents for Sweden and 0.82 equivalents for Brazil. However, correlation does not guarantee causation.

Table 2: Correlation coefficients between global oil and consumer prices

Countries	Lag (months)			
	No lag	1	2	3
Brazil	0.8174	0.8161	0.8226	0.8255
Denmark	0.7744	0.7728	0.7705	0.7686
Germany	0.7163	0.7141	0.7114	0.7091
Italy	0.7111	0.7093	0.7072	0.7051
Netherlands	0.7656	0.7623	0.7586	0.7553
Sweden	0.6289	0.6293	0.6290	0.6287
US	0.7809	0.7796	0.7766	0.7732
Canada	0.7701	0.7694	0.7675	0.7653
Norway	0.7377	0.7374	0.7365	0.7355
Mexico	0.7409	0.7374	0.7340	0.7309

4 Empirical Methodology

4.1 Stationarity tests

There are several methods of estimating the order of integration. To select a proper test, the first criterion considered is sharing the parameters across panel units. Some tests such as the Levin–Lin–Chu (LLC), Harris–Tsavalis (HT) and Breitung assume that all panels share the same autoregressive parameter, while others such as Im–Pesaran–Shin (IPS), Fisher-type and Hadri LM tests assume an autoregressive parameter to be panel specific. In most of these cases, the assumption is too restrictive in practice (Maddala and Wu, 1999).

The second criterion is the restrictions on the number of cross-sectional units and time dimensions. While microeconomic data usually overspread with an infinite number of cross-sections during a fixed period, macroeconomic data are typically restricted to a limited number of cross sections with infinite time dimension. Thus, the size of the sample and number of periods prescribes the type of unit root test (for further technical discussion about the size of *N* and *T*, see Moon and Phillips, 1999 and Phillips and Moon, 2000). As our unbalanced panel includes 10 cross-sectional units with more than 500 periods, we select the Fisher-type and (to some extent) IPS tests to measure the panel data order of integration.

The Fisher unit root test employs Augmented Dickey Fuller (ADF) and Phillips–Perron (PP) tests. Using four methods proposed by Choi (2001), the Fisher unit root test combines *p*-values from panel-specific unit root tests. These methods apply inverse Chi-square, inverse normal, inverse logit and modified inverse chi-square transformations of *p*-values. Each method has different assumptions in the size of panel. While the majority of these test statistics apply to infinite samples, the reverse chi-square *p*-statistic is applicable for finite panels. The *p*-statistic has a chi-square distribution with 2N degree of freedom. We test the null hypothesis of the existence of a unit root across all of cross sections against the alternative hypothesis, which is at least one stationary panel.

The second test we conduct is the IPS, which allows heterogeneity across panels with serially uncorrelated errors. This test is applicable to the unbalanced panel data and allows *N* to be finite or infinite and reports three statistics: t-bar, t-tiled-bar and z-t-tiled bar. Among all, the t-bar statistic delivers our desired stationary test results regarding the finite *N*. due to assumption of finite time dimension, we assign the IPS test following the Fisher-type ADF test. Finally, to test the order of integration for our country-specific and nonlinear models, we perform Augmented Dicky-Fuller (ADF), Elliot–Rothenberg–Stock (DF-GLS) and Philips–Perron (PP) tests using the time series.

4.2 Panel linear causality tests

One of the best available econometric methods to investigate possible dynamic relationships within panel data is the panel vector autoregressive (PVAR) approach. This method has least bias when the cross sections and time tend to infinity. However, given the finite cross sections in our data, the PVAR estimators are biased and hence, this method is not applicable. Juessen and Linnemann (2010) compared several panel estimation models using Monte-Carlo simulation. Because of biased estimations using instrumental variables and GMM estimators in models with a restricted number of cross-sectional units, Juessen and Linnemann (2010) recommend a bias-corrected least squares dummy variables (LSDV) model, which is easy to implement and suits samples with large time dimension. Consequently, we implement the bias-corrected LSDV model modified by Bruno (2005), for panels with a small number of cross-sectional units. Consider the following dynamic standard model:

$$y = D\eta + W\delta + \epsilon \tag{1}$$

where D is the matrix of individual dummies, $W = (y_{-1} \vdots X)$ is the matrix of stacked observations, η is the vector of individual effects and δ is the vector of coefficients. To select the usable observations from within unbalanced panel data, we use a selection index as below:

$$s_{it} = \begin{cases} 1 & if\ (r_{it}, r_{it-1}) = (1,1) \\ 0 & otherwise \end{cases} \tag{2}$$

where $r_{it} = 1$ if y_{it} and x_{it} are observed and $r_{it} = 0$ otherwise, i denotes the size of the cross-sectional series and t is the time dimension. We now rewrite Equation 1 as follows:

$$Sy = SD\eta + SW\delta + S\epsilon \tag{3}$$

In this equation, δ is the LSDV estimator that should be measured. Through the estimation procedure of δ, which has been explained in detail in Bun and Kiviet (2003) and Bruno (2005), one of the Anderson and Hsiao (1982), Arellano and Bond (1991) or Blundell (1998) estimators are employed to measure three types of bias approximations. Assuming B_i indicates estimated bias approximation extracted from formulations presented in Bruno (2005), the bias-corrected LSDV model (LSDVC) is estimated through the second stage of estimation as below:

$$LSDVC_i = LSDV - \hat{B}_i \tag{4}$$

where $i=1, 2, 3$ denotes one of the bias approximations.

The linear Granger causality tests suggest the predictability of a variable by its past values, and the current and past values of the cause variable. We use bias-corrected LSDV method to estimate the Granger linear causation between global oil price changes and consumers' cost of living. Thus, in a regression of CPI_t on lagged values of CPI_t and OP_t, OP_t would not be Granger-cause of CPI_t if the coefficients of OP_t are jointly zero:

$$CPI_t = \sum_{i=1}^{m} a_i CPI_{t-i} + \sum_{j=1}^{n} b_j\, OP_{t-j} + D_t + e_t \tag{5}$$

where a_i and b_j are coefficients, D_t is deterministic trend and e_t is the random error term. Rejection of the null hypothesis of $b_1 = b_2 = b_3 = \cdots = b_n = 0$ indicates that OP_t is the Granger cause of CPI_t. This model, as Guilkey and Salemi (1982) describe, rejects false null hypothesis by 3.26 per cent and 2.64 per cent more than Sims and Modified Sims causality tests, respectively. The direct Granger causality test as a powerful tool describes both the existence and direction of causality. Finally, we run bootstrapping simulation to see whether desired coefficients are statistically significant.

3.3 Nonlinear causality tests

As the existence of nonlinear relationships between economic variables is a given in the existing literature, linear causality tests may cover only a portion of such existing relationships (Ajmi *et al.,* 2013). Furthermore, linear Granger causality tests omit the possibility of higher order structure, such as conditional heteroscedasticity. Thus, in order to extend our estimations beyond linear methods, we perform nonlinear parametric and nonparametric causality models.

In this paper, we employ Baek and Brock's (1992) nonlinear nonparametric model, as modified by Hiemstra and Jones (1994). Denote that m-length lead vector of CPI_t by CPI_t^m and the *Lcpi*-length and *Lop*-length lag vectors of CPI_t and OP_t by CPI_{t-Lcpi}^{Lcpi} and OP_{t-Lop}^{Lop}. As a result;

$$
\begin{aligned}
&CPI_t^m = (CPI_t, CPI_{t+1}, \dots, CPI_{t+m-1}) \\
&CPI_{t-Lcpi}^{Lcpi} = \left(CPI_{t-Lcpi}, CPI_{t-Lcpi+1}, \dots, CPI_{t-1}\right) \qquad (6) \\
&OP_{t-Lop}^{Lop} = (OP_{t-Lop}, OP_{t-Lop+1}, \dots, OP_{t-1})
\end{aligned}
$$

where $m = 1, 2, ...$; $t = 1, 2, ...$; $Lcpi = 1, 2, \dots, t$ and $Lop = 1, 2, \dots, t$. For CPI, $t = Lcpi + 1$, $Lcpi + 2, ...$ and in case of OP, $= Lop + 1, Lop + 2, \dots$. For given values of $m, Lcpi, Lop \geq 0$ and for $e > 0$, OP does not strictly Granger cause CPI if:

$$
\begin{aligned}
&\Pr\left(\|CPI_t^m - CPI_s^m\| < e \middle| \left\|CPI_{t-Lcpi}^{Lcpi} - CPI_{s-Lcpi}^{Lcpi}\right\| < e, \left\|OP_{t-Lop}^{Lop} - OP_{s-Lop}^{Lop}\right\| < e\right) \\
&\qquad = \Pr\left(\|CPI_t^m - CPI_s^m\| < e \middle| \left\|CPI_{t-Lcpi}^{Lcpi} - CPI_{s-Lcpi}^{Lcpi}\right\| < e\right) \qquad (7)
\end{aligned}
$$

where *Pr*(.) denotes the probability and ‖‖ is the maximum norm. The conditional probability stated in the left side of equation 7 explains two arbitrary m-length lead vector of CPI_t within a distance *e* of each other when corresponding *Lcpi*-length lag vectors of CPI_t and *Lop*-length lag vectors of OP_t are given. Likewise, the conditional probability given in the right side of equation 7 denote that two arbitrary m-length lead vectors of CPI_t are within a distance *e* of each other where their corresponding *Lcpi*-length lag vectors within a distance *e* of each other are given. Hiemstra and Jones (1994) show that the following statistic has asymptotic normal distribution:

$$
\sqrt{n}\left(\frac{C_1(m + Lcpi, Lop, e, n)}{C_2(Lcpi, Lop, e, n)} - \frac{C_3(m + Lcpi, e, n)}{C_4(Lcpi, e, n)}\right) \sim N(0, \sigma^2(m, Lcpi, Lop, e) \qquad (8)
$$

where $n = T + 1 - m - \max(Lcpi, Lop)$, and C_1, C_2, C_3 and C_4 are correlation integral estimators of the joint probabilities in equation 7. Also, σ^2 is estimated using the theory of U-statistic for weakly dependent processes and has been measured by Denker and Keller (1983). This test statistic is applied to the estimated residuals of the bivariate VAR model using *CPI* and *OP*. The test statistic is used to examine the null hypothesis of nonlinearly and strictly Granger non-causation *OP* to *CPI*. As Hiemstra and Jones (1994) argue, this model has a very good power in estimating nonlinear Granger causal and non-causal relationships.

Mackey and Glass (1977) first applied our parametric nonlinear model in describing a physiological control system using chaos theory, and since modified by Kyrtsou and Labys (2006). The test is similar to the linear Granger causality test. However, it contains the Mackey–Glass model process with special parameters estimated using ordinary least squares method. In order to examine the existence of nonlinear causality between oil price changes and the *CPI*, we start with the following models:

$$\begin{aligned} DCPI_t = \alpha_{11}\left(DOP_{t-\tau_1}\right)\left(1+DOP_{t-\tau_1}^{c_1}\right)^{-1} - \delta_{11}DOP_{t-1} \\ + \alpha_{12}\left(DCPI_{t-\tau_2}\right)\left(1+DCPI_{t-\tau_2}^{c_2}\right)^{-1} - \delta_{12}DCPI_{t-1} \\ + u_t \end{aligned} \quad (9)$$

$$\begin{aligned} DOP_t = \alpha_{21}\left(DOP_{t-\tau_1}\right)\left(1+DOP_{t-\tau_1}^{c_1}\right)^{-1} - \delta_{21}DOP_{t-1} \\ + \alpha_{22}\left(DCPI_{t-\tau_2}\right)\left(1+DCPI_{t-\tau_2}^{c_2}\right)^{-1} - \delta_{22}DCPI_{t-1} \\ + \varepsilon_t \end{aligned} \quad (10)$$

where $DCPI_t$ and DOP_t are the first differences of the *CPI* and *OP*, respectively, $\tau = max(\tau_1, \tau_2)$ is the calculated integer delays, c is the constant and $t = \tau, \tau+1, \ldots, N$. The parameters α and δ present the linear and nonlinear effects of the cause variables on dependent variables, respectively. Finally, the two error terms u_t and ε_t are assumed to be $N(0,1)$. We select the integer delays τ_i and constants c_i prior to the model estimation using the Schwarz criterion and likelihood ratio. If *OP* nonlinearly Granger-causes *CPI*, α_{11} should be significantly different from zero (the null hypothesis). Thus, we need to estimate Equation 9 first with no constraint and then with the constraint of zero value of α_{11}. Assuming that $\hat{\vartheta}$ and $\hat{\mu}$ are the residuals of such unconstrained and constrained Mackey–Glass models, respectively. We then calculate a Fisher-distributed statistic as below:

$$S_F = \frac{(S_c - S_u)/n_c}{S_u/(T - n_u - 1)} \sim F(n_c, T - n_u - 1) \quad (11)$$

where $S_u = \sum_{t=1}^{T} \hat{\vartheta}^2$, $S_c = \sum_{t=1}^{T} \hat{\mu}^2$, $n_u=4$ given the four parameters in the Mackey–Glass model and $n_c=1$ as there is one parameter needed to be zero when estimating the constrained model. The parametric nonlinear causality test also applies to asymmetric cases. Thus, in order to investigate the asymmetric nonlinear causation of *OP* to *CPI*, we can consider positive and negative values of *OP,* respectively. That is, (OP_t, CPI_t) is used as observation in the Mackey–Glass process if $OP_{t-\tau} \geq 0$ in case of studying nonlinear causation of positive *OP*'s to *CPI*. Conversely, negative changes of oil price may be used in studying the nonlinear causation of negative *OP*'s to *CPI*. It is worth noting that the whole mentioned symmetric and asymmetric procedure is repeated for Equation 10 to consider the nonlinear causation of *CPI* to *OP*.

5 Empirical Results

5.1 Panel linear causality tests

Table 3 demonstrates the results of the Fisher-type ADF and IPS panel unit root tests. The test statistics reported in the first two rows of the table indicate that both the *CPI* and *OP* are integrated of order one. However, the IPS test statistic delivers stationary *OP* in trend while we justify Fisher-type ADF in preference to IPS. The second two rows of Table 3 outline such panel unit root tests for the first differences of the variables. The results reveal that the null hypothesis of no stationary existence is rejected in all of the cases with 99 percent level of confidence. Consequently, we employ the first difference of the variables.

Now, we place the first difference of the variables in our bias-corrected LSDV model and simulate statistical significance of the coefficients by bootstrapping. It is worth noting that following Hamilton (2011), we primarily enter 24-month lags and choose the optimum lag order using Akaike Information Criterion (AIC). Table 4 details the results. As shown, it is evident that *OP* do not Granger-cause the *CPI*. Likewise, we cannot reject the null hypothesis of no causality running from the *CPI* to *OP*. This finding is consistent with Hooker (2002), LeBlanc and Chinn (2004), Barsky and Kilian (2004), Gregario *et al.* (2007), Bachmeier *et al.* (2008) and Chen (2009).

5.2 Traditional linear causality tests

Following our results in finding no evidence of panel linear causation between *OP* and the *CPI*, we now test such causation using a traditional country-specific causality test. As the test requires stationary data, we first consider the country-specific order of integration. Table 5 indicates the results of the ADF, DF-GLS, and PP unit root tests. The results suggest that *CPI* and *OP* are integrated of order one. However, their first differences are stationary across all countries at the 99 percent level of confidence. Thus, we enter the first difference of the variables into the test.

The results of the country-specific Granger causality tests, presented in Table 6, reveal that despite of rejecting the null hypothesis of no panel linear causation, *OP* fluctuations may affect the *CPI* in each country individually. However, while the test statistics are statistically

Table 3: Panel unit root test

Variable	Fisher-type ADF				IPS			
	Constant		Trend		No trend		Trend	
	P-statistic	*p*-value	*P*-statistic	*p*-value	*t*-bar	*p*-value	*t*-bar	*p*-value
CPI	11.6928	0.9262	21.2389	0.3832	−0.3102	1.0000	−1.4195	0.7277
OP	4.8110	0.9998	28.0935	0.1072	−0.9054	0.9898	−2.6777	0.0000
DCPI	670.6648	0.0000	667.2005	0.0000	−16.4909	0.0000	−16.6190	0.0000
DOP	720.8731	0.0000	720.8731	0.0000	−12.8518	0.0000	−12.8396	0.0000

This table shows panel unit root test results. The null hypothesis is nonstationarity. The *P*-statistic has a chi-square distribution with *2N* degrees of freedom and the *t*-bar statistic has a normal distribution.

Table 4: Panel linear causality test

Causality	Net oil consuming countries			Net oil producing countries		
	Test statistic (Chi-square)	*p*-value	Result	Test statistic (Chi-square)	*p*-value	Result
$\Delta OP \rightarrow \Delta CPI$	0.51	0.9730	Non-causality	4.38	0.3569	Non-causality
$\Delta CPI \rightarrow \Delta OP$	0.86	0.9299	Non-causality	1.94	0.7471	Non-causality

This table provides the results of panel linear causality tests. The null hypothesis is noncausality. P-values extracted from bootstrapping simulation.

significant in all net oil-consuming countries, they are not in net oil producing countries. Furthermore, the results reported for the US, Italy and Canada are statistically significant at the 99 percent level of confidence. Finally, other than Netherlands and Canada, the causation direction is unilateral across the other sample countries.

To conduct further investigation of the subject and due to heterogeneous outcomes within panel and country-specific linear causality tests, we apply nonlinear causality tests in the next section.

5.3 Nonparametric nonlinear causality tests

To implement our nonparametric nonlinear test, we first need assurance that the data are stationary. Table 5 reports the results, indicating that the first difference of the variables is integrated of order zero. Monte-Carlo simulations as conducted by Hiemstra and Jones (1994) suggest that the lead lengths = 1, the lag lengths = 1, …, 8, and $e = 1.5\sigma$. Estimating the model by entering such predetermined values, our nonparametric nonlinear test results are displayed in Table 7. The results indicate that *OP* have significant nonlinear causal effects on the *CPI* of three of the seven net oil-consuming countries and the three net oil-producing countries.

The summary results for net oil-consuming countries are as follows. First, Germany and Sweden exhibit a strong nonlinear unilateral causation running from *OP* to the *CPI*. The test statistics are significant at the 99 percent level of confidence. Second, the nonlinear causation in the US is bilateral and statistically significant. Finally, there is a unilateral causation running from the *CPI* to *OP*, which is statistically significant at the 90 percent level of confidence in Denmark.

In contrast, our net oil-producing sample countries display strong causal effects running from *OP* to the *CPI*. Canada exhibits a unilateral causation from the *OP* to the *CPI* at the 99 percent level of confidence. Norway and Mexico display bilateral causality between the *OP* and the *CPI* at the 95 and 99 percent level of confidence, respectively. In short, our nonlinear

Table 5: Time series unit root test

Country	ADF		DF-GLS		PP	
	Level	Fist difference	Level	Fist difference	Level	First difference
Unit root test for CPI						
Brazil	–2.099	–6.367*	–1.823	–5.977*	–1.426	–6.378*
Denmark	–1.647	–19.358*	–0.698	–16.697*	–1.750	–19.098*
Germany	–1.556	–24.421*	–0.824	–13.203*	–1.545	–24.368*
Italy	0.341	–16.028*	–0.475	–7.635*	0.157	–17.147*
Netherlands	–1.125	–17.041*	–1.380	–17.815*	–1.376	–16.596*
Sweden	–2.232	–19.007*	–0.062	–15.154*	–2.058	–18.862*
US	0.548	–13.726*	–2.365	–13.863*	0.363	–13.206*
Canada	–1.488	–19.564*	–0.614	–12.414*	–1.309	–19.665*
Norway	–1.108	–20.943*	–0.727	–15.091*	–1.123	–20.862*
Mexico	7.265	–8.453*	–0.112	–8.322*	3.883	–8.417*
Unit root test for OP	–0.905	–12.852*	–2.550**	–4.422*	–1.563	–12.833*

This table provides country-specific unit root test results. The null hypothesis is nonstationarity. * and ** denote significance at the 1% and 10% levels, respectively.

Table 6: Traditional country-specific linear causality tests

Causality	$\Delta OP \rightarrow \Delta CPI$	$\Delta CPI \rightarrow \Delta OP$
	Test statistic	Test statistic (chi-square)
Brazil	1.92***	0.81
Denmark	2.78**	0.88
Germany	1.95***	1.52
Italy	4.20*	1.05
Netherlands	2.38**	1.87**
Sweden	1.96***	0.99
US	3.92*	1.15
Canada	4.14*	1.85***
Norway	1.23	1.40
Mexico	1.01	0.80

This table provides the results of country-specific linear Granger causality tests. The test statistic is F-distributed. The null hypothesis is noncausality. *, ** and *** indicate significance at 1%, 5% and 10% levels, respectively.

nonparametric causality test reveals that *OP* have statistically significant nonlinear effects on the *CPI* of some net oil-consuming countries and all net oil-producing countries.

5.4 Parametric nonlinear causality tests

To estimate the parametric nonlinear Mackey–Glass model, we first select the model parameters using the Schwarz criterion and likelihood ratio. The first and second columns of the results reported in Table 8 show that the lag-length periods from *OP* to the *CPI* vary from 1 to 10 months for all countries. However, the *CPI* affects *OP* after only a month across all countries. The lag orders in Table 8 supply guidelines to policy decision makers regarding the time needed for the appearance of *OP* on the *CPI*.

Now, we use the symmetric modified Mackey–Glass model to test whether *OP* cause the *CPI* nonlinearly. The test results presented in Table 9 display very weak evidence on the unidirectional nonlinear causation of *OP* to *CPI*. We reject the null hypothesis of no causation of *OP* to *CPI* in just two cases: Denmark (a net oil consumer) and Canada (a net oil producer). Furthermore, there is no evidence to prove that the *CPI* causes oil price changes nonlinearly. This finding is in conjunction with Hooker (2002), LeBlanc and Chinn (2004), Barsky and Kilian (2004), Gregario *et al.* (2007), Bachmeier *et al.* (2008) and Chen (2009).

Table 7: Hiemstra–Jones nonlinear causality test

	OP →*CPI*		*CPI* →*OP*	
Lags	CS	TVAL	CS	TVAL
Brazil				
1	0.0001	0.0020	–0.0113	–0.1782
2	–0.0040	–0.0625	–0.0160	–0.2509
3	–0.0215	–0.3361	–0.0161	–0.2518
4	–0.0374	–0.5830	–0.0176	–0.2752
5	–0.0668	–1.0394	–0.0250	–0.3889
6	–0.0675	–1.0473	–0.0297	–0.4612
7	–0.0675	–1.0451	–0.0297	–0.4603
8	–0.0632	–0.9768	–0.0345	–0.5341
Denmark				
1	0.0274	0.4896	0.0242	0.4323
2	0.0485	0.8643	0.0359	0.6399
3	0.0685	1.2186	0.0485	0.8624
4	0.0631	1.1209	0.0561	0.9963
5	0.0560	0.9928	0.0593	1.0520
6	0.0531	0.9404	0.0681	1.2059
7	0.0435	0.7681	0.0868	1.5334*
8	0.0440	0.7754	0.0906	1.5984*
Germany				
1	0.0293	0.5225	0.0124	0.2218
2	0.0603	1.0743	0.0220	0.3929
3	0.0923	1.6414*	0.0175	0.3120
4	0.1144	2.0314***	–0.0051	–0.0911
5	0.1409	2.4977***	–0.0422	–0.7486
6	0.1632	2.8875***	–0.0734	–1.3000
7	0.1675	2.9585***	–0.0882	–1.5591
8	0.1528	2.6944***	–0.1034	–1.8250
Italy				
1	0.0224	0.3987	0.0231	0.4120
2	0.0525	0.9356	0.0292	0.5202
3	0.0549	0.9757	0.0213	0.3802
4	0.0528	0.9364	0.0041	0.0742
5	0.0431	0.7631	–0.014	–0.2609
6	0.0480	0.8497	–0.0209	–0.3713
7	0.0412	0.7277	–0.0078	–0.1378
8	0.0424	0.7478	0.0062	0.1105
Netherlands				
1	0.0336	0.5999	0.0052	0.0942
2	0.0320	0.5701	0.0092	0.1654
3	0.0404	0.7178	0.0083	0.1480
4	0.0385	0.6834	–0.0014	–0.0256
5	0.0394	0.6981	–0.0042	–0.0745
6	0.0388	0.6865	–0.0170	–0.3016
7	0.0285	0.5038	–0.0292	–0.5164
8	0.0238	0.4197	–0.0466	–0.8233

	OP →*CPI*		*CPI* →*OP*	
Lags	CS	TVAL	CS	TVAL
Sweden				
1	0.0250	0.4457	–0.0023	–0.0418
2	0.0412	0.7337	0.00334	0.0595
3	0.0606	1.0765	0.0228	0.4054
4	0.0833	1.4777***	0.0250	0.4452
5	0.0957	1.6965**	0.0139	0.2478
6	0.1107	1.9583**	–0.0090	–0.1609
7	0.1231	2.1738***	–0.0276	–0.4887
8	0.1262	2.2251***	–0.0357	–0.6305
US				
1	0.0662	1.1813	0.0409	0.7295
2	0.0915	1.6298*	0.0822	1.4644*
3	0.0997	1.7722**	0.0979	1.7418**
4	0.0949	1.6846**	0.1109	1.9698***
5	0.0791	1.4018*	0.1177	2.0873***
6	0.0562	0.9949	0.1184	2.0952***
7	0.0365	0.6456	0.1062	1.8775***
8	0.0196	0.3462	0.0991	1.7477**
Canada				
1	0.0424	0.7567	0.0148	0.2640
2	0.0605	1.0774	0.0275	0.4904
3	0.0991	1.7615**	0.0524	0.9315
4	0.1186	2.1047***	0.0652	1.1574
5	0.1235	2.1895***	0.0484	0.8578
6	0.1135	2.0089***	0.0310	0.5490
7	0.0923	1.6310**	0.0233	0.4132
8	0.0785	1.3849*	0.0264	0.4669
Norway				
1	0.0457	0.8155	0.0202	0.3605
2	0.0783	1.3937	0.0633	1.1280
3	0.0966	1.7182**	0.1004	1.7854**
4	0.0883	1.5680*	0.1121	1.9908***
5	0.0759	1.3455*	0.1097	1.9441**
6	0.0564	0.9977	0.1119	1.9800***
7	0.0340	0.6006	0.1054	1.8626**
8	0.0309	0.5450	0.0976	1.7228**
Mexico				
1	0.0254	0.4538	0.0033	0.0602
2	0.0625	1.1135	0.0225	0.4010
3	0.0977	1.7378**	0.0361	0.6419
4	0.1102	1.9566***	0.0490	0.8709
5	0.1070	1.8970**	0.0543	0.9627
6	0.1012	1.7898**	0.0870	1.5405**
7	0.1058	1.8682**	0.1257	2.2207***
8	0.1165	2.0552***	0.1670	2.9465***

CS and TVAL denote the difference between the two conditional probabilities and the standardized test statistic, respectively. *, ** and *** denote significance at the 1%, 5% and 10% levels, respectively. Canada, Norway, and Mexico are net oil producing countries and the remainder are net oil consuming countries.

Table 8: Parameter-prior selection in the Mackey−Glass model

Country	τ_1	τ_2	c_1	c_2
Brazil	1	1	2	1
Denmark	10	1	1	1
Germany	1	1	1	1
Italy	2	1	1	1
Netherlands	9	1	1	3
Sweden	6	1	1	1
US	2	1	1	2
Canada	1	1	1	1
Norway	8	1	1	1
Mexico	1	1	2	2

τ_1 and τ_2 are the optimal integer delay variables for causality from *OP* to *CPI* and for causality from *CPI* to *OP*, respectively. c_1 and c_2 are the powers of the lagged values of *OP* and *CPI*, respectively.

Table 9: Symmetric nonlinear causality test

Country	H0: *OP* does not cause *CPI*		H0: *CPI* does not cause *OP*	
	F-statistic	Probability	*F*-statistic	Probability
Brazil	0.6180	0.4325	0.2420	0.6231
Denmark	–11.9473	0.0006	–0.6238	0.9801
Germany	1.6002	0.2067	0.1330	0.7155
Italy	2.2219	0.1370	–0.7420	0.3896
Netherlands	1.9388	0.1647	0.8106	0.3685
Sweden	2.0887	0.1493	0.1125	0.7374
US	–0.0616	0.8040	–0.7957	0.3730
Canada	3.8751	0.0498	1.0860	0.2981
Norway	1.6377	0.2015	0.1022	0.7493
Mexico	0.0121	0.9123	0.2106	0.6465

This table provides the results of symmetric nonlinear Mackey–Glass causality test. The null hypothesis is noncausality. F-statistic is Fisher-distributed with N–4 and N–1 degrees of freedom.

To test the assumption of asymmetric nonlinear effects of *OP* on *CPI*, we run the asymmetric version of the Mackey–Glass model. Tables 10 and 11 display the results. The tables indicate that unidirectional causation of *OP* to *CPI* is asymmetric in the case of Denmark and Canada. That is, only positive changes in *OP* cause movements in the *CPI* of these two countries. In short, the results of the parametric nonlinear causality test supplies only very weak evidence on *OP* causing changes in the *CPI*.

Table 10: Asymmetric nonlinear causality test for negative changes of the causing variable

Country	H0: *OP* does not cause *CPI*		H0: *CPI* does not cause *OP*	
	F-statistic	Probability	*F*-statistic	Probability
Brazil	0.3421	0.5599	NA	NA
Denmark	–0.9473	0.3397	–0.1335	0.7158
Germany	–0.2022	0.6564	–0.0521	0.8200
Italy	–0.5081	0.4820	0.1780	0.6947
Netherlands	0.3744	0.5457	0.0679	0.7949
Sweden	0.4780	0.4951	–1.0342	0.3122
US	–0.9760	0.3248	–0.3397	0.5637
Canada	0.8972	0.3519	–0.8839	0.3511
Norway	–1.6051	0.2159	0.3488	0.5567
Mexico	0.2038	0.6523	–0.3647	0.5593

This table provides the results of Mackey–Glass nonlinear causation of negative changes of *OP* to *CPI*. Fisher-statistic is F-distributed with N–4 and N–1degree of freedom.

Table 11: Asymmetric nonlinear causality test for positive changes in the causing variable

Country	H0: *OP* does not cause *CPI*		H0: *CPI* does not cause *OP*	
	F-statistic	Probability	*F*-statistic	Probability
Brazil	–0.5849	0.4456	0.2506	0.6171
Denmark	–11.7646	0.0006	–0.4070	0.5240
Germany	1.9928	0.1591	0.3308	0.5657
Italy	1.7840	0.1827	–0.4052	0.5249
Netherlands	0.4141	0.5203	0.9672	0.3264
Sweden	2.0311	0.1551	1.1013	0.2950
US	0.6457	0.4227	3.0407	0.0823
Canada	6.2296	0.0131	1.5443	0.2151
Norway	1.6441	0.2007	0.7199	0.3970
Mexico	–0.2130	0.6449	0.2194	0.6398

This table provides the results of Mackey–Glass nonlinear causation of positive changes of *OP* to *CPI*. F-statistic is Fisher-distributed with N–4 and N–1 degrees of freedom.

6 Conclusions

In this paper, we compare the causal relationships between oil price movements and consumer costs of living in net oil-consuming and net oil-producing countries. First, we specify countries as net oil-consumers or producers so that we reflect the interrelationship between domestic oil production and consumption and international oil exports and imports. Second, we implement two types of linear Granger causality tests including panel and country-specific. Our bias-corrected panel linear causality test supplies no evidence on the causal effects of oil price changes on consumers' cost of living. Following the assumption of country-specific effects of global oil price changes, we conduct country-specific linear causality tests. As opposed to the panel test results, we find evidence that country-specific linear causality running from oil prices to consumer prices in net oil-consuming countries is stronger than in net oil-producing countries.

Finally, due to weakness of linear models in finding all possible linkages within economic and financial variables, we employ two powerful nonlinear causality tests. Whereas the parametric test rejects the existence of any nonlinear causal effects of oil prices on consumer prices across the sample countries with the exception of Denmark and Canada, the nonparametric test displays evidence of strong causality in all net oil producing and three of the seven net oil-consuming countries. The significant test results using the parametric model are also asymmetric.

Consequently, the results of our comparative study show that oil prices affect consumer prices in both net oil-consuming and net oil-producing countries. The nature of these effects is mostly linear in net oil-consuming countries and generally nonlinear in net oil-producing countries. The shorter lag lengths in net oil-producing countries also indicate that efficient policy decisions have a shorter deadline in these countries in avoiding the unwanted effects of increasing oil prices.

Although we find significant nonlinear causation, mainly running from oil prices to consumer prices, we note two important points. Firstly, the nonlinear models we apply provide no guidance on the source of these nonlinearities. For this, we may need specific parameterized structural models. Second, b it is not possible to determine whether the significant nonlinear predictive power is evidence of positive or negative nonlinear causality. Beside the evidence that nonlinear models supply, linear causality tests may provide an incorrect assessment of the true relationship between oil prices and monetary aggregates, which are of nonlinear nature with respect to our results, and may suggest misleading policy actions.

For further study, we recommend an even more powerful statistical test, which accounts for not only nonlinearity, asymmetry and time-variations, but also the conditional heteroscedasticity in the VAR model's variances. Additionally, consideration of domestic oil prices is highly recommended. Finally, it would be interesting to consider the effects of oil price changes on the components of general consumer prices.

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