Tapering the U.S carbon emissions during good times: Evidence from nonlinear ARDL

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Abstract In light of a slow buildup in CO_2 emissions since the recovery, this paper revisits the relationship between CO_2 emissions and the U.S economy using a nonlinear ARDL model, in which the determinants are identified through an expanded real business cycle model. We find convincing evidence that CO_2 emissions decline more rapidly during recessions than increase during expansions over the long run. Of all determinants considered, long-run asymmetry is fostered once vehicle miles travelled is controlled. This calls for a greater attention to public transportation development and vehicle miles travelled tax for slowing down stock buildup of CO_2 emissions during good times.

Keywords CO_2 emission, nonlinear autoregressive distributed lags, climate change

JEL classification Q43, C32

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1. Introduction

News about carbon dioxide emissions occupied the headlines of popular media in the second half of the year 2013 when the total energy-related CO_2 emission in 2012 hit the level of 1994, reaching a historical twenty-year low in the United States. It is not unusual for CO_2 emissions to fall during economic contraction, as a shortfall of gross domestic product instigates adverse income effect that reduces the demand for energy from households to industry. What is remarkable about U.S. CO_2 emission in the past five years is the fact that the record low level of CO_2 emission occurred at a time when the economy already started to regain momentum to find solid footing.

A natural question to ask is what events led to the sharp reduction in emissions. Three candidate explanations typically stand out: recession-driven low demand for energy, switching away from dirty coal to cleaner natural gas, and improvements in energy efficiency. Through a counterfactual exercise, *CEA Annual Report* (2013, p. 195-196) argued that 52% was due to recession, 40% because of switching to cleaner energy, and 8% came from accelerated improvements in energy efficiency. The conjecture that recession was the main culprit for CO_2 emission reduction gains further credibility when emissions have risen again from the historical low level as a result of economic rebound, as illustrated in Figure 1.

[INSERT FIGURE 1]

Procylicality, however, does not rule out asymmetry. This brings us to a less-discussed fact about the relationship between CO_2 emission and the economy over the business cycles. Table 1 makes a comparison of changes in CO_2 emission between recession and expansion periods in the U.S. over more than three decades. Although CO_2 emissions rise and fall along with business cycles, the magnitude has obviously been asymmetrically changing over the cycles. In particular, while the magnitude of increase in CO_2 emission has been about the same 3.07% to 3.94% during economic expansions from August 1980 throughout June 1981 and from July 2009 right through April 2014, respectively, the size of the decline in CO_2 emission has stepped up from approximately 1.37% to 11.37% over the recession periods preceding these expansion periods.

More striking is the observable asymmetric evolution of magnitude when we normalize changes in CO_2 emissions by the length of business cycles. In particular, whereas per cycle reduction in CO_2 emission has increased from 0.196% to 0.598%, per cycle increase in CO_2 emission has dropped from 0.279% to a trivial 0.068%. Similar diverging patterns in the magnitude of changes in CO_2 emission over the business cycles can also be obtained if the magnitude of business cycles becomes the normalizing factor.

[INSERT TABLE 1 HERE]

Against this backdrop, one can ask two questions in succession: Is the relationship between CO_2 emission and the economy asymmetric over the short and long run? If so, 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 for the first time in forty years, global energy-related CO_2 emissions in 2014 have remained unchanged from the previous year despite an expanding world economy (IEA 2015). However, almost all of the discussions on these questions were based on the anecdotal accounts of the pundits and institutions without offering scientific estimates.

This paper fills the gap by addressing all of 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 the 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 CO_2 emission and the economy during economic upturn from downturn periods over the short run and long run, giving us a dynamic coefficient that sheds light on the asymmetric output elasticity of CO_2 emissions over time.

To formulate testable hypotheses on the potential driving force of asymmetry, we lay out a simple real business cycle model, in which pollution emission is treated as input of production a la Copeland and Taylors (2004). Given the concavity of the production function, the model hypothesizes that an increasing output tends to increase emissions at a rate smaller than that of emission reduction when output is decreasing. The model also presents a nonseparable utility function for consumption and environmental degradation. While expanding consumption increasingly emits pollution, as the hypothesis goes, environmental degradation in terms of temperature anomaly will prompt risk-adverse households to take measure to reduce emissions, especially if households are intolerable to environmental degradation. Lastly, the model also hypothesizes that rising (falling) coal-natural gas ratio leads to increasing (decreasing) emissions, as coal is dirtier than natural gas.

Based on the case of the U.S. over the period ranging from 1980 to 2014 in monthly frequency, the paper makes three main empirical points. First, CO_2 emissions in the U.S. are procyclical to the economy. Second, and more important in our context, CO_2 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 a 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.

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

This brings us to the third finding. Of all popular reasons deemed to be important to account for the gradual decoupling of CO_2 emissions from output expansion in recent years, reduction in vehicle miles travelled (VMT), the proxy for polluting consumption, turns out to be most important empirically. 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 is found to be accounting for the structural breaks as seen in Figure 1 in the relationship between CO_2 emissions and the economy.

Beyond its novel results and interpretation, the paper calls for attention to the implication 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 CO_2 emissions in 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). However, 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 a 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 a co-integrated relationship between energy consumption and industrial output with a productivity-driven common cyclical relationship, we cannot identify such a co-integrating relationship between CO_2 emissions and industrial output in a symmetric model. Co-integrating relationships can be found only in a long-run asymmetric model in the case of the United States.

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 CO_2 emissions (see Fischer and Heutel 2013 for the most recent review). By bringing evidence of asymmetric procyclicality to the table, a natural consequence is the revision of optimal policy responses. Although giving a clear answer with explicit mechanism is beyond the scope of this paper, it is reasonable to infer that cyclicality of optimal policy itself would also be altered.

Lastly, our paper also relates to the sizeable literature on the relationship between CO_2 emissions and economic growth. Typically known as the environmental Kuznets curve (EKC), emissions are hypothetically 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 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 with the short-run elasticity of 0.567, suggesting that U.S. has reduced CO_2 emissions as its income has increased over time. In other words, following Narayan and Narayan’s (2010) line of argument, the EKC is there in the U.S. with VMT as the underlying mechanism. From another vantage point, though implicitly, the findings 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.

2. A toy model

In this section, we lay out a simple macroeconomic model to identify a combination of factors one has to control when carrying out empirical investigation on the interaction between CO_2 emissions and production. Following Copeland and Taylors (2004), pollution emissions function Z_t at time t can be written as

$$Z_t = (1-\theta)^{\varphi^{-1}} Y_t \tag{1}$$

where $0 < \varphi < 1$ and θ denotes abatement requirement. Y_t is production which takes a Cobb-Douglas form

$$Y_t = \mathbb{E}_t^{\alpha} N_t^{1-\alpha} \tag{2}$$

$\mathbb{E}_t$ can be generally interpreted as energy used for production in conjunction with labors hired N_t. The parameter $0 < \alpha < 1$ measures the share of energy used in production. For a firm which can resort to the dirtier coal $\mathcal{CO}_t$ and cleaner natural gas $\mathcal{G}_t$ with a constant elasticity of substitution $\rho > 1$ to generate energy, $E_t = \left(\mathcal{CO}_t^{\rho} + \mathcal{G}_t^{\rho}\right)^{1/\rho}$, the function can be rewritten as

$$\mathbb{E}_t \equiv \frac{E_t}{\mathcal{G}_t} = (1 + (\mathcal{CO}_t/\mathcal{G}_t)^{\rho})^{1/\rho} \tag{3}$$

In this way, $\mathbb{E}_t$ can also be comprehended as carbon intensity in the energy bundle. More coal used in the bundle relative to natural gas, greater the carbon intensity of the production is.

Turning to household's utility function, adapted from Acemoglu et al. (2012), we allow environmental quality directly affects utility in such a way that

$$u(C_t, T_t, N_t) = (1-\sigma)^{-1}[C_t(|T_t/\bar{T}|)^{\eta}]^{1-\sigma} - (1+\chi)^{-1}N_t^{1+\chi} \tag{4}$$

where $0 < \sigma < \infty$ is constant relative risk aversion coefficient, the reciprocal $\chi > 1$ is wage elasticity of labor supply, and $-\infty < \eta < 0$ measures household's tolerance toward environmental degradation. For illustration, we relate environmental degradation to global warming which results in rising or falling temperature T_t over the historical average. Either way, environmental degradation reduces comfortability, eroding utility. Disutility is stronger when households are more intolerant to temperature anomaly. A non-separable function implies that disutility due to abnormality in temperature would also affect consumption. The interaction cuts two ways. One uses more intensively air-conditioning facilities during warmer days and heating facilities during colder days. Increasing consumption of durable goods, e.g., purchasing more cars and driving longer mileage, which releases greenhouse gas, contributes to rising temperature over the historical average.

By setting the Lagrange multiplier λ on the flow budget constraint $W_t N_t = C_t$, where W_t is real wage, the first order conditions are

$$[C_t(T_t/\bar{T})^{\eta}]^{-\sigma}(T_t/\bar{T})^{\eta} = \lambda \tag{5}$$

$$N_t^{\chi} = \lambda W_t \tag{6}$$

$$[C_t(T_t/\bar{T})^{\eta}]^{-\sigma}(T_t/\bar{T})^{\eta-1}\eta C_t = \lambda \tag{7}$$

which give us the following optimal conditions after simple substitutions

$$N_t^{\chi} = [C_t(T_t/\bar{T})^{\eta}]^{-\sigma}(T_t/\bar{T})^{\eta} W_t \tag{8}$$

$$\eta C_t = |T_t/\bar{T}| \tag{9}$$

$$N_t = \left(\eta C_t^{1-\sigma}(|T_t/\bar{T}|)^{\eta(1-\sigma)-1} W_t N_t\right)^{1/(1+\chi)} \tag{10}$$

Eq. (8) is marginal rate of substitution between consumption and labor supply, Eq. (9) shows the relationship between consumption and environmental degradation when they are non-separable in utility function, and Eq. (10) indicates marginal rate of substitution between labor supply and environmental degradation. Putting Eqs. (1) – (3) and (10) together with income distribution of total income, $W_t N_t = Y_t$, we can get a function of pollution emissions

$$Z_t = (1-\theta)^{\varphi^{-1}}(1+(\mathcal{CO}_t/\mathcal{G}_t)^{\rho})^{\alpha/\rho}\left(\eta C_t^{1-\sigma}(|T_t/\bar{T}|)^{\eta(1-\sigma)-1}Y_t\right)^{(1-\alpha)/(1+\chi)} \qquad (11)$$

from which we can infer six testable hypotheses pertaining to the relationships between emissions and its contributors. Holding other constant,

Hypothesis 1 (*Emission-output*): Production is positively associated with pollution emissions: expanding (shrinking) production leads to rising (declining) emission.

Hypothesis 2 (*Abatement cost*): Emission falls should abatement requirement gets tighter.

Hypothesis 3 (*Coal-natural gas ratio*): Rising (falling) coal-natural gas ratio leads to increasing (decreasing) emissions, as coal is dirtier than natural gas.

Hypothesis 4 (*Environmental degradation*): When households are risk averse ($\sigma < 1$), environmental degradation in terms of temperature anomaly $|T_t \neq \bar{T}|$ will prompt households to take measure to reduce emissions, especially if households are intolerable to environmental degradation ($\eta \longrightarrow -\infty$).

Hypothesis 5 (*Consumption of transportation service*) Consumption expansion (contraction) contributes to increasing (decreasing) emissions.

Hypothesis 6 (*Nonlinearity/Asymmetry*) Given that $-\alpha < \chi$, Eq. (11) is a concave function, meaning a nonlinear relationship between emissions and production. In particular, an increasing output tends to increase emissions at a rate smaller than that of emission reduction when output is decreasing.

3. Empirical framework: Nonlinear autoregressive distributed lag approach

Drawing on the work of Shin *et al*. (2014), we empirically revisit the CO_2 emission-output relationship by addressing the possibility of asymmetric output responses of CO_2 emission over upbeat and downbeat business cycles over the short run and long run, as evidenced by observations discussed earlier and informed by Eq. (11). 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 CO_2 emission-output relationship. In addition, the model also maintains the celebrated advantage of a typical ARDL model in that, irrespective of whether the underlying variables are trend- or first-difference stationary, the nonlinear long-run level relationship between the variables can be estimated and tested by using a simple ordinary-least-square estimator.

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

$$Z_t = \beta^+ Y_t^+ + \beta^- Y_t^- + u_t, \text{ for } \Delta Y_t = \text{v}_t \tag{12}$$

where Δ is the first-difference operator, and $\beta^+ and\, \beta^-$ 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:

$$Z_t = \sum_{j=i}^{p} \phi_j Z_{t-j} + \sum_{j=0}^{q}\left(\theta_j^{+} Y_{t-j}^{+} + \theta_j^{-} Y_{t-j}^{-}\right) + \varepsilon_t \tag{13}$$

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

$$\Delta Z_t = \rho Z_{t-1} + \theta^{+} Y_{t-1}^{+} + \theta^{-} Y_{t-1}^{-} + \sum_{j=1}^{p-1} \gamma_j \Delta Z_{t-j} + \sum_{j=0}^{q-1}\left(\varphi_j^{+} \Delta Y_{t-j}^{+} + \varphi_j^{-} \Delta Y_{t-j}^{-}\right) + \varepsilon_t \tag{14}$$

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,…,p-1; $\varphi_0^{+} = \theta_0^{+}$, $\varphi_j^{+} = -\sum_{i=j+1}^{q} \theta_j^{+}$ for j=1,…, q-1, $\varphi_0^{-} = \theta_0^{-}$, $\varphi_j^{-} = -\sum_{i=j+1}^{q} \theta_j^{-}$ for j = 1,…, q-1. The long-run asymmetric parameter that corresponds to (1) can be defined as $\beta^{+} = -\theta^{+}/\rho$ and $\beta^{-} = -\theta^{-}/\rho$.

3.1. Dealing with endogeneity

Given the potential feedback of pollution emissions on output, especially in the short run, regression of Eq. (14) 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 $\Delta Y_t = \sum_{j=1}^{q-1} \Lambda_j \Delta \mathrm{Y}_{t-j} + \nu_t$ to bridge ε_t over ν_t such that

$$\varepsilon_t = \omega'\left(\Delta Y_t - \sum_{j=1}^{q-1} \Lambda_j \Delta Y_{t-j}\right) + e_t = \omega' \nu_t + e_t \tag{15}$$

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

$$\Delta Z_t = \rho Z_{t-1} + \theta^+ Y_{t-1}^+ + \theta^- Y_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta Z_{t-j} + \sum_{j=0}^{q-1} \left(\pi_j^+ \Delta Y_{t-j}^+ + \pi_j^- \Delta Y_{t-j}^-\right) + e_t \tag{16}$$

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,…, q-1. As a result, the conditional specification of Eq. (16) 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).

3.2. Developing empirical hypothesis of asymmetry

The conditional nonlinear ECM model (16) 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,…, 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 (16) over both the short run and long run;

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

$$\Delta Z_t = \rho Z_{t-1} + \theta^+ Y_{t-1}^+ + \theta^- Y_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta Z_{t-j} + \sum_{j=0}^{q-1} \pi_j \ \Delta Y_{t-j} + e_t \tag{17}$$

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

$$\Delta Z_t = \rho Z_{t-1} + \theta Y_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta Z_{t-j} + \sum_{j=0}^{q-1} \left(\pi_j^+ \Delta Y_{t-j}^+ + \pi_j^- \Delta Y_{t-j}^-\right) + e_t \tag{18}$$

(iv) A non-rejection of short-run and long-run symmetries, which strips the NARDL model down to a standard symmetrical ARDL (*p*,*q*) model, as in Pesaran and Shin (1999) and Pesaran *et al*. (2001)

$$\Delta Z_t = \rho Z_{t-1} + \theta Y_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta Z_{t-j} + \sum_{j=0}^{q-1} \pi_j \Delta Y_{t-j} + e_t \tag{19}$$

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 in Eq. (12) can be estimated as $\beta^+ = -\theta^+/\rho$ and $\beta^- = -\theta^-/\rho$, or $\beta_1 = -\theta/\rho$ if the model, which takes the form $Z_t = \alpha_0 + \beta_1 Y_t + \varepsilon_t$, is symmetric in the long run. Lastly, as in Shin *et al*. (2014), we compute recursively the asymmetric responses of Z_t to a unit change in Y_t^+ and Y_t^-, respectively, from the estimated parameters of Eq. (16) as follows

$$m_h^+ = \sum_{j=0}^{h} \frac{\partial Z_{t+j}}{\partial Y_t^+}$$

$$m_h^- = \sum_{j=0}^{h} \frac{\partial Z_{t+j}}{\partial Y_t^-}$$

$$\text{for } h = 0,1,2,\dots \tag{20}$$

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

3.3. Statistical robustness against spurious regression

When economic variables are non-stationary, stochastic processes exhibiting cointegration help avoid the problem of spurious regression. Specifications in Eq. (16) through Eq. (19) allow a pragmatic bound-test procedure to identify the existence of cointegrating relationship between a dependent variable and a set of regressors with unknown order of integrations. To detect cointegration, two statistics are deemed 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). In particular, we set up and test a null of no cointegrating relationship between levels of Z_t, Y_t^+, and Y_t^- (H_0: $\rho = \theta^+ = \theta^- = 0$) for Eqs. (16) and (17) and that of Z_t and Y_t (H_0: $\rho = \theta = 0$) for Eqs. (18) and (19) 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 (below) above the upper bound, the variables are (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.

3.4. In search of the driving forces

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

$$Z_t = \beta^+ Y_t^+ + \beta^- Y_t^- + \boldsymbol{\beta}_w' \mathbf{W}_t + u_t \tag{21}$$

where $\mathbf{W}_t$ is a g x 1 vector of additional covariates entered symmetrically, and $\boldsymbol{\beta}_w'$ is the corresponding K x 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

$$\Delta Z_t = Z_{t-1} + \theta^{+} Y^{+}_{t-1} + \theta^{-} Y^{-}_{t-1} + \boldsymbol{\theta}_w \mathbf{W}_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta Z_{t-j} + \sum_{j=0}^{q-1} \left(\pi^{+}_j \Delta Y^{+}_{t-j} + \pi^{-}_j \Delta Y^{-}_{t-j} + \boldsymbol{\pi}'_{w,j} \mathbf{W}_{t-j} \right) + e_t \tag{22}$$

Eq. (22) is thus the empirical model that corresponds to the theoretical model in Eq. (11) in the sense that decomposition of positive and negative shocks hitting production in Eq. (22) account for asymmetry in the relationship between emissions and production (Hypotheses 1 and 6), whereas the vector of additional covariates $\mathbf{W}_t$ addresses Hypotheses 2 to 5.

4. Results and discussion

4.1. Proxy and data

We use U.S. monthly data on total energy-related carbon emissions measured in million metric tons of carbon dioxide provided by the U.S. Energy Information Administration that spans from January 1980 to April 2014 to indicate carbon dioxide emissions (CO_2). Because gross domestic product measured on a monthly basis is not available, in keeping with the literature, we use the industrial production index (2007=100) (IPI) as a proxy for the economy, sourced from St Louis Fred database. The vector of additional covariates $\mathbf{W}_t$ which addresses Hypotheses 2 to 5 includes

(i) Energy Policy Act 2005 as a proxy for abatement measure,

(ii) A ratio between coal and natural gas consumption (CGAS),

(iii) Cooling degree days (CDD) and heating degree days (HDD), which, respectively, refer to outdoor temperature that exceeds (fall short of) the mean daily temperature of 65 Fahrenheit (18.3 Celsius) as proxy for environmental degradation (in terms of temperature anomaly), and

(iv) U.S. vehicle miles travelled (VMT) as a proxy for polluting consumption of transportation services.

Data on coal and natural gas consumption are sourced from the U.S. Energy Information Administration, whereas data on HDD and CDD are taken from the Annual Energy Review published by the U.S. Energy Information Agencies. VMT is sourced from the St Louis Fred database. We transform all data into natural logarithm form, which explains the letter L preceding shorthand of each proxy, and seasonally adjust the series using the Census Bureau's X-12-ARIMA procedure to account for seasonal patterns during the winter and summer months.

4.2. Stochastic properties of the time series

As a preliminary test, we conduct augmented Dickey-Fuller unit root test on the time series involved to ensure that none of the series has an order of integration of $I(2)$ (Dickey and Fuller 1979). To ensure that results of the unit root testing are not contaminated by the presence of structural breaks, we also conduct Lee and Strazizich's (2003) unit root test, which endogenously accounts for two structural breaks. The results of unit root tests reported in Table 2 suggest that the series are mostly $I(1)$ and robust to the inclusion of structural breaks. Most importantly, none of them is $I(2)$. In short, the findings of a mixture of $I(0)$ and $I(1)$ without $I(2)$ series make the NARDL approach practically relevant and useful.

[INSERT TABLE 2 HERE]

4.3. Emission-output relationships in bivariate models

We start the exercise by estimating a bivariate model of Eq. (14). We consider four different model specifications according to Eqs. (16) - Eq. (19): Model AA, which admits both long-run and short-run asymmetries; Model SA, which permits short-run asymmetry along with symmetric long run; Model AS, which accommodates long-run asymmetry but imposes symmetrical short-run dynamics, and lastly, Model SS as a simple linear ARDL model that does not allow for any asymmetric relationship. We follow the general-to-specific approach to obtain a statistically appropriate NARDL model specification. Beginning with a maximum lag of nine and using a unidirectional 5% decision rule, we eliminate all statistically insignificant regressors. The most parsimonious model that passes a battery of diagnostic checks is preferred. Table 3 summarizes the estimated results for all four models.

[INSERT TABLE 3 HERE]

Generally, the simple bivariate CO_2 emission-output NARDL models are unsatisfactory in many aspects. We cannot reject the null of no cointegration relationship in all cases using Pesaran *et al.*'s (2001) *F*-test, which is more appropriate for models with mixed orders of integration, suggesting that the regression results could suffer from spurious regression problems. Furthermore, the residuals are not normally distributed. Together with diagnostic tests that show the presence of the ARCH effects and autocorrelated residuals, we believe that important variables may have been omitted, indicating the relevance of multivariate models in our context. Lastly, inferred from the Quandt-Andrews unknown breakpoint tests (SupD, ExpF, and AveF statistics), we may ignore the presence of structural breaks in all four cases at our own perils (see Andrews, 1993; and Andrews and Ploberger, 1994).

4.4. What shape the asymmetry? Evidence from multivariate model

In search of the empirical proxy for driving forces theoretically identified in Eq. (11) which shape the dynamics between emissions and the economy, we decompose total emissions into four major emitters according to the data released by the EIA. Exhibited in Figure 2, these include commercial and residential combined (for an obvious reason, as both consume energy mainly through air-conditioners for cooling and heaters for heating, besides lighting etc.), electric power, transportation, and industry. The first two categories apparently are the main emitters. An interesting observation is how CO_2 emissions from the electric power sector track almost perfectly those emissions from commercial and residential sectors. Transportation has taken over industry as the next most important source of emissions since the 2000s.

[INSERT FIGURE 2 HERE]

Given the empirical importance of transportation as source of emitter, we specify consumption in Eq. (11) as consumption of transportation services, for which we use the U.S. VMT as a proxy in the estimation of Eq. (22). On the other hand, we use CDD and HDD as proxy for temperature anomaly. This proxy shall also be explanatory on total emissions from commercial and residential sectors, as energy demand and thus emission are greater due to heating and cooling purposes during days with anomalous temperature. Lastly, given the fact that electric power sector and industry belong to production activities, IPI serves as the indicator.

It is worth noting that CO_2 emission of activity X can actually be decomposed into energy-intensity of the activity, that is the ratio between energy demand (ED) and the activity, and its carbon intensity in terms of CO_2 emitted per energy used.

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

What VMT, HDD/CDD and IPI have captured is the energy intensity of the economic activity: more energy is needed when longer mileages are travelled, more productions are ongoing, and heating (cooling) degree-days are greater, given the carbon intensity. However, carbon 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 incorporate CGAS that serves as the proxy for coal-to-natural-gas fuel switching and hence carbon intensity, which corresponds to Eq. (3).

We start with a multivariate NARDL model of Eq. (22) in the specification that hypothesizes asymmetry in both short and long run (Model AA). Added sequentially to Model AA are a set of explanatory variables to establish the empirical Model AA1 to Model AA9.

We first take stock of the role of the Energy Policy Act (EPA) of 2005, which has often been touted as the first omnibus energy legislation that addresses the issue of energy security plaguing the U.S. for decades and advances energy efficiency through incentives, as a policy proxy for abatement. Although CO_2 emissions reduction is not intended in the EPA, it may be of interest to take a statistical glimpse of its unintended indirect impact on CO_2 emissions reduction.

To do so, we assign a policy dummy variable in three ways. First, the dummy variable in Model AA1 is a one-time off dummy, where the variable takes a value of one in August 2005 and zero otherwise. Alternatively, as for Model AA2, the dummy variable takes a value of one from August 2005 onwards and zero otherwise. Lastly, to capture the potential indirect impact on carbon intensity, we assign an interactive variable in Model AA3 that involves a dummy variable as defined in Model AA2 and the lagged logged coal-to-natural-gas consumption ratio (LCGAS(-1)).

We estimate the role of temperature anomaly in Model AA4 that incorporates HDD, Model AA5 that considers CDD, and Model AA6 that examines the impact of HDD and

CDD simultaneously. Meanwhile, the role of carbon intensity as indicated by coal-to-gas fuel switching is gauged in Model AA7. Model AA8 examines the empirical role of VMT, and lastly, Model AA9 is a full model that incorporates all driving forces at once.

Of all the results reported in Table 4, a finding consistently found across all Model AA specifications (except for a marginal case for Model AA8): we can reject the null hypothesis of long-run symmetry, although we fail to do so for the null hypothesis of short-term symmetry. The fact that growth rates in CO_2 emissions respond identically to output growth rates over business cycle horizons but asymmetric over the long run, meaning emission 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 Model AS, of which we repeat the model specifications as for Model AAs and check for diagnostic tests. The results are reported in Table 5. In terms of the sign, size, and statistical significance of the variables in Model AS and its variants are actually barely different from those exhibited in Model AAs. More important, the hypothesis of asymmetry remains intact. As Model AS9 stands out as the most robust and convincing model of all we have tested statistically, our discussion focuses mainly on Model ASs, as reported on Table 5, which leads to Model AS9 at the end.

[INSERT TABLE 5 HERE]

We can comprehend the results reported in Table 5, as well as those in Table 4, according to the hypotheses derived in Section 2.

Hypothesis 1 (*Emission-output*): Emissions is found to be procyclical to the economy over both short and long run across all variants of the model. While economic expansion contributes to increasing emission, economic contraction results in falling emission. On statistical front, of all model specifications, we find that Model AS9, reported in the last column in Table 5, which includes all identified factors, is empirically most appropriate to capture the interactions between CO_2 emissions and the economy because it does not suffer from any econometric problems. There is neither an autocorrelation nor an autoregressive conditional heteroscedasticity problem. Normally distributed residuals make our hypothesis testing reliable. Furthermore, the null of no cointegration relationship is rejected by both the t_{BDM} statistics of Barnejee *et al*. (1998) and the *F*-test of Pesaran *et al*. (2001), indicating that the regression results are not spurious.

Hypothesis 2 (*Abatement cost*): The policy coefficient, however defined, is statistically not significant.

Hypothesis 3 (*Coal-natural gas ratio*): Coal-to-gas fuel switching is clearly an important driving force in two ways. On the one hand, it is statistically significant with correct sign. On the other hand, through Quandt-Andrews unknown breakpoint tests, it is found 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 finding corroborates informal conjecture that a decline in carbon intensity due to fuel switching accounts for the observable breaks in CO_2 emissions as exhibited in Figure 1.

Hypothesis 4 (*Environmental degradation*): HDD are trivial in magnitude and statistically insignificant. Second, in contrast to the statistically insignificant HDD, temperature anomaly in terms of higher cooling degree-days is more critical not only for being statistically significant, the overall model performance also improves once CDD is accounted for in the estimation. In particular, variables become cointegrated, and there are neither autocorrelated residuals nor ARCH effects, although the null of no structural breaks remains rejected. Moreover, the negative sign is consistent with what the theory has inferred: when the outdoor day's temperature exceeds 65 degree Fahrenheit more frequently due to global warming, altruistic and risk-adverse households take measures to reduce emission, holding other factors constant.

Hypothesis 5 (*Consumption of transportation services*): Consistent with the theoretical hypothesis, increasing (decreasing) consumption on transportation services as indicated by longer vehicle miles travelled contributes to rising (falling) emissions. The magnitude is impactful (in fact, size of the coefficient is the largest among all driving forces) and statistically significant.

Hypothesis 6 (*Asymmetry*): What causes asymmetry? We capture the asymmetries of the model by taking a ratio of long-run coefficients for positive and negative output changes (β^{+}/β^{-}), and check for its for statistical significance using Wald test. A value of (approximately) one simply indicates long-run symmetry. A value that approximates zero implies long-run asymmetry with stronger emission-output nexus during recessions. In contrast, a value that drifts above one suggests long-run asymmetry with stronger emission-output nexus during expansions.

This brings us to the role of vehicle miles travelled. In Model AS8, which includes LVMT, long-run positive output elasticity of the emissions has substantially dropped from the range of 0.551 to 0.613 for all other model specifications excluding LVMT to 0.215. Although CO_2 emissions also become less elastic to a decrease in industrial output over the long run, interestingly, the extend of asymmetry is nearly halved from the range of 0.642 to 0.709 in all other model specifications to 0.362, with convincing statistical significance.

In other words, once controlling for the total vehicle miles travelled, not only can output expansion be much less polluting, but emissions also reduce at a rate approximately three times faster than that of any 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, as in Model AS9, an output expansion can be decarbonizing $\left(\sum_{j=1}^{q-1} \pi_j \quad = -0.29\right)$.

Another interesting finding that may shed light on environmental Kuznets curve (EKC) is worth noting. 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 then declines after 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. This is exactly what we have found in our long-run results.

In our bivariate Model AA, which omits the driving forces but flexibly accommodates both short and long-run asymmetry, the short-run income elasticity of emission, which equals 0.523, is approximately similar to that of the long-run value at 0.568. However, once we account for VMT as in our multivariate Model AA8, the long-run income elasticity drops substantially to 0.211 compared with the short-run elasticity of 0.567, suggesting that the U.S. has reduced CO_2 emissions as its income has increased over time. In view of this finding, we suggest that technological and infrastructural advancement, which can reduce carbon and energy intensity of VMT, constitutes the underlying mechanism of EKC. To speak differently, the failure to identify nonlinear EKC in developing countries can be attributed to the lack of infrastructural and technological advancements that help reduce miles travelled and its energy intensity even when the income level has risen.

4.5. Cumulative dynamic multiplier

The shape of the cumulative dynamic multipliers, as exhibited in Figure 3, can illustrate our statistically finest Model AS9 of long-run asymmetry with short-run symmetry. Specifically, the upper (lower) solid dashed line in Figure 3 represents the cumulative dynamics of CO_2 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 cumulative 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, the gap between the two responses starts to widen, inclining toward negative responses. Consistent with the results reported in Table 5, such evolution of dynamic multipliers starkly illustrates a case in which the magnitude of CO_2 emission reduction during bad time overwhelms CO_2 emission buildup during good time in the long run.

[INSERT FIGURE 3 HERE]

5. Conclusion with policy remarks

Factoring in potential asymmetric responses of CO_2 emissions toward the ups and downs of the economy 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 vehicle miles travelled and coal-to-natural-gas fuel switching into the limelight, this paper bestows empirical support to the role of the former in prompting favorable asymmetric output responses of CO_2 emissions in the long run, whereas the latter is responsible for the structural break observed in CO_2 emission-output relationship. The results are robust to varying model specifications and convincingly pass a battery of diagnostic checks.

Extending from the above results, this paper naturally calls for attention on the importance of strategies for reducing VMT, which has been largely absent all this while, in the design of climate policy. Policy discussions pertaining to the reduction of CO_2 emissions from the transportation sector focus almost exclusively on identifying alternative types of fuel and on increasing vehicle fuel efficiency. 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 CO_2 emissions and industrial output, the policy scope for reducing VMT can be extended, for instance, to the domain of public transportation network and VMT tax. A better developed public transportation, while directly reducing total energy consumption and improving public's acceptance toward carbon tax, underpins the favorable asymmetric responses of CO_2 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 to remain even when the economy recovers.

Our paper is a first step toward a more comprehensive empirical study in search of a larger set of explanatory factors for the relationship between CO_2 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 will 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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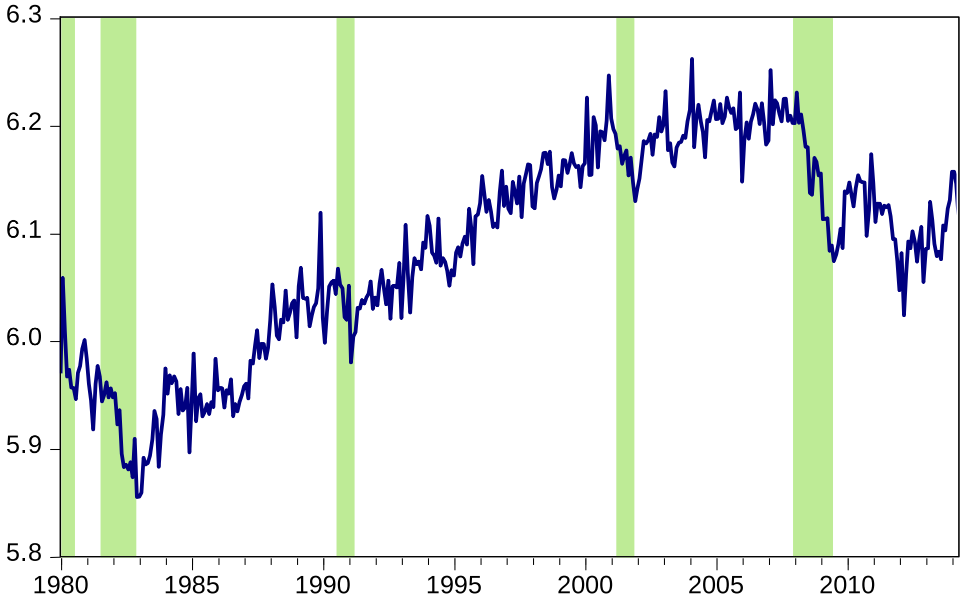
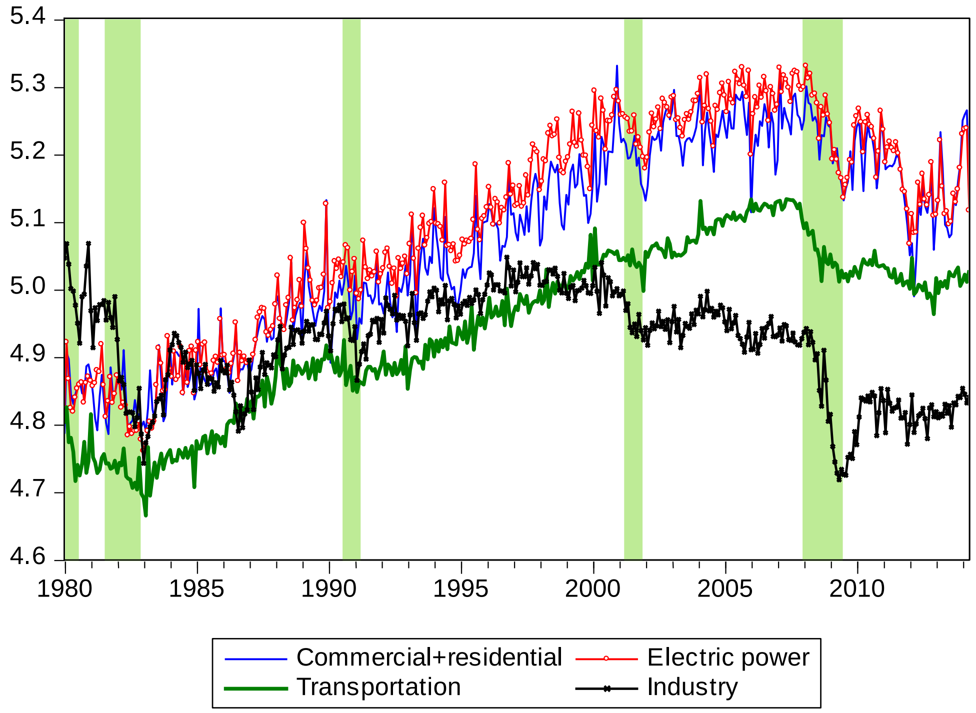


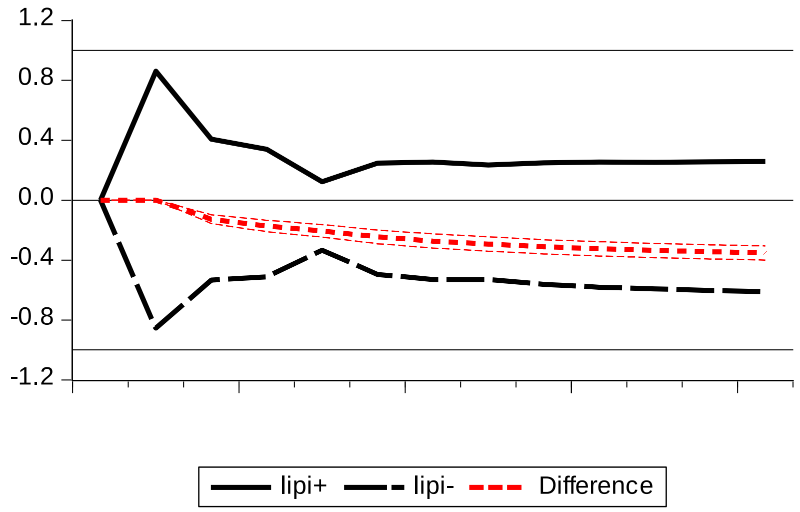
Notes: Seasonally adjusted in natural logarithms. Green shaded areas are U.S recession periods as defined by NBER Dating Committee.

Fig. 1 Total carbon dioxide emissions in the U.S, January 1980 – April 2014



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

Fig. 2 Tracking the main emitters



Notes: lipi+ and lipi-, respectively, are the cumulative dynamic multiplier of CO_2 emissions with respect to a 1% positive and negative shock hitting industrial output. The thick dashed red lines compute the difference between the positive and negative effects, whereas the light dashed red lines provide the confidence interval of two standard errors for the difference line computed by stochastic simulation. Tick marks on the horizontal axis denote monthly intervals, whereas the vertical axis is in percentage point.

Fig. 3 The long-run multiplier

Table 1 A comparison of changes in U.S carbon dioxide emissions across recession and expansion periods

Recession Periods						Expansion Periods					
				%ΔCO_2 normalized by						%ΔCO_2 normalized by	
Start	End	% ΔCO_2	% ΔIPI	% ΔIPI	Periods	Start	End	% ΔCO_2	% ΔIPI	% ΔIPI	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: Dates of business cycles are defined by NBER Business Cycle Dating Committee. %ΔCO2 and %ΔIPI, 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}
LEVEL								
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
FIRST DIFFERENCE (D)								
$DLCO_2$	-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 criterion. *** (**) * denotes significance at 1% (5%) and 10%. LIPI denotes industrial production index (2007=100), LCO_2 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 CO_2 emission-output relationships in bivariate models

Estimated Coefficients	**LR & SR Asymmetry (Model AA)**	**LR Asymmetry & SR Symmetry (Model AS)**	**LR 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} (Ho:$\beta^+ = \beta^-$)	15.617***	17.278***	-	-
W_{SR}(H_0: $\pi_j^+ = \pi_j^-$ for all j =0,…,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)]				
Sup$F$	37.478***	32.216**	33.179**	30.657*
Exp$F$	15.586***	12.833****	12.939**	10.587
Ave$F$	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 *et al.* (1998) for testing $\rho = 0$ against $\rho < 0$ whilst F_{PSS} is the F-test proposed by Pesaran *et al*. (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,…, 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. Sup$F$, Exp$F$ and Ave$F$ 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 Estimates of dynamic CO_2 emission-output relationships in multivariate models of asymmetry

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)]									
Sup*F*	-	-	-	37.347**	37.345**	36.914*	37.632*	34.761**	46.451
Exp*F*	-	-	-	15.561**	15.533**	15.492**	15.581*	13.933**	20.373
Ave*F*	-	-	-	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 $\mathbf{DUM_1}$ = 1, for the period 2005:08, 0 otherwise; $\mathbf{DUM_2}$ = 1 for the period after 2005:08, 0 otherwise; and $\mathbf{DUM_3}$ **=** is the interaction term between DUM_2 with LCGAS(-1). F_{pss} is the *F*-test proposed by Pesaran *et al.* (2001) for the joint null of $\rho = \theta^+ = \theta^- = 0$ whilst t_{BDM} is the *t*-statistic proposed by Banerjee *et al.* (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,…,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. Sup*F*, Exp*F* and Ave*F* 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

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***	0.406***
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									
Sup*F*	-	-	-	32.089**	36.145**	35.680*	30.127	36.427**	49.344
Exp*F*	-	-	-	12.785**	14.787**	14.751**	12.040	13.860**	21.687
Ave*F*	-	-	-	19.563**	23.962***	25.702**	19.768**	21.685**	38.141

Notes: As in Table 4.