

TOWARD A DECARBONIZING ECONOMIC EXPANSION: EVIDENCE FROM NONLINEAR ARDL APPROACH

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In light of a slow buildup in CO₂ emissions since the recovery, this paper investigates the relationship between CO₂ emissions and the economy in the U.S using a nonlinear ARDL multivariate model. We find convincing evidence that CO₂ emissions decline more rapidly during recessions than increase during expansions in the long run, despite a symmetric short-run output elasticity of emissions over business cycle horizons. Long-run asymmetries are strengthened once vehicle miles travelled is controlled, calling for a rethinking on climate policy design that rarely pays attention to public transportation development and vehicle miles travelled tax. (*JEL* Q43, C32).

*This paper is written when the second author is hosted by SCERI as Visiting Research Fellow. He is grateful to SCERI for stimulating research environment and Lars-Erik Thunholms Stiftelse for Vetenskaplig Forskning for generous stipend. This research is part of a project financially funded by e-Science fund from the Ministry of Science, Technology, and Innovation, Malaysia (MOSTI) (06-02-11-SF0174). We gratefully thank Matthew Greenwood-Nimmo and Yongcheol Shin for their kindness to share the program code.

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I. INTRODUCTION

News about carbon dioxide emissions occupied the headlines of popular media in the second half of year 2013 when the total energy-related CO₂ emission in 2012 hit the level of 1994, reaching a historical twenty-year low in the United States. It was not unusual if CO₂ emissions fall during economic contraction, as shortfall of gross domestic product instigates adverse income effect that reduces demand for energy from household to industry. What is remarkable about U.S CO₂ emission in the past five years is the fact that the record low level of CO₂ emission occurred at a time when the economy already regained momentum to find solid footing.

With green shaded areas denote periods of economic contraction as defined by NBER Business Cycles Dating Committee, Figure 1 vividly corroborates a widely held intuition that CO₂ emissions are generally procyclical to the economy (Doda, 2014). Greater spending, more driving and flying for vacations, and expanding industrial production during the tranquil time use more energy, emitting more carbon dioxide, and vice versa. However, the historical low level of total CO₂ emission took place in 2012 although industrial production index has already increased by 16 percent from the trough of the Great Recession, and real GDP steadily grew by 2.5 percent.

[INSERT FIGURE 1 HERE]

A natural question is what events led to the sharp reduction in emissions. Three candidate explanations typically stand out: improvements in energy efficiency, switching away from dirty coal to cleaner natural gas, and recession-driven low demand for energy. Through a counterfactual exercise, *CEA Annual Report* (2013, p. 195-196) argued that 52 percent was due to below-trend GDP, 40 percent because of switching to cleaner energy, and 8 percent came from accelerated improvements in energy efficiency. The conjecture that recession was the main culprit for CO₂ emission reduction gains further credibility when the

emission has risen again from the historical low level in tandem with the shrinking output gap due to continuous economic rebound, as illustrated in Figure 1.

However, simply by observing a procyclical pattern in emissions is not inconsistent with the equally popular view that transition from coal to natural gas in electricity generation in the past decades has greatly reduced CO₂ content of output expansion (see, for instance, Trembath *et al.*, 2013). While switching to the use of cleaner energy may not be able to completely overturn the procyclicality of emissions, it may likely instigate an asymmetric procyclicality.

This brings us to a less discussed fact about the relationship between CO₂ emission and the economy over the business cycles. Table 1 makes a comparison of changes in CO₂ emission between recession and expansion periods in the U.S over more than three decades. Despite the fact that CO₂ emission rises and falls along with the business cycles, the magnitude has obviously been asymmetrically changing over the cycles. In absolute term, while magnitude of increase in CO₂ emission has been about the same 3 to 4 percent during economic expansions from August 1980 throughout June 1981 and from July 2009 right through April 2014, respectively, size of the decline in CO₂ emission has stepped up from approximately 1.37 percent to 11.37 percent over the recession periods preceding these expansion periods.

More striking is the observable asymmetric evolution of magnitude when changes in CO₂ emission are normalized by the length of business cycles. In particular, whereas per cycle reduction in CO₂ emission has increased from 0.196 percent to 0.598 percent, per cycle increase in CO₂ emission has dropped from 0.279 percent to a trivial 0.068 percent. Similar diverging pattern in the magnitude of changes in CO₂ emission over the business cycles is also obtained if the magnitude of business cycles becomes the normalizing factor.

[INSERT TABLE 1 HERE]

Against this backdrop, one can ask three questions in succession: What is the relationship between CO₂ emission and the economy over the business cycles? Is the relationship asymmetric over the short and long run? If yes, what are the factors that bring about the asymmetry? These questions become even more relevant and not bounded to the case of the U.S when global energy-related CO₂ emissions in 2014 for the first time in forty years have remained unchanged from the previous year despite an expanding world economy (IEA, 2015). However, almost all of the discussion on these questions was based on the anecdotal accounts of the pundits and institutions without offering precise estimates on the asymmetric relationship and its determinants over the short and long run.

This paper fills the gap by addressing all these questions within an empirical framework of nonlinear autoregressive distributed lag (NARDL) model developed by Shin *et al* (2014). This model maintains the beauty of conventional ARDL approach that allows us to estimate a model encompassing variables with different orders of integration without the fear of endogeneity bias. At the same time, it allows us to disentangle interactions between CO₂ emission and the economy during tranquil time from recession periods over the short run and long run, giving us a dynamic coefficient that sheds light on the asymmetric output elasticity of CO₂ emissions over time.

Based on the case of the United States over the period ranging from 1980 to 2014 in monthly frequency, there are three main empirical results of this paper. First, CO₂ emissions in the U.S are procyclical to the economy, as emissions increase when the economy grows but decline when the economy slides. Second, and more important, CO₂ emissions respond asymmetrically to economic fluctuations in such a way that emissions increase at a rate much slower amid a growing economy than that of decrease in the middle of a shrinking economy in the long run. On impact and over the short run horizon, however, responses are symmetric

over the business cycles. These results are foolproof to the presence of potential endogeneity bias and structural breaks, and are robust to a variety of model specifications and the inclusion of control variables.

While our finding of asymmetries largely corroborates Doda (2013), Shahiduzzama (2015), and Shelton (2015), joining the troop to rebut York (2012) which found asymmetry of opposite direction, our results are also compatible with Burke *et al*'s (in press) which found short-run symmetry but long-run asymmetry for a sample of 189 countries. Different from these papers that are silent on the question of the drivers of asymmetries, we contribute to the literature by sorting out who tapers the emission during the good time.

This brings us to the third finding. Of all popular reasons deemed to be important to account for the gradual decoupling of CO₂ emissions from output expansion in recent years, reduction in vehicle miles travelled (VMT) turns out to be empirically most important. By controlling for VMT, output expansion becomes less polluting. This goes without denying a critical role for fuel switching from the dirtier coal to cleaner natural gas, as the switching has accounted for the structural breaks as seen in Figure 1 in the relationship between CO₂ emissions and the economy.

Beyond its novel results and interpretation, the paper contributes to the rethinking of the role of reducing miles travelled and its energy intensity in the design of climate policy through, for instance, improving public transportation network, introducing VMT tax, and developing electronic cars. Policy discussions pertaining to the reduction of CO₂ emissions in the past years focus nearly exclusively on the role of carbon tax in discouraging fuel consumption, the importance of alternative cleaner energy, and the benefit of increasing energy efficiency (see, for instance, *CEA Annual Report* 2013). But as Fay *et al* (2015, p.p 104-108) have iterated, citing Avner *et al* (2014), urban planning that promotes densification

and investments in public transportation infrastructure not only directly reduces total energy consumption but also substantially improves the public's acceptance toward carbon tax, increasing elasticity of energy demand to carbon price.

In broader view, this paper can be placed along with Doda (2014), Heutel (2012), and Narayan *et al* (2011) that assume symmetric responses. In contrast to Narayan *et al* (2011) that found cointegrated relationship between energy consumption and industrial output with a productivity-driven common cyclical relationship, we cannot identify such cointegrating relationship between CO₂ emissions and industrial output in a symmetric model. Cointegrating relationship can only be found in long-run asymmetric model.

Doda (2014) in a panel sample that includes the U.S and Heutel (2012) found that CO₂ emissions procyclically move with the output in the U.S. Although both papers point to inelastic emissions with respect to output, the former has a lower average value of 0.297 in the full-sample model but the latter exhibits a higher value of 0.758. Our findings based on the statistically most robust model that allows for long-run asymmetries and controls for VMT are richer: while instantaneous output elasticity can be as high as 0.856 with short-run elasticity of -0.29, long-run output elasticity during good times is 0.263, two fifth only of that during bad times.

Extending the symmetric cyclical property to the context of optimal environmental policy over the business cycles, Heutel (2012) argued for procyclical environmental instruments that dampen the procyclicality of CO₂ emissions (see Fischer and Heutel, 2013, for most recent review). By bringing evidence of asymmetric procyclicality to the table, a natural consequence is hence the revision of optimal policy responses. Although giving a clear answer with explicit mechanism is beyond the scope of this paper, it is not unreasonable to infer that cyclicity of optimal policy itself would be altered.

Lastly, our paper also relates to the sizeable literature on the relationship between CO₂ emissions and economic growth. Typically known as the environmental Kuznets curve (EKC), emission is hypothesized to be related to the level of national income in an inverted-U pattern. Empirical evidence accumulated thus far remains skeptical (Copeland and Taylor, 2004; Stern, 2004), and the nonlinearity of the EKC is indeed not guaranteed, which generally occurs in the rich countries but not developing countries (Bernard *et al* 2015; Jaunky, 2011; Narayan and Narayan, 2010).

In our bivariate model that accommodates both short and long-run asymmetries, short-run income elasticity of emission, which equals 0.523, is approximately similar to that of long-run value at 0.568. By accounting for VMT, however, long-run income elasticity drops substantially to 0.211 compared to the short-run elasticity of 0.567, suggesting that U.S has reduced CO₂ emissions as its income has increased over time. In other words, following Narayan and Narayan's (2010) line of argument, EKC is there in the U.S with VMT as the underlying mechanism. From another vantage point of view, we conjecturally attribute the failure to identify nonlinear EKC in developing countries to the lack of infrastructure and technology that helps reduce miles travelled and its energy intensity even when the income level has risen.

The remaining part of the paper is organized as follows. Section II elaborates the nonlinear ARDL model, and Section III discusses the empirical findings. There, we check the robustness of the results against a battery of control variables. In particular, we figure out which candidate wins the horse race in accounting for the slowing-down magnitude of emissions during tranquil time since 2000s, especially post Great Recession. Section IV concludes, in particular by discussing how the empirical results found in this paper can be

used to shed light on the way forward in U.S climate policy debate specifically, and to inform the design of optimal environmental policy over business cycles in general.

II. EMPIRICAL FRAMEWORK

A. *Inadequacy of Linear Model*

A simple static model that postulates a relationship between carbon dioxide emissions (CO_2) and output (Y) in natural logarithm can take the form

$$(1) CO_{2,t} = \beta_0 + \beta_1 Y_t + \varepsilon_t$$

where β_1 indicates the output elasticity of CO_2 emission, which typically takes a positive value. This means output expansion (contraction) leads to a rise (fall) in CO_2 emission. With a linear and symmetric setting, emission responses to a change in output during tranquil time is no more than a mirror image of those during recession periods.

Motivated by the occurrence of emission reduction during ongoing U.S economic rebound and the diverging patterns of CO_2 emissions across upbeat and downbeat business cycle intervals as shown in Table 1, we hold the view that “Rockets and Feathers hypothesis” can be found in the interaction between CO_2 emission and the economy over the business cycles.

Theoretically, although more business and leisure activities during good time are almost certainly contribute to the increase in energy-related CO_2 emissions, it is also likely that favorable income effect combined with government’s R&D subsidies in the development of clean technology induces technical and taste change toward cleaner production inputs and consumer goods, respectively. One cannot know a priori whether these offsetting forces are going to stay in parallel across roaring cycles. Likewise, one cannot rule out the possibility of

having greater magnitude of reduction in CO₂ emissions during contraction cycles, thanks to the unfavorable income effect and continuous policy-induced technical and taste change toward environmental friendly outputs.

In the search of more convincing evidence on the possibilities of nonlinearity that underlies the interaction between CO₂ emissions and the economy, a handful of studies have adopted different varieties of regime-switching nonlinear models. Kim *et al* (2010), for instance, showed that both growth rates of CO₂ emissions and industrial production exhibit a significant nonlinear asymmetric dynamics in Korea through the smooth transition autoregressive model (STAR) model (see also Park and Hong, 2013). By resorting to nonlinear threshold cointegration test, Fosten *et al* (2012) found temporary disequilibrium in U.K pollution-output relationship in an asymmetric fashion, and suggested that technological change can partially account for the asymmetric adjustment.

B. The Nonlinear ARDL Approach

Drawn on the work of Shin *et al* (2014), we revisit CO₂ emission-output relationship by addressing the question whether output responses of CO₂ emission are asymmetric over upbeat and downbeat business cycles over the short run and long run. Unlike the existing nonlinear models used in the literature, the key strength of Shin *et al*'s (2014) nonlinear autoregressive distributed lag model (NARDL) lies in the flexibility of modeling strategy to encompass all likely combinations of short-run and long-run (a)symmetry in CO₂ emission-output relationship. On top of this, the model also maintains the celebrated advantage of a typical ARDL model in that the nonlinear long-run level relationship between the variables can be estimated and tested by using a simple ordinary-least-square estimator irrespective of whether the underlying variables are trend- or first-difference stationary.

Building on the works of Pesaran and Shin (1999), and Pesaran *et al* (2001), NARDL model decomposes regressor into positive and negative changes.

$$(2) CO_{2,t} = \beta^+ Y_t^+ + \beta^- Y_t^- + u_t, \text{ for } \Delta Y_t = v_t$$

where Δ is the first-difference operator, and β^+ and β^- are the asymmetric long run parameters. We define Y_t^+ as the partial sum processes of positive change in Y_t , that is, $Y_t^+ = \sum_{j=1}^t \Delta Y_j^+ = \sum_{j=1}^t \max(\Delta Y_j, 0)$, and Y_t^- as the partial sum of processes of negative change in Y_t , where $Y_t^- = \sum_{j=1}^t \Delta Y_j^- = \sum_{j=1}^t \min(\Delta Y_j, 0)$. Y_0 is the initial value such that $Y_t = Y_0 + Y_t^+ + Y_t^-$.

The long-run regression model can be embedded into a standard autoregressive distributed lag (p, q) framework (in levels) to give us a NARDL(p, q)-in-levels model as follows

$$(3) CO_{2,t} = \sum_{j=i}^p \phi_j CO_{2,t-j} + \sum_{j=0}^q (\theta_j^+ Y_{t-j}^+ + \theta_j^- Y_{t-j}^-) + \varepsilon_t$$

where the ϕ_j are autoregressive parameters, θ_j^+ and θ_j^- refer to asymmetric distributed-lag parameters, and ε_t is an i.i.d process with zero mean and constant variance. The associated error-correction representation (ECM) for NARDL model can be derived as

$$(4) \Delta CO_{2,t} = \rho CO_{2,t-1} + \theta^+ Y_{t-1}^+ + \theta^- Y_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta CO_{2,t-j} + \sum_{j=0}^{q-1} (\varphi_j^+ \Delta Y_{t-j}^+ + \varphi_j^- \Delta Y_{t-j}^-) + \varepsilon_t$$

where $\rho = \sum_{j=1}^p \phi_j - 1$, $\theta^+ = \sum_{j=0}^q \theta_j^+$, $\theta^- = \sum_{j=0}^q \theta_j^-$, $\gamma_j = -\sum_{i=j+1}^p \phi_i$ for $j=1, \dots, p-1$; $\varphi_0^+ = \theta_0^+$, $\varphi_j^+ = -\sum_{i=j+1}^q \theta_i^+$ for $j=1, \dots, q-1$, $\varphi_0^- = \theta_0^-$, $\varphi_j^- = -\sum_{i=j+1}^q \theta_i^-$ for $j=1, \dots, q-1$. Long-run asymmetric parameter that corresponds to (1) can be defined as $\beta^+ = -\theta^+/\rho$ and $\beta^- = -\theta^-/\rho$.

Given the potential feedback of energy-related CO₂ emission on output, especially in the short run, regression of (4) is likely to suffer from endogeneity bias that induces non-zero contemporaneous correlation between regressors and residuals. To address this problem, we can specify a marginal data generating process for ΔY_t wherein $\Delta Y_t = \sum_{j=1}^{q-1} \Lambda_j \Delta Y_{t-j} + \nu_t$ to bridge ε_t over ν_t such that

$$(5) \varepsilon_t = \omega'(\Delta y_t - \sum_{j=1}^{q-1} \Lambda_j \Delta y_{t-j}) + e_t = \omega' \nu_t + e_t$$

By construction e_t and ν_t are uncorrelated. The conditional nonlinear ECM can thus be derived as follows:

$$(6) \Delta CO_{2,t} = \rho CO_{2,t-1} + \theta^+ Y_{t-1}^+ + \theta^- Y_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta CO_{2,t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta Y_{t-j}^+ + \pi_j^- \Delta Y_{t-j}^-) + e_t$$

where $\pi_0^+ = \theta_0^+ + \omega$, $\pi_0^- = \theta_0^- + \omega$, $\pi_j^+ = \varphi_j^+ - \omega' \Lambda_j$, and $\pi_j^- = \varphi_j^- - \omega' \Lambda_j$ for $j = 1, \dots, q-1$. As a result, the conditional specification of (6) perfectly corrects for the potential weakly endogeneity of non-stationary regressors for a NARDL model, ensuring that causal relationship only runs from the economy to the emission both in the short and long run (Coers and Sanders, 2013, Jaunky, 2011).

The conditional nonlinear ECM model (6) encompasses both short-run and long-run asymmetric effects. By specifying a null hypothesis of symmetric adjustment over the long run, where $\beta^+ = \beta^-$, and short run, $\pi_j^+ = \pi_j^-$ for all $j = 0, \dots, q-1$, we can detect the presence of asymmetries through the use of a simple Wald test. In general, there are four combinations of asymmetries to be tested.

- (i) A rejection of short-run and long-run symmetries, which implies a NARDL model as in (6) over both short run and long run;

(ii) A rejection of long-run but not short-run symmetry, which yields the following model

$$(7) \Delta CO_{2,t} = \rho CO_{2,t-1} + \theta^+ Y_{t-1}^+ + \theta^- Y_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta CO_{2,t-j} + \sum_{j=0}^{q-1} \pi_j \Delta Y_{t-j} + e_t$$

(iii) A rejection of short-run but not long-run symmetry to give us

$$(8) \Delta CO_{2,t} = \rho CO_{2,t-1} + \theta Y_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta CO_{2,t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta Y_{t-j}^+ + \pi_j^- \Delta Y_{t-j}^-) + e_t$$

(iv) A non-rejection of short-run and long-run symmetries, which strips NARDL model

down to a standard symmetrical ARDL (p,q) model as in Pesaran and shin (1998) and

Pesaran *et al* (2001)

$$(9) \Delta CO_{2,t} = \rho CO_{2,t-1} + \theta Y_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta CO_{2,t-j} + \sum_{j=0}^{q-1} \pi_j \Delta Y_{t-j} + e_t$$

Decomposition of a time series into its positive and negative partial sums may give way to complex interdependencies that result in nonlinear cointegration (Shorderet, 2003). To detect asymmetric cointegration two statistics are deemed to be appropriate, namely, the t_{BDM} -statistic proposed by Barnejee *et al* (1998) on testing the null of $\rho = 0$ against the alternative of $\rho < 0$, and the F_{PSS} statistic by Pesaran *et al* (2001). The latter instrumentally provides a valid inference on asymmetric cointegration in the coexistence of both stationary and non-stationary variables.

Against this spirit of Pesaran *et al* (2001), the specifications as in (6), (7), (8) and (9) allow for a pragmatic bound-test procedure to identify the existence of a level relationship between a dependent variable and a set of regressors with unknown order of integrations or cointegration. In particular, we set up and test a null of no cointegrating relationship between levels of $CO_{2,t}$, Y_t^+ , and Y_t^- ($H_0: \rho = \theta^+ = \theta^- = 0$) for (6) and (7), and that of $CO_{2,t}$ and Y_t

($H_0: \rho = \theta = 0$) for (8) and (9) using a standard F test. The critical bounds for all classifications are readily available in Pesaran *et al* (2001). If the F_{PSS} statistic computed lies above (below) the upper bound, the variables are said to be (not) cointegrated. If it lies within the bounds, a conclusive inference about the long-run relationship cannot be made without knowing the order of integration of the regressors.

To be in line with much of the existing literature (i.e, Greenwood-Nimmo and Shin, 2013), we also evaluate the symmetry of the impact multiplier, that is, $H_0: \pi_0^+ = \pi_0^-$. Once a long-run relationship is detected in the NARDL model, the parameters for long-run asymmetry as in (2) can be estimated as $\beta^+ = -\theta^+/\rho$ and $\beta^- = -\theta^-/\rho$, or $\beta_1 = -\theta/\rho$ for (1) if the model is symmetric in the long run. Lastly, as in Shin *et al* (2001), we compute recursively the asymmetric responses of $CO_{2,t}$ to a unit change in Y_t^+ and Y_t^- , respectively, from the estimated parameters of (6) as follows

$$(10) m_h^+ = \sum_{j=0}^h \frac{\partial CO_{2,t+j}}{\partial Y_t^+}, m_h^- = \sum_{j=0}^h \frac{\partial CO_{2,t+j}}{\partial Y_t^-}, \text{ for } h = 0, 1, 2, \dots$$

where $m_h^+ \rightarrow \beta^+$ and $m_h^- \rightarrow \beta^-$ when $h \rightarrow \infty$ by construction. This dynamic multiplier (m_h^i) is able to illuminate the dynamic adjustments from the initial point to long-run equilibrium through short-run disequilibrium between the system variables in the aftermath of a shock hitting the system.

To address the succeeding question of what drives the asymmetries, we extend the bivariate emissions-output model to a multivariate model in such a way that

$$(11) CO_{2,t} = \beta^+ Y_t^+ + \beta^- Y_t^- + \beta'_w \mathbf{W}_t + u_t$$

where \mathbf{W}_t is a $g \times 1$ vector of additional covariates entered symmetrically, and β'_w is the corresponding $K \times 1$ vector of coefficients. Following the discussion as in the bivariate case,

it is straightforward to see that the estimation and inferences for this multivariate model can be carried out in a similar fashion regardless of the order of integration for Y_t and \mathbf{W}_t , or whether they are mutually cointegrated. Embedding this long-run regression within the NARDL approach, we have

$$(12) \Delta CO_{2,t} = \rho CO_{2,t-1} + \theta^+ Y_{t-1}^+ + \theta^- Y_{t-1}^- + \boldsymbol{\theta}_w \mathbf{W}_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta CO_{2,t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta Y_{t-j}^+ + \pi_j^- \Delta Y_{t-j}^- + \boldsymbol{\pi}'_{w,j} \mathbf{W}_{t-j}) + e_t$$

For reasons to be discussed in section III.D, we consider three control variables:

- (i) U.S vehicle miles travelled (LVMT)
- (ii) cooling degree days (LCDD) and heating degree days (LHDD), which, respectively, refer to outdoor temperature that exceeds (fall short of) the mean daily temperature of 65 Fahrenheit (18.3 Celsius).
- (iii) A ratio between coal and natural gas consumption (LCGAS)

III. RESULTS AND DISCUSSION

A. The Data

We use U.S. monthly data on total energy-related carbon emissions measured in million metric tons of carbon dioxide provided by U.S. Energy Information Administration that spans from January 1980 to April 2014 to indicate carbon dioxide emissions (LCO_2). Due to the fact that gross domestic product measured on monthly basis is not available, to keep with the literature we use industrial production index (2007=100) (LIPI) as a proxy for the economy, sourced from St Louis Fred database. Besides, LVMT is also sourced from St Louis Fred database. LHDD and LCDD are taken from Annual Energy Review published by

U.S Energy Information Agencies, and data on coal and natural gas consumption are retrieved from sourced from U.S Energy Information Administration. All data is transformed into natural logarithm form. As the seasonally unadjusted monthly data may exhibit peak during the winter and summer months, the data is seasonally adjusted using the Census Bureau's X-12-ARIMA procedure.

B. The Stochastic Properties of the Time Series

The ability of the NARDL model to accommodate mixed $I(0)$ and $I(1)$ variables provides a pragmatic approach to examine the cointegration between variables. Nevertheless, variables are likely to be $I(2)$. Therefore, as a preliminary test we conduct a simple Dickey and Fuller's (1979) Augmented Dickey-Fuller unit root test on the time series involved to ensure that none of the series has an order of integration of $I(2)$. On top of this, we also conduct Lee and Strazizich's (2003) unit root test that endogenously accounts for two structural breaks to ensure that the results of unit root testing are not contaminated by the presence of structural breaks.

The results of unit root tests reported in Table 2 suggest that LCO_2 and LPI are not $I(2)$, as the series are mostly $I(1)$. The results are robust to the inclusion of structural breaks. Although $LCDD$, $LHDD$, $LCGAS$, and $LVMT$ are $I(0)$, taking endogenous structural breaks in trend and intercept into account turns them into $I(1)$. Most importantly, none of them is $I(2)$. Overall, unlike the conventional time series regressions that require variables to have same order of integration, the findings of a mixture of $I(0)$ and $I(1)$ series in this case make the NARDL approach practically relevant and useful.

[INSERT TABLE 2 HERE]

C. The Emission-Output Relationships in Bivariate Models

To arrive at an appropriate NARDL model specification, we follow the general-to-specific approach. Beginning with a maximum lag of nine, using a unidirectional 5% decision rule, all insignificant regressors are eliminated. The most parsimonious model that passes a battery of diagnostic checks is preferred. Table 3 summarizes the estimated results for models that range from the NARDL model specification expanded with long-run and short-run asymmetric effects to the simplest linear ARDL model. Specifically, we consider four model specifications: Model AA that admits both long-run and short-run asymmetries, Model AS that accommodates long-run asymmetry but imposes symmetrical short-run dynamics, Model SA that permits short-run asymmetries along with long-run symmetries, and lastly, Model SS as a simple linear ARDL model that does not allow for any asymmetric dynamics.

[INSERT TABLE 3 HERE]

In general, the simple CO₂ emission-output NARDL models are unsatisfactory in many aspects. In particular, the null of no cointegration relationship cannot be rejected in all cases using Pesaran *et al*'s (2001) *F*-test that is more appropriate for models with mixed orders of integration, suggesting that the regression results might be suffering from spurious regression problems. Together with a battery of diagnostic tests that shows the presence of the ARCH effects and autocorrelated residuals, it gives rise to the possibility of the omission of some important factors. Furthermore, the residuals are non-normally distributed. Lastly, the Quandt-Andrews unknown breakpoint tests (SupD, ExpF and AveF statistics) reveal that there is an issue for not controlling for the presence of structural breaks in all four cases (see Andrews, 1993; and Andrews and Ploberger, 1994).

D. The Emission-Output Relationships in Multivariate Models: Who Tape the Breaks?

With the benefit of hindsight, as exhibited in Figure 1 and Table 1, the evolution of total energy-related CO₂ emissions starts showing a sign of break in trend growth over the

business cycle horizons since the Aughties. By hitting the 20-year low of CO₂ emissions in 2012 whilst industrial production has already expanded by 16 percent since the U.S economy recovers, the trend emission is obviously broken. Of interesting question is who tapes the breaks? What constitutes the asymmetries?

Figure 2 provides some hints. In Figure 2, sources of total emissions are decomposed into four major sectors according to the data released by EIA, namely commercial and residential combined (for an obvious reason as both consume energy mainly on air-conditioner for cooling and heater for heating, besides lighting and elevators), electric power, transportation, and industry. The first two categories apparently are the main emitters. An interesting observation is how CO₂ emissions from electric power sector track almost perfectly those from commercial and residential sectors. Transportation has taken over industry as the next most important source of emissions since 2000s. Most interesting, all four sources demonstrate a trend break in the emissions from the historical evolution in the aftermath of the recent recession with slower growth rates of emissions during the latest recovery and expansion periods.

[INSERT FIGURE 2 HERE]

As a proxy for total energy-related CO₂ emission from transportation we use the U.S VMT. Besides, due to the fact that energy-intensive heating and cooling purposes in commercial and residential sectors constitutes part and parcel demand for energy, we thus include the LCDD and LHDD for the estimation of (12). Whereas for electric power sector and industry that belong to production activities, industrial production index serves as the indicator.

It is worthwhile to note that CO₂ emission of an activity, be it a X , can actually be decomposed into energy-intensity of the activity, that is the ratio between energy demand (ED) and the activity, and its emission intensity in terms of CO₂ emitted per energy used.

$$\frac{CO_2}{X} = \underbrace{\frac{CO_2}{ED}}_{\text{Emission intensity}} \times \underbrace{\frac{ED}{X}}_{\text{Energy intensity}}$$

What VMT and HDD/CDD, as well as industrial output, have captured is the energy intensity of the economic activity. More energy is needed when longer mileages have been travelled, and heating (cooling) degree days are greater that result in more intensive use of heater (air-conditioner), given the emission intensity.

However, emission intensity cannot be held constant in the long run especially when technology advances, allowing fuel switching from dirtier coal to cleaner natural gas in the electricity power sector. Many have claimed that coal-to-gas fuel switching has been the major driver of the reduction of emission intensity in recent years (see, for instance, *CEA Annual Report*, 2013; Trembath *et al*, 2013). Hence, we expand the bivariate NARDL model by incorporating LCGAS that serves as the proxy for coal-to-gas fuel switching.

Seeing that bivariate NARDL models perform the worst in accounting for the relationship between CO₂ emission and the economy, we estimate a multivariate NARDL model in the specification that hypothesizes asymmetries in both short and long run (Model AA). Of all results reported in Table 4, a finding is consistently found across all Model AA specifications (except for a marginal case for Model AA8): the null hypothesis of short-term symmetry cannot be rejected, whereas the null hypothesis of long-run symmetry is rejected. The fact that growth rates in CO₂ emissions respond identically to output growth rates over business cycle horizons, whilst in the long run the level of emissions is less responsive when the economy expands than when it recesses can thus be convincingly established.

[INSERT TABLE 4 HERE]

In view of the non-rejection of short-run symmetry, we check the robustness of the findings in Table 4 by restricting the model to be symmetric in the short run, giving us the Model AS, of which we repeat the estimations as for Model AAs and check for diagnostic tests. The results are reported in Table 5. What we have found through Model AS and its variants is actually barely different from those of Model AAs. Hence, our discussion focuses mainly on Model ASs as reported on Table 5, leading to Model AS9 that stands out as best-suited model that is statistically most robust and convincing.

[INSERT TABLE 5 HERE]

Prior to examining the importance of LVMT, LHDD/LCDD, and LCGAS, we take stock on the role of the Energy Policy Act (EPA) of 2005, which has often touted as the first omnibus energy legislation addressing the issue of energy security that plagues the U.S for decades, and advancing energy efficiency as well as renewable energy through incentives. Although CO₂ emissions reduction is not intended in the EPA, it may be of interest to take a statistical glimpse on its unintended indirect impact on CO₂ emissions reduction through the improvement in emission intensity.

To do so we assign a policy dummy variable in three ways. First, the dummy variable in Model AS1 is a one-time off dummy, where the variable takes a value of 1 in August 2005 and zero otherwise. Alternatively, as for Model AS2, the dummy variable takes a value of 1 from August 2005 onwards and zero otherwise. Lastly, to capture the potential indirect impact, we assign an interactive variable in Model AS3 that involves a dummy variable as defined in Model AS2 and the lagged logged coal-to-natural-gas consumption ratio (LCGAS(-1)). As shown in the first three columns of Table 5, irrespective of how it is defined, the policy coefficient is trivial and statistically insignificant.

Model AS4 expands Model AS by incorporating HDD. The variable is statistically insignificant, however. Model AS5 considers CDD, whereas Model AS6 examines the impact of HDD and CDD simultaneously. Overall model properties did improve by accounting for HDD and CDD in the estimation. In particular, variables become cointegrated, and there are neither autocorrelated residuals nor ARCH effects. Nonetheless, in spite of the statistical significance, magnitude of the coefficients is small with wrong sign. Furthermore, what took place in residential and commercial sector is certainly not able to account for the break in CO₂ emission trend. It is evidenced by its rejection of the null of no structural breaks.

How about the asymmetries? We capture the “*asymmetry-ness*” of the model by taking a ratio of long-run coefficients for positive and negative output changes (β^+/β^-). A value of (approximately) one simply indicates long-run symmetry. Value that approximates zero implies long-run asymmetry with stronger emission-output nexus during recessions. In contrast, value that drifts above one suggests long-run asymmetry with stronger emission-output nexus during expansions. In this respect, as shown in Model AS4 to AS6, HDD and CDD are not the candidates to account for the asymmetries given its asymmetry-ness in between 0.642-0.649 that is clearly identical to 0.642 of Model AS.

Neither is coal-to-gas fuel switching the underlying factor for the asymmetries. Although the coefficient for LCGAS in Model AS7 is statistically significant with correct sign, long-run coefficients for output changes are approximately similar to the bivariate Model AS in Table 3, leaving the indicator of asymmetry-ness largely unchanged. This brings us to the role of miles travelled. In Model AS8 that includes LVMT, long-run positive output elasticity of the emissions has substantially dropped from the range of 0.551-0.613 for model specifications excluding LVMT to 0.215. Although CO₂ emissions also become less elastic to a decrease in industrial output over the long run, interestingly, the asymmetry-ness

is nearly halved from the range of 0.642-0.709 in all other model specifications to 0.362. In other words, once controlling for the total vehicle miles travelled, not only that output expansion can be much less polluting, emissions also reduces at a rate approximately three times faster than that of increase in emissions. This finding is robust to an estimation that incorporates all conditional factors concurrently as in Model AS9. What's more interesting is the role of VMT even in the short run: once it is controlled, a change in output growth rate has nearly negligible impact on emission growth rate (Model AS8). In fact, along with other controlled variables, especially LCGAS, as in Model AS9, an output expansion can be decarbonizing ($\sum_{j=1}^{q-1} \pi_j = -0.29$).

Another interesting finding that may shed light on environmental Kuznets curve (EKC) is worth-penning. EKC hypothesizes an inverted-U relationship between the emission and the level of national income in such a way that pollution emission first arises when the economy expands but declines after which an income threshold is surpassed (Copeland and Taylor, 2004; Stern, 2004; Bernard *et al* 2015). Narayan and Narayan (2010) argue that a smaller long-run vis-à-vis short-run income elasticity of emission is an indicator for the presence of EKC.

In our bivariate Model AA that accommodates both short and long-run asymmetries, short-run income elasticity of emission, which equals 0.523, is approximately similar to that of long-run value at 0.568. By accounting for VMT, however, long-run income elasticity drops substantially to 0.211 compared to the short-run elasticity of 0.567, suggesting that U.S has reduced CO₂ emissions as its income has increased over time. In view of this finding, devices that can reduce energy and emission intensity of VMT are brought into limelight as the underlying mechanism of EKC. On the flipside, we can also conjecturally attribute the failure to identify nonlinear EKC in developing countries to the lack of infrastructure and

technology that helps reduce miles travelled and its energy intensity even when the income level has risen.

Turning to structural breaks, through Quandt-Andrews unknown breakpoint tests we know that the null of no structural breaks survives only when LCGAS is included in the model (either Model AS7 or Model AS9), leaving the regression not controlling for the presence of structural breaks without implication. This indirectly corroborates our earlier conjecture that coal-to-gas fuel switching is responsible for the breaks we have witnessed in the relationship between CO₂ emissions and the economy, whereas vehicle miles travelled remains the underlying reason for long-run asymmetries.

In conclusion, of all model specifications, we find that Model AS9 reported in the last column in Table 5 is empirically most appropriate to capture the interactions between CO₂ emissions and the economy because it does not suffer from any econometric problems. There is neither autocorrelation nor autoregressive conditional heteroscedasticity problem. Residuals are normally distributed, validating our hypothesis testing. Furthermore, the null of no cointegration relationship is rejected by both t_{BDM} statistics of Barnejee et al. (1998) and F -test of Pesaran *et al* (2001), indicating that the regression results are not spurious.

E. The Long-Run Multiplier

Our finest result of short-run symmetry with long-run asymmetry exhibited by Model AS9 can actually be illustrated by the shape of the cumulative dynamic multipliers as in Figure 3. Specifically, the upper (lower) solid dashed line represents the cumulative dynamics of CO₂ emissions with respect to a 1% increase (decrease) in industrial output, the thick dashed lines compute the difference between positive and negative responses, and the thin dash lines provide bootstrapped 95% confidence intervals. One can observe that the carbon emission respond symmetrically to positive and negative changes in the output in the short

run, as depicted by the difference line that stays on the zero line for the first two quarters. Throughout a longer time horizon, however, gap between the two responses starts widen, inclining toward negative responses. In line with the results reported in Table 5, such evolution of dynamic multipliers starkly illustrates a case for “feathers and rockets” hypothesis, wherein CO₂ emission reduction during bad time overwhelms CO₂ emission buildup during good time in the long run.

[INSERT FIGURE 3 HERE]

IV. CONCLUSION WITH POLICY REMARKS

Factoring in potential asymmetric responses of CO₂ emissions toward the ups and downs of the economy in the U.S brings new light on the empirical validity over different claims on the evolving linkages between emissions and the economy. In particular our analysis suggests that output elasticity of emissions is stronger during recessions than that during expansions in the long run, although changes in emissions vary symmetrically over the business cycle horizons in the short run. Furthermore, by bringing coal-to-natural-gas fuel switching and vehicle miles travelled into limelight, this paper bestows empirical support to the role of the latter in prompting favorable asymmetric output responses of CO₂ emissions in the long run, whereas the former is responsible for the structural break observed in CO₂ emission-output relationship. The results are robust to varying model specifications and pass a battery of diagnostic checks convincingly.

Extending from the above results, this paper naturally calls for a rethinking on the importance of strategies for reducing VMT, which has been largely absent all this while, in the design of the climate policy. Policy discussions pertaining to the reduction of CO₂ emissions from transportation sector focus almost exclusively on identifying alternative types of fuel and on increasing vehicle fuel efficiency (EPA 2015a, 2015b). While not denying the

importance of fuel switching from dirtier to cleaner types, as our results also suggest that coal-to-gas switching accounts for the presence of structural breaks in the relationships between CO₂ emissions and industrial output, policy scope for reducing VMT can be extended, for instance, to the domain of public transportation network and VMT tax. In addition to the benefits of a better developed public transportation that reduce total energy consumption and improve public's acceptance toward carbon tax (see Fay *et al*, 2015, p.p 104-108; Avner *et al*, 2014), it underpins the favorable asymmetric responses of CO₂ emissions by providing a cleaner substitute to the usual car drivers who tighten the belt during recessions, a habit that is likely to be locked-in and remained even when the economy recovers.

Our paper is a first step toward a more comprehensive empirical study in search of larger set of explanatory factors for the relationship between CO₂ emissions and the economy that factors in the asymmetries. Several directions of future research appear fruitful. First, it would be useful to probe into a cross-country investigation to identify the degree and pattern of asymmetries across countries. Second, it would also be valuable to examine the implications of controlled factors in time varying manner in view of the fact that factors underlying the asymmetries may vary over the time. Lastly, setting up a model that can coherently account for the asymmetries and offer a structural interpretation on its underlying mechanism shall be of great relevance to the design of optimal environmental policy that curbs the emissions without amplifying business cycles and putting long-run growth at stake.

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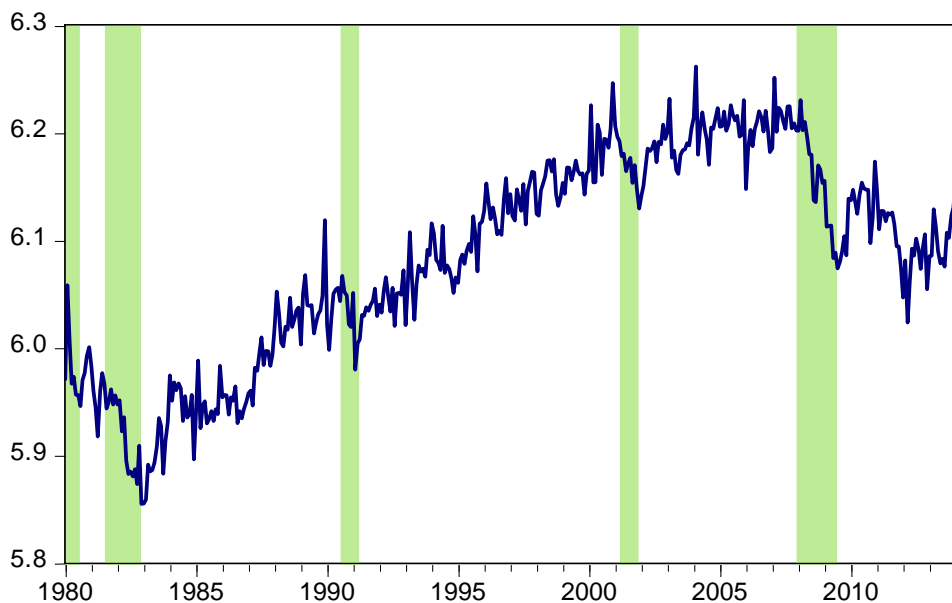
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FIGURE 1

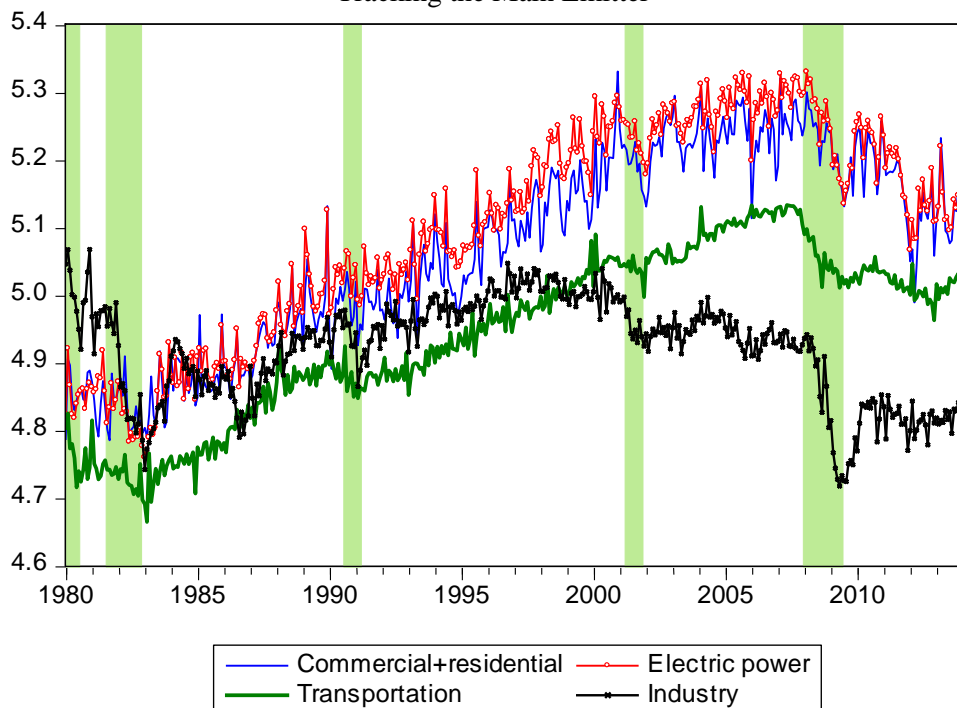
Total Carbon Dioxide Emissions in US, January 1980 – April 2014



Notes: Seasonally adjusted in natural logarithms. Green shaded areas are U.S recession periods as defined by NBER Dating Committee.

FIGURE 2

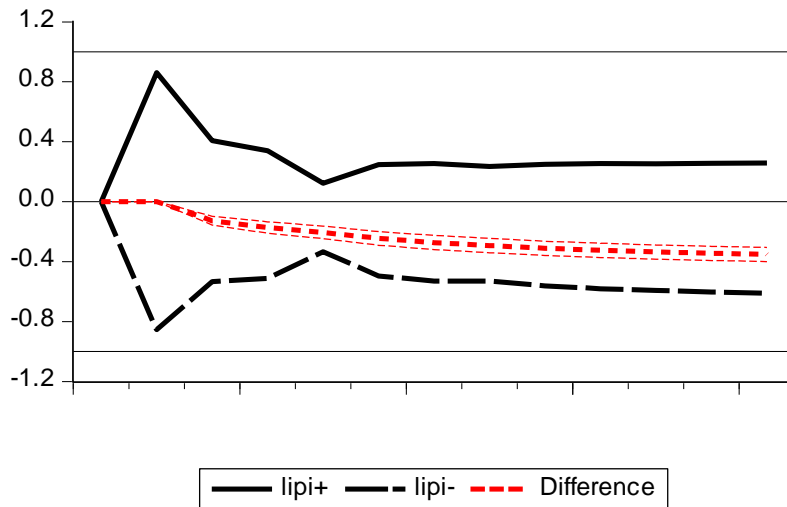
Tracking the Main Emitter



Notes: Seasonally adjusted series in natural logarithm. Green shaded areas are U.S recession periods defined by NBER Dating Committee

FIGURE 3

The Long-Run Multiplier



Notes: lipi+ and lipi-, respectively, denote the effects of a 1% positive and negative shock hitting industrial output on CO₂ emissions. The thick dashed lines compute the difference between the positive and negative effects, whereas the light dashed lines provide two standard error intervals.

TABLE 1

A Comparison of Changes in U.S Carbon Dioxide Emissions between Recession and Expansion Periods

Recession Periods						Expansion Periods					
Start	End	% Δ CO ₂	% Δ IPI	Normalized % Δ CO ₂ by		Start	End	% Δ CO ₂	% Δ IPI	Normalized % Δ CO ₂ by	
				% Δ IPI	Periods					% Δ IPI	Periods
1980M01	1980M07	-1.371	-7.289	0.188	-0.196	1980M08	1981M06	3.071	5.414	0.567	0.279
1981M07	1982M11	-5.776	-8.746	0.660	-0.340	1982M12	1990M06	19.088	29.124	0.655	0.210
1990M07	1991M03	-3.987	-3.775	1.056	-0.443	1991M04	2001M02	18.858	40.877	0.461	0.158
2001M03	2001M11	-4.596	-3.808	1.207	-0.511	2001M12	2007M11	7.927	28.958	0.274	0.345
2007M12	2009M06	-11.369	-18.354	0.619	-0.598	2009M07	-	3.941	20.076	0.196	0.068

Notes: Date of business cycle is defined by NBER Business Cycle Dating Committee. % Δ CO₂ and % Δ IPI, respectively, refer to percentage change in total carbon dioxide emissions and in industrial production index.

TABLE 2
Results of Unit Root tests

	Augmented Dickey Fuller (ADF)			LM Unit Root Test with Two Structural Breaks				
	Constant	Constant and Trend	Break in Intercept	T _{B1}	T _{B2}	Break in Intercept and Trend	T _{B1}	T _{B2}
<u>LEVEL</u>								
LCO ₂	-1.147 (5)	-1.822 (4)	-2.606 (2)	1994:05	2005:12	-5.954 (11)**	2000:02	2008:06
LIPI	-0.556 (13)	-1.813 (13)	-1.864 (12)	1983:11	2008:11	-4.456 (12)	1997:03	2000:03
LIPI+	-1.070 (3)	-2.036 (3)	-2.519 (6)	1985:11	1991:04	-4.213 (9)	1990:03	1998:11
LIPI-	-1.089 (5)	-2.640 (5)	-1.855 (10)	2008:09	2008:11	-4.721 (16)	1986:03	2008:07
LCDD	-4.887 (11)**	-5.310 (11)**	-3.329 (11)	1997:02	2004:12	-8.989 (11)**	1984:12	1996:03
LHDD	-17.728 (0)**	-17.857 (0)**	-5.003 (15)**	1983:08	1984:07	-8.186 (11)**	1983:07	2006:07
LCGAS	-3.469 (12)**	-4.434 (11)**	-3.565 (15)*	1983:05	1984:12	-9.265 (11)**	1993:01	2007:02
LVMT	-3.074 (17)**	1.182 (8)	-1.773 (17)	1994:12	2003:10	-4.455 (13)	1995:01	2007:12
<u>FIRST DIFFERENCE (D)</u>								
DLCO ₂	-12.274 (5)**	-12.261 (4)**	-3.123 (12)	1983:08	1983:12	-13.982(17)**	1989:11	1991:10
DLIPI	-5.607 (12)**	-5.599 (12)**	-6.528 (12)**	1992:08	2010:10	-9.684 (11)**	2005:07	2007:10
DLIPI+	-8.741 (2)**	-8.787 (2)**	-8.770 (2)**	1983:05	1983:08	-11.634 (1)**	1995:06	1998:07
DLIPI-	-5.943 (4)**	-5.952 (4)**	-5.987 (11)**	2006:11	2010:09	-10.025 (11)**	2005:07	2008:08
DLCDD	-8.707 (17)**	-8.698 (17)**	-3.119 (16)	1983:10	1984:08	-17.328 (14)**	1984:10	1986:02
DLHDD	-17.402 (11)**	-17.381 (11)**	-4.340 (14)**	1983:06	1984:05	-14.087 (14)**	2000:05	2003:08
DLCGAS	-9.513 (10)**	-9.502 (10)**	-3.283 (17)	1983:12	1985:03	-13.718 (13)**	1993:01	1993:05
DLVMT	-3.947 (16)**	-11.420 (7)**	-3.563 (12)*	1983:05	1983:11	-14.725 (12)**	2007:11	2010:02

Notes: Number of the parenthesis is the lag selected based on Akaike information criterio. *** (**) * denotes significance at 1% (5%) and 10%. LIPI denotes industrial production index (2007=100), LCO₂ is the carbon dioxide emission, LCDD denotes the Cooling Degree Days, LHDD refers to the Heating Degree Days, LCGAS is the coal-to-natural-gas consumption ratio, and LVMT is the vehicle miles traveled. “+” and “-” refer to positive and negative partial sums. All variables are in natural logarithms.

TABLE 3
Estimates of Dynamic CO₂ Emission-Output Relationships

Estimated Coefficients	LR		LR	
	LR & SR Asymmetry (Model AA)	Asymmetry & SR Symmetry (Model AS)	Symmetry & SR Asymmetry (Model SA)	LR & SR Symmetry (Model SS)
ρ	-0.138***	-0.141***	-0.057**	-0.046*
θ	-	-	0.020*	0.017
θ^+	0.078***	0.081***	-	-
θ^-	0.121***	0.126***	-	-
π_0^+	0.911***	-	0.921***	-
π_0^-	0.738***	-	0.667**	-
$\sum_{j=1}^{q-1} \pi_j^+$	0.523**	-	-	-
$\sum_{j=1}^{q-1} \pi_j^-$	0.536*	-	1.195***	-
Normalized long-run estimates:				
β	-	-	0.346***	0.365***
β^+	0.568***	0.573***	-	-
β^-	0.880***	0.893***	-	-
Cointegration tests:				
F_{PSS}	4.001	4.375	2.047	1.387
t_{BDM}	-3.422**	-3.539**	-2.012	-1.665
Symmetry tests:				
$W_{LR} (H_0: \beta^+ = \beta^-)$	15.617***	17.278***	-	-
$W_{SR} (H_0: \pi_j^+ = \pi_j^- \text{ for all } j=0, \dots, q-1)$	0.088	-	3.741*	-
Diagnostics tests:				
\bar{R}	0.299	0.299	0.288	0.323
LM(2)	3.221	2.267	5.041*	6.545**
LM(12)	11.944	13.405	17.548	15.936
ARCH(2)	7.574**	5.772*	8.916**	4.243
ARCH(12)	24.085**	21.090**	25.299**	20.041*
JB	21.606**	28.546***	18.270***	10.182***
Test for structural breaks				
Quandt-Andrews breakpoint test ^(a)				
SupF	37.478***	32.216**	33.179**	30.657*
ExpF	15.586***	12.833***	12.939**	10.587
AveF	23.875***	19.095	16.599*	14.929

Notes: General-to-specific lag selection is employed for the NARDL estimation starting from an optimal max of 9 lags using a unidirectional 5% decision rule. Notations for the estimated coefficients are as in Eqs. (6) – (9). β 's are the long-run elasticities estimated from the normalized equations based on the NARDL models. Full NARDL estimation results are available upon request. “+” and “-” refer to positive and negative partial sums, respectively. t_{BDM} is the t -statistic proposed by Banerjee, Dolado and Mestre (1998) for testing $\rho = 0$ against $\rho < 0$ whilst F_{PSS} is the F-test proposed by Pesaran, Shin and Smith (2001) for the joint null of $\rho = \theta^+ = \theta^- = 0$. The critical values for both statistics are tabulated in Pesaran *et al* (2001). W_{LR} and W_{SR} are the long-run and short-run symmetrical Wald test on the null of $\beta^+ = \beta^-$ and $\pi_j^+ = \pi_j^-$, respectively, for all $j = 0, \dots, q-1$. LM test is the Lagrange multiplier test for serial correlation, ARCH(k) is the autoregressive conditional heteroscedasticity test for detecting the present of ARCH effect, and JB test for normality. SupF, ExpF and AveF are Quandt-Andrews unknown breakpoint tests with the null of no breakpoints within 15% trimmed data. P-values for the test statistic are calculated according to Hansen (1997).

TABLE 4

Who tape the breaks of emissions? Evidence from conditional Long and Short-run Asymmetric (AA) model

Estimated Coefficients	(AA1)	(AA2)	(AA3)	(AA4)	(AA5)	(AA6)	(AA7)	(AA8)	(AA9)
ρ	-0.138***	-0.195***	-0.138***	-0.138***	-0.178***	-0.166***	-0.210***	-0.310***	-0.338***
θ^+	0.078***	0.106***	0.078***	0.078***	0.108***	0.102***	0.123***	0.065***	0.085***
θ^-	0.121***	0.150***	0.121***	0.121***	0.167***	0.158***	0.187***	0.184***	0.214***
π_0^+	0.910***	0.943***	0.911***	0.910***	0.875***	0.877***	0.887***	0.999***	1.093***
π_0^-	0.739***	0.730***	0.738***	0.738***	0.870***	0.859***	0.901***	0.659***	0.471**
$\sum_{j=1}^{q-1} \pi_j^+$	0.524**	-	0.523**	0.523**	-	-	-	0.567**	-
$\sum_{j=1}^{q-1} \pi_j^-$	0.536**	-	0.537*	0.536*	-	-	-0.504*	-	-
α_{DUM1}	-0.002	-	-	-	-	-	-	-	-
α_{DUM2}	-	-0.006	-	-	-	-	-	-	-
α_{DUM3}	-	-	3.16E-05	-	-	-	-	-	-
Normalized long-run estimates:									
β^+	0.569***	0.543***	0.569***	0.568***	0.607***	0.613***	0.585***	0.211***	0.252***
β^-	0.881***	0.766***	0.881***	0.880***	0.936***	0.953***	0.887***	0.591***	0.634***
β^+/β^-	0.646	0.709	0.646	0.645	0.649	0.643	0.660	0.357	0.397
β_{LHDD}	-	-	-	-0.001	-	-0.070***	-	-	-0.168***
β_{LCDD}	-	-	-	-	-0.156***	-0.192***	-	-	-0.043**
β_{LCGAS}	-	-	-	-	-	-	0.065***	-	0.090***
β_{LVMT}	-	-	-	-	-	-	-	0.433***	0.421***
Cointegration tests									
F_{PSS}	3.980	8.370***	3.992	2.994	13.365***	11.777***	8.579***	11.953***	9.206***
t_{BDM}	-3.411**	-4.985**	-3.416*	-3.389*	-4.860***	-4.532***	-5.370***	-6.715***	-7.301***
Symmetry tests									
W_{LR}	15.543***	8.669***	15.103***	15.533***	34.615***	31.776***	35.985***	116.865***	167.490***
W_{SR}	0.086	0.223	0.086	0.086	0.0001	0.002	0.996	3.503*	2.555
Diagnostics tests									
\bar{R}	0.297	0.282	0.297	0.297	0.416	0.426	0.302	0.3793	0.492
LM(2)	3.326	8.425**	3.215	3.270	4.235	3.410	6.799*	0.9426	0.514
LM(12)	12.106	21.380**	11.935	12.075	12.978	11.431	15.460	12.2684	15.323
ARCH(2)	7.579**	9.730***	7.590**	7.573**	0.632	0.204	4.387	7.248**	0.066
ARCH(12)	24.092**	26.674***	24.076**	24.079**	15.113	13.742	21.441**	21.161**	19.580*
JB	21.712***	15.681***	21.757***	21.721***	0.355	3.110	1.823	26.429***	0.506
Test for structural breaks: Quandt-Andrews breakpoint test ^(a)									
SupF	-	-	-	37.347**	37.345**	36.914*	37.632*	34.761**	46.451
ExpF	-	-	-	15.561**	15.533**	15.492**	15.581*	13.933**	20.373
AveF	-	-	-	24.355**	25.825***	27.660***	23.102	21.711**	35.798

Notes: “+” and “-” refer to positive and negative partial sums. α_i refers to the coefficient of dummy variable in the NARDL model where $DUM_1 = 1$, for the period 2005:08, 0 otherwise; $DUM_2 = 1$ for the period after 2005:08, 0 otherwise; and DUM_3 is the interaction term between DUM_2 with $LCGAS(-1)$. F_{PSS} is the F -test proposed by Pesaran, Shin and Smith (2001) for the joint null of $\rho = \theta^+ = \theta^- = 0$ whilst t_{BDM} is the t -statistic proposed by Banerjee, Dolado and Mestre (1998) for testing $\rho = 0$ against $\rho < 0$. The critical values for both statistics are tabulated in Pesaran *et al* (2001). W_{LR} and W_{SR} are the long-run and short-run symmetrical Wald test, respectively, on the null of $\beta^+ = \beta^-$ and $\varphi_j^+ = \varphi_j^-$ for all $j = 0, \dots, q-1$. LM test is the Lagrange multiplier test for serial correlation, ARCH(k) is the autoregressive conditional heteroscedasticity test for detecting the present of ARCH effect, and Jarque Bera (JB) test for normality. SupF, ExpF and AveF are Quandt-Andrews unknown breakpoint tests with the null of no breakpoints within 15% trimmed data. P-values for the test statistic are calculated according to Hansen (1997).

TABLE 5

Further Evidence from the Model of Long-Run Asymmetry with Short-Run Symmetry (AS)

Estimated Coefficients	(AS1)	(AS2)	(AS3)	(AS4)	(AS5)	(AS6)	(AS7)	(AS8)	(AS9)
ρ	-0.140***	-0.149***	-0.141***	-0.141***	-0.178***	-0.166***	-0.149***	-0.293***	-0.334***
θ^+	0.081***	0.082***	0.081***	0.081***	0.108***	0.101***	0.085***	0.063***	0.088***
θ^-	0.126***	0.116***	0.126***	0.125***	0.167***	0.158***	0.131***	0.174***	0.216***
π_0	0.829***	0.796***	0.829***	0.829***	0.873***	0.868***	0.782***	0.878***	0.856***
$\sum_{j=1}^{q-1} \pi_j$	0.417**	0.400***	0.417**	0.417**	-	-	0.374**	0.068**	-0.290**
α_{DUM1}	-0.002	-	-	-	-	-	-	-	-
α_{DUM2}	-	-0.005	-	-	-	-	-	-	-
α_{DUM3}	-	-	2.94E-05	-	-	-	-	-	-
Normalised long-run estimates									
β^+	0.573***	0.551***	0.573***	0.573***	0.607***	0.613***	0.568***	0.215***	0.263***
β^-	0.893***	0.777***	0.894***	0.893***	0.935***	0.952***	0.878***	0.594***	0.646***
β^+ / β^-	0.642	0.709	0.641	0.642	0.649	0.644	0.647	0.362	0.407
β_{LHDD}	-	-	-	-0.001	-	-0.070***	-	-	-0.174***
β_{LCDD}	-	-	-	-	-0.156***	-0.193***	-	-	-0.047**
β_{LCGAS}	-	-	-	-	-	-	0.008***	-	0.093***
β_{LVMT}	-	-	-	-	-	-	-	0.423***	0.410***
Cointegration tests									
F_{PSS}	4.355	4.769	4.364	3.273	13.503***	11.881***	5.311**	10.980***	9.438***
t_{BDM}	-3.529**	-3.706**	-3.535**	-3.511*	-4.902***	-4.566***	-3.790**	-6.419***	-7.330***
Symmetry tests									
W_{LR}	17.195***	5.319**	16.630***	17.202***	34.712***	31.794***	18.694***	104.293***	165.035***
W_{SR}	-	-	-	-	-	-	-	-	-
Diagnostics tests									
\bar{R}	0.298	0.301	0.298	0.298	0.418	0.428	0.305	0.384	0.495
LM(2)	2.380	2.684	2.251	2.298	4.228	3.415	3.661	0.493	0.260
LM(12)	13.285	13.762	13.416	13.441	12.976	11.438	13.168	15.498	15.975
ARCH(2)	5.776**	6.091**	5.770*	5.771*	0.634	0.209	4.909*	6.503**	0.227
ARCH(12)	21.097**	21.787**	21.068**	21.089**	15.117	13.762	19.033*	20.722*	16.288
JB	28.579***	27.242***	28.705***	28.560***	0.355	3.099	15.373***	23.821***	0.595
Test for structural breaks: Quandt-Andrews breakpoint test									
SupF	-	-	-	32.089**	36.145**	35.680*	30.127	36.427**	49.344
ExpF	-	-	-	12.785**	14.787**	14.751**	12.040	13.860**	21.687
AveF	-	-	-	19.563**	23.962***	25.702**	19.768**	21.685**	38.141