The asymmetric relationships between pollution, energy use and oil prices in Vietnam: Some behavioural implications for energy policy-making

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ABSTRACT

With rapidly expanding real GDP in Vietnam, it is anticipated that the Vietnamese energy production will increase to meet its rising energy consumption. An important corollary is that pollution will also rise since the energy sector is considered a big polluter in the developing world. This paper brings two important insights to this literature: first and foremost, this paper seeks to establish if any behavioural biases of policy makers have clouded the decision to adopt suitable energy technologies and policies in Vietnam with far-reaching consequences for sustainability in the region. Secondly, in order to detect behavioural biases, it considers the *asymmetric* effects of increases vis-à-vis decreases in regressors by using the non-linear autoregressive distributed lags (NARDL) models, to examine how such increases or decreases really impact on pollution in Vietnam. Using annual data from 1982 to 2015, the analysis finds that the long-run relationships between pollution, energy use and oil prices have been characterised by non-linear and asymmetric interlinkages to indicate hidden cointegration. We further argue that such hidden cointegration can signal important behavioural biases in (energy) policy-making.

Keywords: Pollution; energy consumption; openness; Vietnam; ARDL and NARDL

JEL Classifications: Q430; O530; P280

1. Introduction

Rising energy demand has traditionally tracked increasing economic growth at least for the past two centuries in the global economy with serious impacts on our fragile environment. Developing economies of Asia and Africa will absorb more than 50% of the global population growth through the 21st century with (anticipated) massive increases in energy use due to high economic growth. In such a scenario, the penetration of renewable energy sources in the energy mix along with adoption of new technologies can limit ecological footprints of economic growth in developing nations like Vietnam. Thus energy policy thus holds the key to the future ecological sustainability in a country like Vietnam. Yet, the energy policy of Vietnam cannot be examined in isolation from the regional energy policies of the Asia-Pacific nations. For the effectiveness of our collective policy response to fight human insecurity from climate change, the Asia-Pacific Economic Cooperation (APEC) represents a critically important region (Asian Development Bank, 2019). This region's 21 economies have long been beset with unprecedented energy insecurity, it is officially held that the APEC will further experience a massive 21 per cent rise in energy demand over the next three decades, which will put their vulnerable, degraded and fragile environment under terrible pressure with serious climatic consequences for the entire globe. A major source of the soaring energy demand in APEC, and hence climate change, is enmeshed with population and economic growth in Southeast Asia, as per several APEC studies (APEC, 2019). This paper seeks to establish that the making of energy policies can be seriously contaminated by behavioural biases, which can in turn have long-term adverse consequences on sustainability for entire the region.

The challenges to energy policy-making in APEC, and especially Southeast Asia, are often summarized as an energy policy trilemma: first, policy makers from the APEC region will have to increase energy supplies to match massive increases in energy demand by 2030 to overcome energy poverty. This urgent need to ensure energy security creates short-termism in policy-making in the entire region (Dent, 2014). Secondly, short-termism in energy policy-making has caused environmental degradation in the region due to the traditional reliance on the cheap but polluting energy sources such as coal (see Asian Development Bank, 2019). Finally, it is imperative for policy makers - given the above problems with energy (in)security - to give a big push for developing and deploying new technologies for energy production and use to fight the first two challenges. In so doing policy makers in the APEC region will be required to diversify their energy portfolio and, given the prevailing subsidy regime to promote cheap energy, a suitable diversification of the energy portfolio will face an uphill task in the region especially in Southeast Asia. This paper identifies behavioural issues in policy-making, which might have prevented policy makers from achieving a desirable energy portfolio in Vietnam with severe consequences for regional and global sustainability.

There is no gainsaying to the fact that the relationship between an economy, mainly its gross domestic product (GDP), and its energy absorption has been widely examined in the existing literature. Given the technology of production, an increasing use of energy has also been linked with environmental pollution as the energy sector is considered to be the major polluting sector in a developing economy. In the developing world, the issue of pollution and GDP growth has, hence, attracted its fair share of attention – especially, in the context of China, as the pollution assiduously accompanies the economic growth (Zhang and Gangopadhyay, 2015; Wang et al., 2011; Zhang and Chen, 2009; Zhang and Chen, 2009; among others). Many recent works find similar evidence of the rising production of energy as a major source of pollution in many developing countries in the APEC region - Anwar and Alexander (2016), Tang and Tan (2015), and Dang et el. (2013) for Vietnam.

Vietnam has often been labelled as an interesting case study to explore the relationship between its economy and pollution because of its transition from one of the poorest countries of

Asia to a middle-income country (World Bank, 2012). In the existing literature, two important studies on Vietnam are noteworthy: first and foremost, Tang and Tan (2015) apply the Johansen cointegration method for establishing both long- and short-run relationships between pollution and other variables, such as GDP, energy use, and FDI. The pollution elasticities are estimated on the basis of this method for the macro variables expressed in *per capita* terms, assuming a specific functional form. Secondly, Anwar and Alexander (2016) document the weakness in the modelling approach in Tang and Tan (2015). In order to avoid the problems of the Johansen cointegration method, many papers - like Gangopadhyay and Nilakantan (2018) and Anwar and Alexander (2016) - apply an Autoregressive Distributed Lagged (ARDL) model to establish the relationship between pollution and certain variables of interest for Vietnam.

It is a well-received doctrine that energy use and other economic variables significantly impact on pollution especially from the existing studies in the context of developed nations (Tingvall and Ljungwall, 2012). Energy efficiency in the developed world has been driven by technological advancements, awareness for energy efficiency and appropriate energy pricing schemes due to the adoption and enforcement of effective energy policies (see World Bank, 2014b; Friedl and Getzman, 2003; Farrington and Needle, 1997 among others). Due to the stickiness in production technologies along with a lack of awareness about energy efficiency and distorted energy prices caused by widespread energy subsidies, it is still a moot point whether energy policies can overcome the adverse environmental impacts of continually rising energy use in the developing world (World Bank, 2014b). Despite some encouraging evidence from the developing world (Zhang and Gangopadhyay, 2015; Agras and Chapman, 1999 among others), the key question is two-fold for the developing world: first, whether energy policies can induce the optimal use of energy to control environmental degradation. Secondly, if not, why do energy policies fail in the developing world? By adopting an alternative econometric framework, namely, the non-linear autoregressive distributed lags (NARDL) model of Shin et al. (2011), it will be argued that the NARDL framework, by incorporating the asymmetric impacts of energy use and energy prices on pollution, can effectively answer these key questions.

The plan of the paper is as follows: Section 2 introduces the modified ARDL model and Section 3 discusses the data and basic statistics. Section 4 examines the findings and contrasts and compares with the findings of the recent work on Vietnam by developing a NARDL model. Section 5 offers an extension through the offering of the NARDL model. Finally, Section 6 discusses policy implications and concludes.

2. The baseline model of investigation: Autoregressive distributed lag (ARDL) bounds testing approach

This section examines the relationship between pollution and other variables, as undertaken by other papers (see Anwar and Alexander, 2016) that employed annual data, spanning the period 1982 to 2015 for Vietnam. To begin the analysis, we use the ARDL bounds testing approach, as undertaken in Gangopadhyay and Nilakantan (2018), for dealing with problems of autocorrelation and non-stationarity of key variables. Given the importance of addressing problems of autocorrelation and nonstationarity in order to get reliable results, the analysis uses time series methods to investigate the short- and long-run dynamics of the relationship between some of the relevant variables. The method is that of the autoregressive distributed lag (ARDL) bounds testing approach recommended by Pesaran et al. (2001) to testing for cointegration between pollution and other variables of interest. The ARDL approach involves two steps: Step 1 tests for the presence of a long-run relationship between the variables of interest as predicted by the theory. If such a relationship is shown to exist, then Step 2 estimates the short- and long-run parameters of the relationship.

We begin by verifying that none of our variables of interest is integrated of order greater than one (1). In the recent work, an extensive study of the time series properties of relevant variables has established that there is no variable that is integrated of order greater than one (Gangopadhyay and Nilakantan, 2018; Anwar and Alexander, 2016). The statistical tests indicate the presence of a unit root in some variables, but there is no variable that is integrated of order greater than one, including the new variable *op*. Thus, all the variables of interest are appropriate for the application of the ARDL and NARDL bounds testing methodology. Thus, the postulated model for ARDL bounds testing yields:

$$\Delta y_t = \alpha_0 + \rho y_{t-1} + a x_{t-1} + \tau w_{t-1} + \sum_{i=1}^{p-1} \alpha_i \Delta y_{t-i} + \sum_{i=0}^{q-1} b_i \Delta x_{t-i} + \sum_{i=0}^{q-1} b_i \Delta x_{t-i} + \omega_t \quad (1a)$$

where, y is the dependent variable, such as pollution (*POL*); x is the independent variable, like oil prices (*op*); w is a vector of other deterministic variables such as real national income (*RNI*), energy consumption (*ENC*) and electricity consumption (*ELC)*, trade openness (*OPN*) – definitions of these variables are provided in Table 1 and discussed in Section 3 before Table 1. ω_t is an *iid* stochastic process. Ignoring the time subscript t, both *y, x* and *w* are the variables widely used in the literature and will be fully explained in the data section. *Δ* labels first differences, while ω denotes the error term. All variables are transformed to their natural logarithms. We consider five variants of ARDL model (1a) in this paper to begin the analysis:

Model (1):

$$\Delta POL_t = \alpha_0 + \rho POL_{t-1} + a RNI_{t-1} + \tau OPN_{t-1} + \gamma ENC_{t-1} + \sum_{i=1}^{p-1} \alpha_i \Delta POL_{t-i} + \sum_{i=0}^{q-1} b_i \Delta RNI_{t-i} + \sum_{i=0}^{q-1} c_i \Delta OPN_{t-i} + \omega_t \quad (1b)$$

(1b), which is expressed in an ARDL setting, represents the following long-run regression:

$$POL_t = \gamma_{01} + \gamma_{11}\, RNI_{t-1} + \gamma_{12}\, OPN_{t-1} + \gamma_{13}\, ENC_{t-1} + \omega_t \quad (1b')$$

Model (2):

$$POL_t = \gamma_{02} + \gamma_{21}\, RNI_{t-1} + \gamma_{22}\, OPN_{t-1} + \gamma_{23}\, ENC_{t-1} + \gamma_{24}\, op_{t-1} + \omega_t \quad (1c)$$

Model (3):

$$POL_t = \gamma_{03} + \gamma_{31}\, RNI_{t-1} + \gamma_{32}\, ELC_{t-1} + \gamma_{33}\, op_{t-1} + \omega_t \quad (1d)$$

Model (4):

$$POL_t = \gamma_{04} + \gamma_{41}\, RNI_{t-1} + \gamma_{42}\, OPN_{t-1} + \gamma_{43}\, op_{t-1} + \omega_t \quad (1e)$$

Model (5):

$$POL_t = \gamma_{05} + \gamma_{51}\, op_{t-1} + \omega_t \quad (1f)$$

The two variables, y and x in Equation (1a), are not cointegrated if $\rho = a = 0$. Pesaran et al. (2001) have proposed the F-test to test the presence of cointegration in the estimated ARDL model. The decision is based on two critical bounds: the upper and the lower one. When the F-statistic is greater than the upper bound, the null hypothesis is rejected, which implies that there is a long-run relationship between y and x. The ARDL model in equation (1a) assumes a linear combination of y and x, which indicates a symmetric adjustment in the long- and the short-run of the dependent variable to any shock in x – the variable of interest. Note that this model is consistent with Pesaran et al. (2001) who have developed a linear cointegration autoregressive distributed lag model (ARDL) to evaluate simultaneously long- and short-run effects. In their model, the dependent variable (y_t) responds symmetrically to both increases and decreases in the independent variable (x_t). To do this, we use the ARDL bounds testing approach of Pesaran et al (2001). The advantage of using this approach is that we do not need to worry about endogeneity between variables since coefficient estimates in the presence of cointegration have the superconsistency property, implying that endogeneity does not affect the results (Engle and Granger, 1987). The superconsistency property of the estimates holds even if there are omitted stationary variables (Herzer and Strulig, 2013). Step 1 of the ARDL approach involves estimating an unrestricted ARDL Error Correction Model (ECM), as shown in the generic model in Equation (1a).

In the current literature, a standard model linking pollution to increased energy absorption/use - driven by GDP growth - has been widely applied in the context of developing economies without appropriately incorporating the price of energy in the determination of pollution: for China, Zhang and Chen (2009), Cheng (2010) and Wang et el. (2011); for India, Paul and Bhattacharya (2004) and Jalil and Mahmud (2009); for Taiwan, Chen (2012), among many others, productively employ this standard model. The results, as this strand of research attempts to establish that pollution or carbon emissions are mainly determined by real national income and energy consumption in the long run, document that trade has a positive, albeit statistically insignificant, impact on CO2 emissions. For the developed economies, Tucker (1995) and Brown et el. (1996) highlight the role of oil prices as an important determinant of pollution. In their support, Friedl and Getzner (2003) evidence structural changes in CO2 emission due to rising oil prices during the first oil crisis. To explain the role of energy prices in determining pollution, Agras and Chapman (1999) posit behavioural changes, triggered by changing oil prices, which can impact on pollution. This second strand of research highlights how energy price hikes can be an effective instrument for reducing pollution in developed economies, *ceteris paribus*. Early work in the UK also confirms that rising oil prices can lower pollution (Farrington and Needle, 1997; Lester, 2005). We use Hypothesis 1 below to empirically determine whether energy prices, as the second strand of research unequivocally highlights, can impact upon pollution for Vietnam - for the very first time in our best understanding[1].

Hypothesis 1: *y_t is not cointegrated with w_t and x_t.*

3. Variables and data

The data, spanning the period 1982-2015, come from two sources. We have extracted the relevant data from the United Nations World Development Indicators (WDIs), except for oil prices, which are from the Earth Institute.

Table 1: Definitions of variables of interest for Vietnam and descriptive statistics

Labelling	**Variables**
POL	Pollution measured by CO2 emissions from use of fossil fuels in million tons
RNI	Real national income of Vietnam in billions of US dollar
ELC	Electricity consumption in Vietnam
ENC	Energy consumption in Vietnam in quadrillion btu
OPN	Trade openness measured by the sum of exports and imports as a percentage of GDP
op	Oil price in constant US$.

Variables	Mean	SD	Min	Max
POL	43.89	33.83	13.01	121.35
RNI	13.10	8.14	4.00	30.90
OPN	0.96	0.35	0.59	1.63
ENC	0.70	0.55	0.19	2.09
op	3.41	0.56	2.67	4.60

[1] Crabb and Johnson (2010) show that energy price movements can impact on induced innovation and thereby on energy efficiency and pollution. Impacts of oil prices on pollution are also confirmed in Spain (Balaguer and Cantavella, 2016).

ELC	24.69	27.03	3.29	100.78

SD = standard deviation

It is also well-recognized in the literature that all variables could be non-stationary, as different unit roots can indicate different results. Given these mixed results, the ARDL methodology is usually chosen for detecting cointegration. The possibility of structural breaks and their impacts on cointegration is also an important concern. We note that both variables that we add are I(1). So, all variables of interest are either I(1) or I(0). The unit root results are reported in Table 2.

Table 2 Phillips-Perron (PP) and KPSS unit root tests

Unit root tests.

Variables	Order of Integration	Standard Models*	Our Model**
POL	I(1)	Yes	Yes
RNI	Mixed, I(1)/I(0)	Yes	Yes
OPN	I(1)	Yes	Yes
ENC	Mixed, I(1)/I(0)	Yes	Yes
OP	I(1)	No	Yes
ELC	I(1)	No	Yes

***:** In column 2 we present the results from Anwar and Alexander (2016) who use Phillips and Perron (PP) test, KPSS test and Perron test to conclude that the unit root testing results are mixed and hence the autoregressive distributive lags (ARDL) based bounds testing approach to cointegration is the most suitable.
**: We also confirm that the KPSS test results show that *RNI* is I(0), though the results of ADF and PP tests show that *RNI* is I(1). We similarly know that *ENC* is I(0) according to the KPSS test results, while both ADF and PP test results show that *ENC* is I(1). The two new variables, *OP* and *ELC*, are I(1) as per the ADF, PP, KPSS and Zivot-Andrews test results with one structural break.

4. Findings

Once we introduce oil prices (*op*) in the ARDL model, some significant changes are observed in Models 2 through 5 (Table 3). Model 1 is a modified model of the standard one in the existing literature (Anwar and Alexander, 2016 for Vietnam), with no time trend for pollution. Note that a linear trend-line usually indicates that pollution increases or decreases at a steady state over time because of factors other than the regressors. Since, pollution is an induced outcome and driven by the regressors, we choose not to use the linear trend-line assuming that there is no explanatory variable that can drive a steady state increase or decrease in pollution over time other than the chosen variables. In Model 2, ignoring the actual values of the coefficients, as highlighted in the existing literature, the coefficients of *ENC*, *RNI*, *OPN* are all positively correlated with pollution (*POL*) and they are all statistically significant. Model 2 shows three important things: first of all, the introduction of op_t as a regressor still confirms that there is a stable long-run relationship among *RCN*, *RNI*, *OPN* and *op* at the 10% level of significance. However, there exists no stable long-run relationship at the 5% level of significance. Secondly, none of the variables *ENC*, *RNI* and *OPN* has statistical significance, though each still has a positive relationship with *POL*. In other words, the introduction of *op* has stirred the long-run relationship among the variables as they lose their statistical significance. An interesting case arises when we compare Models 1 and 2. In Model 1, the only variable that bears a long-run relationship with pollution is energy consumption (*ENC*). In Model 3 we replaced the energy consumption variable (*ENC*) by the total consumption of electricity (*ELC*) and we note some important differences between Model 3 vis-a-vis Models 1 and 2: first, the original relationship highlighted by Anwar and Alexander (2016) between *POL* and *RNI* - the coefficient being positive and statistically significant. Secondly, the introduction of *ELC* also highlights a substitution effect of increases in oil prices, i.e., the economy substitutes the oil by more polluting sources of energy, which is both economically and statistically significant. It is also important to note that for Model 3, the F-statistic establishes a stable long-run relationship among *POL*, *ELC*, *RNI* and *op* at the 1% level of significance.

For the short-run, the presence of significant relationships in first, or second, differences in variables in *RNI* and *op* provide evidence of the direction of the short-run causation. The findings in Table 3 indicate that we do not see any such evidence for *ELC*. It is also important to note that the statistically significant error correction term suggests long-run causation in the Granger sense. Table 3, under the sub-title 'Short-Run', offers the error correction model (ECM) to detect 'hidden cointegration' and if two time-series have their positive and negative components are cointegrated with each other (Granger and Yoon, 2002). The NARDL model allows us to utilise positive and negative partial sum decompositions to allow for the detection of asymmetric effects both in the long-run and the short-run. The superscripts ($^+$) and ($^-$), in Table 3, respectively stand for the positive and negative partial sums decomposition (NARDL????)

The ECM terms (Table 3, Row 4 and Row 5) shows if and how quickly variables converge towards equilibrium. For meaningful convergence the ECM terms must be statistically significant and negative (Pesaran, Shin, and Smith, 2001). But there is evidence of over correction in the first year from the error correction coefficient (ECM) in terms of temporary shocks if we exclude the variable *op*, oil price, as in Model 1 in Table 3 (Row 4, Column 2). Once we incorporate the oil price, Model 2 to Model 4 ensure meaningful convergence towards equilibrium. The convergence to an equilibrium is a complex phenomenon in economics. Unless appropriate variables are included in the estimation of an adjustment process, the empirics cannot establish a system to converge on an equilibrium following perturbations to the system. This is evident from the results in Model (1) and Model (2): in Model (1), as we don't incorporate the oil price (*op*) as a regressor, the adjustment path does not converge to the equilibrium (the ECM term being positive). In Model (2), the adjustment path converges to the long-run equilibrium once we incorporate the oil price (*op*) as a regressor. The important question for is whether the oil price (*op*) is solely responsible for the convergence. In Model (5) we find that the oil price (*op*) on its own cannot ensure long-run convergence (ECM term is positive (Row 5, Column 6 in Table 3). However, it is also important to stress that our dataset is available for thirty (30), which is why the long-term convergence issues should be taken with caution.

The statistical significance of the ECM coefficient along with negative signs, for Model (2), Model (3), Model (4), indicates the presence of a highly stable long-run relationship. Once again, the F-statistic indicates the presence of a stable long-run relationship among *POL*, *ELC*, *RNI* and *op* at the 1% level of significance.

Table 3: The ARDL and ECM results.

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Independent Variable	ΔPOL_t	ΔPOL_t	ΔPOL_t	ΔPOL_t	ΔELC
ECM Terms	-0.037	-0.042	-0.040	-0.039	-0.045
POL_{t-1}	0.41	-0.11	-1.37***	-0.53***	
ELC_{t-1}					0.23***
LONR-RUN					
RNI_{t-1}	-0.65	7.52	5.20***	3.25***	
OPN_{t-1}	-41.8	117.51		10.91	
op_{t-1}		20.7	12.83***	6.92**	5.68***
ELC_{t-1}			-0.32		
ENC_{t-1}	146.8*	-237.28			
SHORT-RUN					
ΔPOL_{t-1}	-1.67***	-0.909	0.05	-0.211	
ΔRNI_{t-1}	-0.171	-1.1	-6.3***		
ΔRNI_{t-2}	5.60***	5.29	-3.641		
ΔOPN_{t-1}	-26.84***	-20.55		-15.5**	
ΔOPN_{t-2}	-12.28	-1.86			
ΔENC_t	49.06***	42.85***			
ΔENC_{t-1}	127.03***	65.82			
ΔENC_{t-2}	74.32***	37.29			
Δop_t		1.18	-15***		0.58
Δop_{t-1}		-1.11	-10***		1.2***
Δop_{t-2}		-1.95	-9.2***		
ΔELC_t			-4.2*		0.06
ΔELC_{t-1}			4.3***		0.55*
Constant	-9.03**	-14.52	-0.72***	-17***	3.52**
No of obs	29	29	29	29	28
Adj R squared	0.94	0.91	0.92	0.86	0.69
F statistic for no cointegration	6.65***	3.814*	8.29***	8.39***	16.80***
Cointegration	Yes	Yes	Yes	Yes	Yes

Model (1) is a standard model utilized in the existing literature without the oil price variable (op_t) – as in Anwar and Alexander (2016). , Model (2) is the new model with *OP*. Models 3 and 4 are modified models of (2). In Model 3 we replace the energy consumption variable (ENC) by the electricity consumption (ELC) variable as an alternative to capture energy use of Model 2 and Model 3. Model 4 is a modified Model 3 in which we drop the openness variable (OPN) used in Model 3. In Model 5, we test if the electricity consumption bears a long-term relationship with oil price (op_t). ***: 1%, **: 5%, *:10%

The interesting addendum in Model 4 is to drop energy consumption (*ENC*) or electricity consumption (*ELC*) and consider the openness variable (*OPN*), along with *RNI* and *OP*. The F-statistic shows that there is a stable long-run relationship among *POL*, *OPN*, *RNI* and *OP* at the 1% level of significance. In the long-run relationship, the coefficients of *RNI, OPN* and *OP* are positive, though the *OPN* coefficient turns out to be statistically insignificant.

In the short-run, the presence of a significant relationship in the first differences in *OPN* provides evidence of the direction of short-run causation. We do not see any such evidence for *RNI* or *OP*. It is also important to note that the statistically significant error correction term suggests long-run causality. But there is evidence of over correction in the first year from the error correction coefficient (ECM) from temporary shocks. The statistical significance of the ECM coefficient, however, indicates the presence of a highly stable long-run relationship. Once again, the F-statistic indicates the presence of a stable long-run relationship among *POL*, *ELC*, *RNI* and *OP* at the 1% level of significance.

Finally, Model 5 seeks to understand the long-run relationship between electricity use (*ELC*) and oil prices (*op*) - after dropping all other variables - to assess if oil price can solely explain the dynamics of *ELC* for Vietnam. The F-statistic shows that there is a long-run relationship between *ELC* and *op* at the 1% level of significance. However, by itself alone, *op* exerts an unstable impact on the variable *ELC* as the ECM coefficient is positive. In the long run, the coefficient of *op* is positive and statistically significant, implying a substitution away from oil and hence an increased reliance on coal or electrical energy with rising oil price increases. It is also important to note that for Model 5, the F-statistic establishes a long-run relationship between

ELC and *op* at the 1% level of significance. It is also noted that the statistically significant error correction term suggests overreaction, as there is evidence of overcorrection (a positive coefficient) in the first year from the error correction coefficient (ECM) of temporary shocks, which creates stability problems for the long-run equilibrium.

5. An extension: Non-linear cointegration and the nonlinear auto-regressive distributed lag model (NARDL)

As we pointed out in the previous section, many empirical studies have argued the presence of asymmetric effects in terms of some regressors - increases or decreases in any independent variable of interest can have different impacts on the dependent variables. If the estimated model in Equation (1a) is non-linear and/or asymmetric, the estimated results are mis-specified. Therefore, the non-linear and asymmetric ECM analysis is extremely important to assess the different responses of the dependent variable in the presence of different shocks associated with the independent variables of interest. It is important to stress that the previous works of Anwar and Alexander (2016), Tang and Tan (2015) and Dang et el. (2013) on Vietnam did not undertake this important analysis, because neither of these works had considered the price of energy (*op*) explicitly introduced. Towards this end, the analysis uses the NARDL approach, as proposed by Shin et el. (2014), to account for the asymmetry issue. Shin et al. (2014) propose the Nonlinear Auto-Regressive Distributed Lag model (NARDL), which allows studying simultaneously dynamic long-run relationships and asymmetries. This specific feature is the main advantage relative to other existing linear and non-linear methods, such as Error Correction Modeling (ECM), the threshold VAR (TVAR) model, the Smooth Transition ECM, and the Markov-Switching ECM. Additionally, the NARDL model can be used to test cointegration among variables even when these variables have not the same order of integration, dissimilar to the ECM, which is mandatory in this sense. Furthermore, the NARDL has the advantage to distinguish perfectly between the linear, the non-linear or the absence of cointegration, (Katrakilidis and Trachanas, 2012). In this context, Granger and Yoon (2002) introduce the concept of hidden cointegration, which is detected if two time-series are not cointegrated in the conventional sense, but their positive and negative sums are cointegrated with each other.

The NARDL model by Shin et al. (2014) enables us to jointly examine the short- and long-run responses of pollution to certain variables of choice so as to detect hidden cointegration, which the ARDL fails to uncover. This methodology employs the decomposition of the exogenous variable *Y* into its positive and negative partial sums of increases and decreases in regressors. Our models have two groups: NARDL Model 1 considers the Anwar-Alexander (2016) model allowing energy consumption (*ECN*) to fluctuate around the long-run mean. NARDL Model 2 substitutes the energy consumption by electricity consumption as an explanatory variable. For the other two models, the analysis introduces energy prices (op_t) as an additional driver. To investigate the short- and long-run responses of the dependent variable (in NARDL Model 3 - NARDL Model 2 prices of oil - op_t) to decreases or increases in the independent variable of interest, the analysis follows the methodology of NARDL. In what follows, we outline a model relevant for NARDL Models 3 and 4. This method decomposes the changes in the values of independent variable (op_t) into its positive (+) and negative (-) partial sums of increases and decreases as follow:

$$op_t = op_0 + op_t^+ + op_t^- \qquad (2)$$

where:

$$op_t^+ = \sum_{i=1}^{t} \Delta op_i^+ = \sum_{i=1}^{t} \max(\Delta op_i, 0)$$

and

$$op_t^- = \sum_{i=1}^{t} \Delta op_i^- = \sum_{i=1}^{t} \min(\Delta op_i, 0)$$

Following Shin et al. (2014), the non-linear asymmetric ARDL model can be expressed as:

$$y_t = \alpha_0 + \tau w_t + \beta^+ op_t^+ + \beta^- op_t^- + \mu_t \quad (3)$$

where β^+ is the long-run coefficient associated with the positive changes in op_t, and β^- is the long-run coefficient associated with the negative changes in op_t. Shin et al. (2014) show that by including Equation (3) in the ARDL (p, q) model presented in Equation (1a), we obtain the following non-linear asymmetric conditional ARDL:

$$\Delta y_t = \alpha_0 + \rho y_{t-1} + a^+ op_{t-1}^+ + a^- op_{t-1}^- + \tau w_{t-1} + \sum_{i=1}^{p-1} \alpha_i \Delta y_{t-i} + \sum_{i=0}^{q-1} (b_i^+ \Delta op_{t-i}^+ + b_i^- \Delta op_{t-i}^-) + \omega_t \quad (4)$$

where $a^+ = -\frac{\rho}{\beta^+}$ and $a^- = -\frac{\rho}{\beta^-}$

p and q denote the lag orders for the dependent variable and the independent variable, respectively. The NARDL method includes four stages. Firstly, Equation (4) is estimated by using the standard OLS approach. Secondly, the cointegration relationship between the levels of the series y_t, op_t^+ and op_t^- is performed by using the F_{pss} statistic proposed by Shin et al. (2014), which refers to the join null hypothesis of no cointegration ($\rho = a^+ = a^- = 0$). Thirdly, the long- and the short-run symmetries are examined by using the Wald test is performed. For long-run symmetries, the null hypothesis to test is $a = a^+ = a^-$. For the short-run symmetry the null hypothesis can take one of the following forms: (i) $b_i^+ = b_i^-$ for all i=1, 2…..q or (ii) $\sum_{i=0}^{q-1} b_i^+ = \sum_{i=0}^{q-1} b_i^-$. Finally, the non-linear ARDL model in Equation (4) is often used in order to derive the two dynamic multipliers

(m_h^+ and m_h^-), where the first one is associated with changes in op_t^+ and the second one with changes in op_t^-:

$$m_h^+ = \sum_{i=0}^{h} \frac{\partial y_{t+i}}{\partial op_t^+} \quad (5)$$

$$m_h^- = \sum_{i=0}^{h} \frac{\partial y_{t+i}}{\partial op_t^-} \quad (6)$$

h=0, 1, 2 …

Note that as $h \to \infty$ then $m_h^+ \to \beta^+$ and $m_h^- \to \beta^-$. In this paper we will focus upon the cumulative and asymptotic valuesβ^+ and β^- as the measures of the asymmetric effects. The examination of the adjustment paths associated with the multiplier effects in response to positive or negative shocks will provide insights on the long-run and short-run asymmetries.

Given that the pollution variable and other variables of interest may be vulnerable to an initial positive or negative shock, associated with variables of interest, the asymmetric analysis will add valuable information to the long- and short-run patterns of equilibrium. We use four variants of the NARDL modelling, which are described in (7a) - (7d):

NARDL Model 1:

$$POL_t = \alpha_1 + \tau_1 w_t + {\beta_1}^+ ENC_t^+ + {\beta_1}^- ENC_t^- + \mu_{1t} \quad (7a)$$

Note that in (7a) w_t represents a vector of *RNI*, *OPN.*

NARDL Model 2:

$$POL_t = \alpha_2 + \tau_2 w_t + {\beta_2}^+ ELC_t^+ + {\beta_2}^- ELC_t^- + \mu_{2t} \quad (7b)$$

Note that in (7b) w_t represents a vector of *RNI*, *OPN.*

NARDL Model 3:

$$POL_t = \alpha_3 + \tau_3 w_t + {\beta_3}^+ op_t^+ + {\beta_3}^- op_t^- + \mu_{3t} \quad (7c)$$

Note that in (7c) w_t represents a vector of *RNI*, *OPN, ENC.*

NARDL Model 4:

$$ELC_t == \alpha_4 + \tau_4 w_t + \beta_4{}^{+} op_t^{+} + \beta_4{}^{-} op_t^{-} + \mu_{4t} \quad (7d)$$

Table 4

NARDL results.

NARDL MODEL 1 *POL - ENC*		***NARDL MODEL 2*** *POL - ELC*		***NARDL MODEL 3*** *POL – op*		***NARDL MODEL 4*** *ELC- op*
ΔPOL		ΔPOL_t		ΔPOL_t		ΔELC_t
$POL(-1)$	-0.97***	POL_{t-1}	-0.80***	POL_{t-1}	-1.02***	
$\Delta POL(-1)$	-1.15***	ΔPOL_{t-1}	-0.23	ΔPOL_{t-1}	-0.71**	
$\Delta POL(-2)$		ΔPOL_{t-2}	0.43*	ΔPOL_{t-2}	-	
RNI	3.16***	RNI_t	2.04**	RNI_t	4.67***	
OPN	8.69	OPN_t	-6.67	OPN_t	1.98	
OP		ENC_t	41.9***	ENC_t	10.58	
Constant	-7.2	*Constant*	-2.92	*Constant*	-10.76**	-0.88**
F Statistics	8.09***	*F Statistics*	6.23*	*F Statistics*	5.98*	10.63***
Cointegration	Yes	*Cointegration*	Yes	*Cointegration*	Yes	Yes
$ENC(-1)^{+}$	19.13	ELC_{t-1}^{+}	0.34	op_t^{+}	-2.62	-3.32***
$ENC(-1)^{-}$	14.52***	ELC_{t-1}^{-}	5.99***	op_t^{-}	7.04**	-1.99***
$\Delta ENC(-1)^{+}$	3.35	ΔELC_t^{+}	-4.02***	Δop_t^{+}	1.42	-2.6**
$\Delta ENC(-1)^{-}$	24.42	ΔELC_t^{-}	249	Δop_t^{-}	-0.01	1.11
		ΔELC_{t-1}^{+}	1.62	Δop_{t-1}^{+}	-0.11	1.29
		ΔELC_{t-1}^{-}	-386*	Δop_{t-1}^{-}	-2.67	2.56**
				ELC_{t-1}		0.22***
				ΔELC_{t-1}		0.19
L_{ENC}^{+}	19.64	$L_{ELC}+$	0.43	L_{op}^{+}	-2.5	14.77***
L_{ENC}^{-}	14.69***	L_{ENC}^{-}	8.81**	L_{op}^{--}	6.8**	-8.87***
J-B	0.44	*J-B*	0.2	*J-B*	0.25	0.89
Ramsey	12.33**	*Ramsey*	4.2*	*Ramsey*	3.43**	6.64***
LM	12.67	*LM*	13.5	*LM*	35.93***	13.33
R^2	0.87	*R2*	0.81	R^2	0.78	0.97
ARCH	0.33	*ARCH*	0.18	*ARCH*	0.12	4.7**

N	30	*N*	30	*N*	30	30

*** p<0.01; ** p<0.05; * p<0.10

Table 5

Wald test results in NARDL models: long-run (LR) and short-run (SR) asymmetry.

Asymmetry Wald Tests, Long-Run (LR_W)	Asymmetry Wald Tests, Short Run (SR_W)	Conclusion
NARDL Model 1	***NARDL Model 1***	
V_{ENC}: *5.64***	*0.44*	*NARDL with LR Asymmetry*
NARDL Model 2	***NARDL Model 2***	
V_{ELC}: *8.8***	*3.08**	*NARDL with LR & SR Asymmetry*
NARDL Model 3	***NARDL Model 3***	
V_{op}: *4.52***	*0.14*	*NARDL with LR Asymmetry*
NARDL Model 4	***NARDL Model 4***	
V_{op}: *8.42****	*6.097***	*NARDL with LR & SR Asymmetry*

***: p<0.01; **: p<0.05; *: p<0.10. The estimation is based on Equations (4), (5) and (6). The table reports the results of the short- and long-run symmetry tests for the oil (energy) price. SR_W denotes the Wald test for short-run symmetry, which tests the null hypothesis in Equation (4). LR_W corresponds to the Wald test for long-run symmetry, which tests the null hypothesis in Equation (5).

The estimation procedure is simple and the NARDL model allows greater flexibility in relaxing the assumptions that the time-series should be integrated of the same order, contrary to the ECM which is binding in this sense[2]. It also enables us to accurately distinguish between:

i) the absence of cointegration,

ii) linear cointegration and

iii) nonlinear cointegration (Katrakilidis and Trachanas, 2012)

These models are also suitable for investigating the short- and long-run interlinkages between the variables when these relationships are linear and symmetric[3]. However, these models will be

[2] Before we draw inferences, we first judge the adequacy of the dynamic specification on the basis of various diagnostics: the Jarque-Bera statistic for error normality (J-B), the LM statistic for autocorrelation up to order 2, and the ARCH statistic for autoregressive conditional heteroskedasticity up to order 2. These are presented at the lower panel of Table 4. The models pass important diagnostics, suggesting error normality, absence of autocorrelation and ARCH effect, and parameter stability. Accordingly, the dynamics of security indices is adequately specified.

[3] It is imperative to note that it performs better in testing for cointegration in small samples (Romilly et al., 2001). The short-run deviations of first-order integrated variables from their common long-run equilibrium can be separated by the linear ECM ARE well-received (Granger, 1981), Engle and Granger (1987), and Johansen (1988).

misspecified when they are non-linear and/or asymmetric. In this context, Granger and Yoon (2002) introduce the concept of hidden cointegration, which is detected if two time-series are not cointegrated in the conventional sense, but their positive and negative sums are cointegrated with each other. The NARDL model of Shin et al. (2014) allows us to jointly examine the short- and long-run responses of variables to each other to detect hidden cointegration. Overall, the NARDL model accounts for the short-run dynamics through the distributed lag part and the long-run dynamics via a single common cointegrating vector. Both parts are allowed to be asymmetric. Further, the NARDL model allows for combinations of I(1) and I(0) variables by making use of a bounds testing procedure for the presence of the equilibrium vector. This means that we are not constrained by the normal requirement of cointegrating models that all variables must be I(1). Given the condition that the bounds testing must not involve any I(2) variables, we reconfirm the background tests of Anwar and Alexander (2016) and find all variables of interest are either I(1) or I(0). Accordingly, we estimate the four (4) models and derive the bounds-test F statistic for each model and present the estimation results and other test results in Table 4. Note that all asymmetric results are in terms of the cumulative values as highlighted in equation (6) and (7).

NARDL Model 1:

From the F-statistic in Table 4 we find that *POL*, *RNI*, *OPN*, *ENC* all co-move in the long-run. The reported F-statistic, 8.36, exceeds the critical upper bound at the 5% level of significance, with the critical bounds being available from Narayan (2005). With this finding, we then look at the *ECN* dynamics and its relation to *POL* and the positive and negative changes from its trend. The long-run coefficient of *RNI* is positive and statistically significant at 1%. So is the case with the *ENC* variable. The findings are in consonance with the existing literature (Anwar and Alexander, 2016). A major change occurs when we consider the *OPN* variable, no statistically meaningful result is found for this variable, which is in contradiction with the previous work. From Table 4, the Wald tests indicate that for the first model, there is clear evidence of a long-run asymmetry when the *ENC* declines, but not when the *ENC* rises. The long-run coefficient (L_{ENC}^{-}) is significant with an elasticity of pollution about 15% regarding to decreases in energy absorption. This is also statistically significant at 1%. Hence, if the *ENC* declines by 1%, *POL* declines by about 15%. The decline in pollution is the cumulative decline given by equation (6). There is no evidence of any short-run asymmetry, while there is no evidence that *ENC* rises above the trend line either.

NARDL Model 2:

In the second model, we replace energy consumption, *ECN*, of the first model by electricity consumption, *ELC*. We note that the F-statistic is lowered to 6.23, which is close to the upper bound value of 6.25 at 5%, rendering it inconclusive. However, there is evidence that the chosen variables co-move in the long-run at 10%. The Wald tests statistics in Table 4 show that both the asymmetries in the long- and short-run are confirmed. There is no evidence than trade openness (*OPN*) has any meaningful relationship with pollution (*POL*), but the other two variables still hold their grounds as highlighted in Anwar and Alexander (2016). Once again, for the long-run asymmetry, the decreases in *ELC* will have a meaningful and cumulative effect on *POL* with an elasticity of 8 and being statistically significant. However, increases in *ELC* have not any significant effect on *POL* in the long-run. The decline in elasticity (L_{ELC}^{-}) is an indication of the substitution effect, which suggests that the economy can diversify away from the more polluting energy source when the *ENC* declines, than when the *ELC* decreases.

NARDL Model 3:

The third model introduces oil prices, op_t, into the first model. We note that the F-statistic is 5.93, the chosen variables still co-move in the long-run at 10%. The Wald tests statistics in Table 4 show that both the asymmetries in the long- and short-run are confirmed at least at 5%. There is no evidence than trade openness (OPN) has any meaningful relationship with pollution (*POL*), nor energy consumption (*ENC*) and *POL* in the long-run. In the long-run, for the *RNI* variable – the elasticity of pollution is 4.67 and statistically significant at 1%. Once again, for the long run asymmetry, decreases in oil prices will have a meaningful cumulative effect with an elasticity of -6.8 and being statistically significant at 5%, indicating that *POL* decreases by 6.8% following a decrease in oil prices by 1%. However, oil price increases have no significant effect on POL in the long-run. In other words, there is no evidence of any short-run asymmetry.

NARDL Model 4:

In the final model, we choose energy consumption (*ENC*) as the dependent variable as opposed to pollution (*POL*) in all other NARDL modelling approaches. The purpose of doing this is to understand whether oil prices have any long-run relationship with *ENC*. The finding indicate that the F-statistic is 10.63, which exceeds the critical upper bound value at 1%. So, there is evidence that the chosen variables (*ENC* and *OP*) co-move in the long-run at 1%. The Wald tests statistics in Table 5 show that both asymmetries in the long- and short-run are confirmed. When oil prices increased, say by 1%, the cumulative effect on *ENC* is positive and the long-run increase in energy absorption is also positive at 14.75%. This is rather counter-intuitive, unless oil price increases induce the economy to move away from using oil and seek alternative sources of energy consumption. If the alternative sources are not energy efficient, then the *ENC* increases with oil prices. However, we note the long-run relationship between oil price decreases and energy consumption (*ENC*): as oil prices decrease by 1%, energy consumption decreases by about 7%.

The short-run elasticities are also negative, although the sensitivity of *ENC* to oil prices increases is 60% stronger compared to the sensitivity of *ENC* to oil price decreases. We find that energy consumption (*ENC*) is influenced by oil price dynamics in curious, non-linear and asymmetric fashions, which calls forth a further study in the overall relationship between pollution and other variables with an appropriate consideration of oil prices.

Finally, the analysis next analyses the asymmetric dynamic multipliers. As shown in Figures 1-4, these multipliers illustrate the pattern of adjustment of either pollution or energy consumption to their new long-run equilibrium in response to a positive or negative shock in oil prices. The lines represent the adjustment of pollution (Figures 1 to 3) to positive and negative shocks to oil prices at a given forecast horizon, and energy consumption (Figure 4) to positive and negative shocks to oil prices at a given forecast horizon. For instance, as shown in Figure 1, a negative oil price shock to pollution decreases before reaching a turning point toward long-run equilibrium, whereas a positive oil price shock to pollution increases before reaching a turning point toward long-run equilibrium.

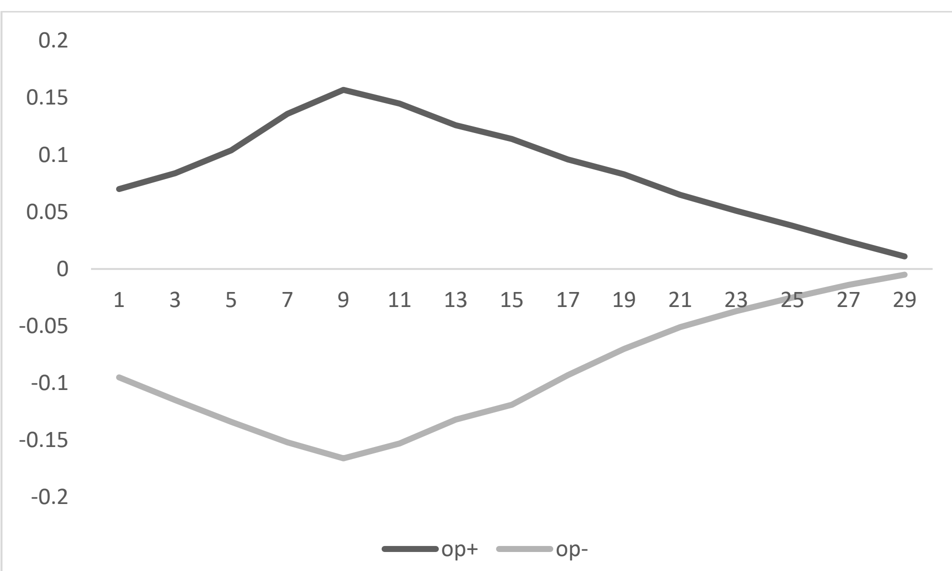

Fig. 1. Dynamic multipliers for pollution to oil price shocks (Model 1)

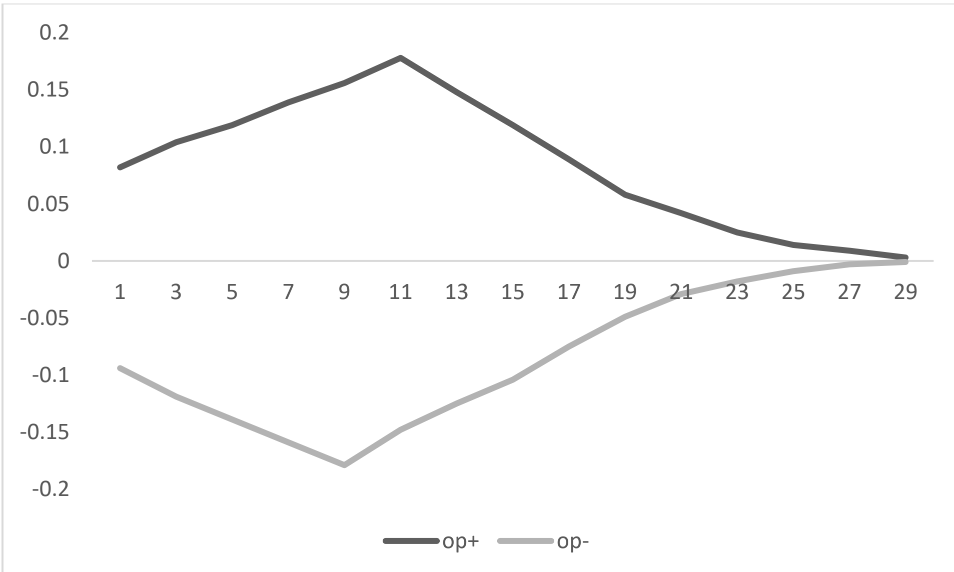

Fig. 2. Dynamic multipliers for pollution to oil price shocks (Model 2)

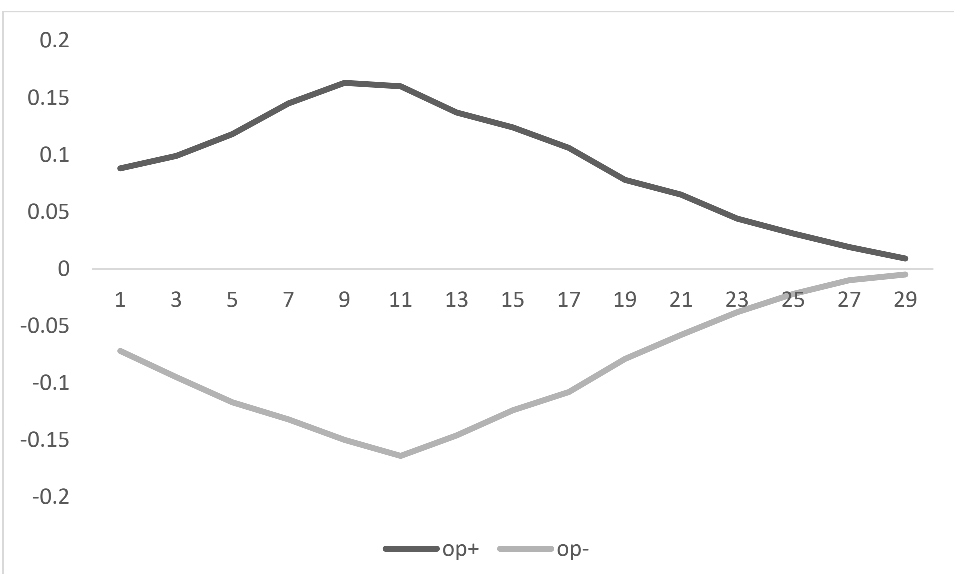

Fig. 3. Dynamic multipliers for pollution to oil price shocks (Model 3)

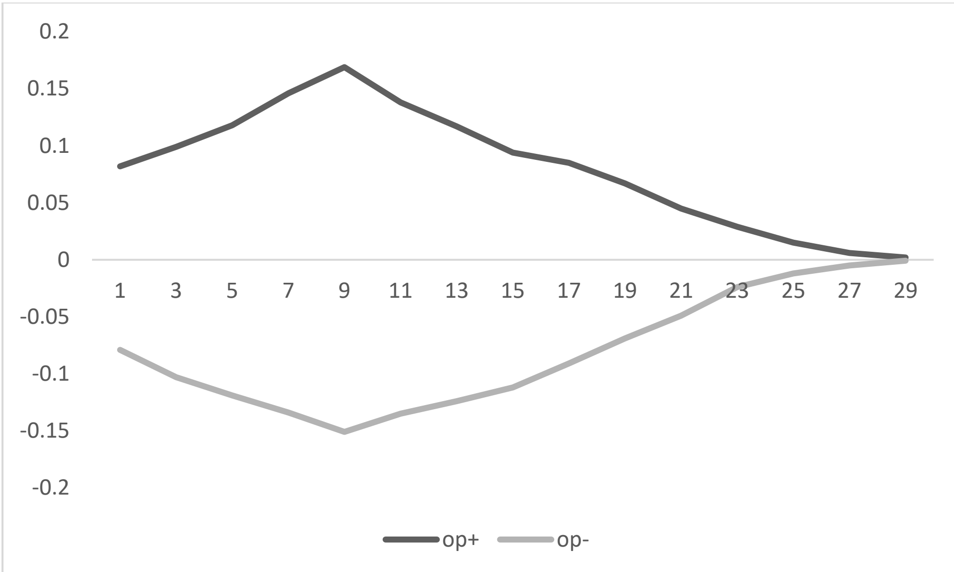

Fig. 4. Dynamic multipliers for energy consumption to oil price shocks (Model 4)

6. Conclusion and policy implications

The NARDL models allow us to jointly examine the short- and long-run (asymmetric) responses of pollution (and other relevant variables) to specific variables of interest for detecting hidden cointegration, which the ARDL approach fails to uncover. Using the NARDL models we decompose changes in the exogenous variables into their positive and negative partial sums (of increases and decreases in regressors) to unravel their effects on the dependent variables – such as pollution (*POL*) and energy consumption (*ENC* and *ELC*) - for Vietnam. We made some important policy observations in this context: from Table 4, the Wald tests indicate that, for the first model, long-run asymmetric effects exist on *POL* since *POL* changes when energy consumption (*ENC*) registers a decrease but not when the *ENC* increases. This long-run coefficient of ($LENC^{-}$) is significant with a cumulative and asymptotic elasticity of pollution about 15, which shows *POL* decreases by 15% following a 1% decline in energy demand/consumption. This is also statistically significant at 1% level of significance. Hence, if the *ENC* decreases by 1%, the cumulative and asymptotic effect of this decrease in *ENC* on pollution (*POL*) will be a decrease in (long-run) *POL* by about 15%. On the other hand, if *ENC* rises by 1%, there is no perceptible impact of this rise in *ENC* on pollution (*POL*). There is absolutely no evidence of any short-run asymmetry. This non-linearity captures a fundamental behavioural trait in energy policy making.

The empirical findings can be explained by behavioural biases like short-termism in policy making: when the demand for energy (*ENC*) increases, policy makers seek to achieve energy security by increasing the energy supply without paying a sufficient attention to the long-term goals of diversification of energy mix. However, when *ENC* decreases policy makers are not under (immediate) pressure to increase energy supply to match rising demand for energy, which enables policy makers to focus upon the longer term goals of diversification. We also checked the robustness of this finding by using electricity consumption (*ELC*) instead of *ENC*: once again we note the long run asymmetry, the decreases in *ELC* will have a meaningful and statistically significant effect in reducing pollution. However, the increases will have no significant effect on *POL* in the long-run. The decrease in *ELC* allows policy makers to diversify away from the more polluting energy sources.

More importantly, our model – by using NARDL model for the first time for understating the behavioural foundation to energy policy-making – can explain the sources of policy inertia for energy policy-making. This is a novel finding, hitherto unknown in the empirical literature, to explain if any behavioural biases of policy makers can deter the adoption of appropriate energy technologies and suitable policies. Building on the work of Galor and Ozak (2016), the importance of behavioural issues for explaining environmental decays in a country has come to the forefront only recently (Falk, Becker, Enke, Huffman and Sunde, 2018; Dioikitopoulos, Ghosh, Karydas, Vella, 2020). According to this strand of theoretical research, an improvement in nurturing and protection of environment in a particular era can alter the long-term orientation of the decision-making. The focus of this strand of literature is two-fold: first, these authors highlight that higher degrees of impatience among decision-makers can result in high environmental decays. Secondly, a temporary decline in impatience, or improvement in patience, can have long-term, or long lasting, consequences due to the rewarding experience. The application of the NARDL methodology supports the theoretical findings of this nascent literature.

NARDL models also extracted long-run asymmetric effects of changes in oil prices as regressors: decreases in oil prices are found to have meaningful effects on *POL* (with a cumulative elasticity of 6.8, which is also statistically significant at 5% level of significance). A decrease in oil price by 1% led to a cumulative and asymptotic decrease in *POL* by 6.8%. However, oil price increases will have no significant effect on POL in the long-run. There is no evidence of any short-run asymmetry. This finding implies that oil price rises (*op*) force policy makers to focus on the short-term energy security over long-terms strategy of reducing pollution, which is why there is no impact on *POL* when oil prices rise.

On the other hand, when the oil price (*op*) declines, policy-makers turn their attention away from a cheap energy policy to the long-term diversification of energy mix, which in turn lowers pollution significantly. For testing the robustness of our findings, we replaced *ENC* by *ELC* and retain the energy price variable (*op*) in the NARDL framework (Model 4 in Table 4). The Wald tests statistics in Table 4 show that the long-run asymmetries are meaningful. When oil prices increased, say by 1%, the cumulative effect on *ELC* is economically and statistically meaningful as *ELC* rises by 14.75% for every 1% increase in the oil price. When the oil price decreases by 1%, *ELC* decreases by 8.87%. This long-term asymmetry in the use of electricity (*ELC*) signifies the presence of importance of behavioural biases such as sunk cost fallacy and short-termism in driving the energy policy-making in Vietnam. In other words, there are behavioural policy traps that can prevent policy-makers to suitably diversify the energy mix with serious consequences for local regional, global environment.

The energy policy trilemma in the APEC region posed serious challenges to long-term policy-making:

- First and foremost, energy demand is projected to double in the Asia Pacific region by 2030 as almost a billion people currently live in developing nations of APEC without access to electricity. In Southeast Asia alone, more than 130b people are 'energy poor' implying virtually no access for them to electricity and other sources of energy. This is the first challenge for policy makers[4] to develop a coherent log-term energy strategy for their countries to fight energy poverty[5]: policy-makers are strongly influenced by *short-termism*, or policy myopia, in extracting, promoting and subsidizing fossil fuels to fight energy poverty and balance the mismatch between demand and supply of energy. Unfortunately, this short termism has come to be recognised as a major weapon in the armory of socio-economic policies in developing countries of the region like Vietnam (Dent, 2014) with unintended consequences for environment.

[4] To overcome energy poverty, energy policies in Southeast Asia have been state-centric: the major player in the power industry of each of these countries is the national government with a major focus upon creating and advancing energy security.

[5] In the region, especially, in Southeast Asia, energy security had called forth heavy reliance on cheap, but polluting, energy from coal. Traditionally, to ensure energy security and fighting energy poverty, governments of developing nations simply seek to keep oil prices and energy prices low. In other words, governments seemingly place significant emphasis upon energy price affordability and, hence, have little choice not to use cheap energy as people have low purchasing power in Asia.

- Secondly, short-termism in energy policy-making[6] - for fighting energy poverty and ensuring energy security- has caused massive environmental degradation in the region. As Asian Development Bank (2019) highlights, the relative abundance and affordability of coal in Southeast Asia still prompts and will continue to propel policy makers from the region to advance energy security by using and subsidizing coal[7]. As a consequence, energy security seems to be in serious conflict with *environmental sustainability* in APEC, especially in Southeast Asia. The second policy challenge is to reduce energy-related carbon dioxide (CO2) emissions in an effort to reduce the adverse environmental impacts of energy production and consumption[8]. Due to anticipated massive increases in demand for transport and housing, driven by rising per capita income, by 30% in the coming three decades – policy makers are concerned that fossil fuels will continue to dominate the energy mix in the Asia Pacific, especially Southeast Asia. Policy makers apprehend that more than 60% of the future energy mix of the APEC region will still be sourced from fossil fuel. As a result, at least two thirds of the future global demand for fossil fuels will generate in the Asia Pacific region, which will further jeopardise environmental sustainability.
- The third challenge for policy makers, due to the over-reliance of the economies on fossil fuels, is to undertake a *cultural revolution* for developing and deploying new technologies

[6] Traditionally, to ensure energy security and fighting energy poverty, policy makers simply seek to keep oil prices and energy prices low. In other words, governments place significant emphasis upon energy price affordability and, hence, have little choice not to use cheap energy as people have low purchasing power in Asia.
[7] ADB anticipates that policy makers by boosting the share of coal in the energy mix from 30% in 2013 to more than 50% by 2035 will seek to ensure energy security. Unsurprisingly, three quarters of the thermal capacity currently under construction are coal fired in Southeast Asia. Such thermal power generation is inefficient in generating energy with an efficiency rate of about 34%.
[8] Two sectors stand out in terms of their pollution in most Asian nations: the transport sector and the industrial sector. The transport sector is heavily dependent on oil, especially imported oil from the Persian Gulf while the manufacturing sector mostly consumes, coal, oil and gas while bioenergy has become an important source only since 2015.

for energy production and use them to fight the first two challenges[9]. In other words, policy makers in the APEC region will need to INVEST heavily to diversify their energy portfolio into biofuels, renewables, smart grids and best available technologies (BAT). Given the prevailing subsidy regime to promote cheap energy, policy makers will find it difficult to invest sufficiently to adequately diversify their energy portfolio, especially in Southeast Asia.

The energy policy trilemma is the impossible or inconsistent trinity: a country must choose two from the three at best, namely, i) short-term energy security by harnessing cheap sources of energy, ii) environmental sustainability by reducing energy-related CO2 emissions, iii) long-term diversification of the energy portfolio towards sustainable sources like renewables. We found that the above trilemma can become a (behavioural) policy trap to create and perpetuate energy policy inertia. This policy inertia can prevent policy-making from adequately diversifying energy portfolio with major implications for human security across the globe. In other words, as our methodology seeks to uncover if there is an energy policy inertia and what causes it. Once policy makers are endowed with a foreknowledge of the precise sources of the policy inertia, it will be feasible to develop appropriate strategies to overcome the problem of underinvestment for diversifying the energy portfolio.

Using the standard behavioural models in economics and finance, one can argue that the energy policy trap can be created and perpetuated by behavioural factors like short-termism: policy/decision-makers suffer from short-termism, which refers to an excessive focus upon short-

[9] For fighting energy poverty in Southeast Asia, to the tune of 130m people lacking electricity, policy makers have developed a complex web of fossil fuel subsidies worth more than $52b. It will be difficult, if not impossible, to remove or drastically reduce these subsidies. It is also important to underscore that energy security is still a major concern: as an example, during 2013-2019 energy demand in Vietnam increased annually by 10.35%. Such surge in energy demand puts policy makers under severe pressure to look for (long-term) alternative energy sources that can be harnessed to balance demand with supply.

term outcomes (e.g. energy security) at the expense of long-term interests (e.g., diversification of energy sources). This bias in decision-making is also known as hyperbolic discount (Grüne-Yanoff, 2015). In the context financial investment, short-term performance becomes a trap when investors excessively focus upon quarterly earnings, with less attention paid to long-term investment strategies and fundamentals to create long-term values. In the corporate world, short-termism is a major deterrence for achieving operational efficiencies, advancing human capital, effectively managing business, environmental and social risks (Kolasinski and Yang, 2018; Kaplan, 2018). The critical question is how to overcome the policy trap: There is a need to reconstruct the decision environment of policy makers to enable them to make more desirable long-term decisions (Thaler and Sunstein, 2008; European Commission, 2016; John, 2015; Kosters and Van der Heijden. 2015), which will suitably diversify the energy portfolio. This strand of behavioural economics, commonly known as the nudge theory, calls forth the re-engineering of the choice architecture of policy/decision-makers in order to improve the design of public policy.

In this context, more desirable long-term choices can also fail to materialize since policy-makers suffer from resource scarcity due to pre-commitment to previous projects for generating energy from coal. This type of behavioural trap is often highlighted as the *sunk cost fallacy* in behavioural economics: policy makers are actuated by the sunk cost fallacy (see Arkes & Blumer, 1985 for details of this bias), when they continue the large fossil fuel subsidies - or find it difficult to scale down the cheap energy policy - as a result of previously invested resources to the tune of $52b as subsidies in Southeast Asia. These subsidies continue to distort energy markets and prevent adoption of environmentally-friendly sources of energy like renewables. Even if the costs outweigh the benefits of the cheap energy policy, the new strategy will not be chosen since the extra costs of the cheap energy policy are held in a *different mental account* than the one with the investment to diversify the energy portfolio (Thaler, 1999). Once again, the effects of the sunk cost fallacy can be lessened by using 'nudges' to help policy makers move from the 'harmful mental account'.

A major focus of policy-makers from the APEC region is how to craft suitable energy policies and adopt appropriate technologies for environmental sustainability[10]. Given the technology of production, increasing energy use is linked with environmental pollution as the energy sector is considered as one of the major pollutants in an economy from the region[11]. In this context, policy research seeks to understand how to rein in the regional environmental degradation caused by massive spurts in economic growth in the region. An extremely important finding of the paper is that the observed behavioural traps, extracted from the NARDL models, can prevent policy makers from adopting suitable policies and technologies to initiate and perpetuate sustainable economic development in the developing economies of APEC. The future research should focus on how to *nudge* policy makers to choose the optimal (long-term) energy mix.

The variable *hitherto* missing from the existing models (Anwar and Alexander, 2016) is the energy price[12]. Though traditionally ignored, it turns out to be an important question for the

[10] In the developing world, as in the APEC region, the issue of pollution vis-a-vis GDP growth is a serious concern – recently in the context of China as the pollution assiduously accompanies the economic growth of the Chinese economy (Wang et al., 2011; Zhang and Chen, 2009; Zhang and Chen, 2009 and many others). Many contemporary research finds similar evidence of rising production of energy as a major source of pollution in many developing countries in APEC - Anwar and Alexander (2016).

[11] Vietnam has often been labelled as an interesting case study to explore the relationship between its economy and pollution because of its transition from one of the poorest countries of Asia to a middle-income country (World Bank, 2012). Furthermore, in 2018 Vietnam has one of the most effective programs to fight energy security as Vietnam surged by 37 places in ranking of nations in terms of World Banks's electricity access index.

[12] The fundamental idea of this omission is that emerging economies choose trade openness as a policy instrument, or means, to give a boost to GDP growth (Tingvall and Ljungwall, 2012) while the increased increase in energy use (both household consumption and industrial use) leads to increased pollution (CO2 emissions). There are two related assumptions: first, it is assumed that the energy intensity of output does not change much due to the fixity of technology. Secondly, it is also assumed that there is not much awareness for energy efficiency, pollution abatement and consumer awareness. Both these sets of factors are important drivers of energy efficiency in the developed world (World Bank, 2014b). Yet, in some work similar evidence has been found in the emerging economies – the principle of Kuznets curve relationship can arise (Zhang and Gangopadhyay, 2014).

developing world in the context of diversifying the energy portfolio: do energy prices impact on the energy efficiency and thereby on pollution? The question is well-settled for the developed nations as energy prices have been shown to play a crucial role in energy efficiency (World Bank, 2014b). In order to assess the role of energy prices, we keep everything unchanged in the standard model, as an example Anwar and Alexander (2016,) and introduce oil prices as a new variable. Our immediate contribution is two-fold: first, we noted that the introduction of this price variable in the standard model Anwar and Alexander (2016) can significantly alter the interrelationship found in the existing work. In other words, the modification of existing models - by introducing energy prices have altered the long-run relationship among the variables as postulated in the existing literature. Our modified model can thus provide a more robust foundation to developing future energy policies.

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