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The impact of urbanization on energy intensity: Panel data evidence considering cross-sectional dependence and heterogeneity

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ABSTRACT

As population grows considerably in the world, the correlation between intensity of population in urban areas and energy intensity becomes an important issue in energy field. This paper aims at examining the effects of urbanization on energy intensity for 10 Asian countries by employing annual data from 1990 to 2014. The Asian countries are Bangladesh, China, India, Indonesia, Malaysia, Nepal, Philippines, South Korea, Thailand and Vietnam, respectively. To this end, the paper, first, follows cross-sectional dependence and heterogeneity tests. Then, the paper conducts unit root and cointegration tests, cointegration analyses and causality analyses. Finally, the paper estimates the short run parameters as well as long-run parameters to capture the possible dynamic relationships among variables.

This paper, thus, employs energy intensity as dependent variable and GDP per capita, the square of GDP per capita, urbanization, and ruralization as regressors within the relevant models and explores that there exists a long-run relationship of energy intensity with GDP per capita, the square of GDP per capita, urbanization, and ruralization in panel data.

The paper, later, observes additional explanatory variables of export, renewable energy consumption and nonrenewable energy consumption, and, concludes that (i) the urbanization variable has significant influences on energy intensity in the short-run and long-run, (ii) despite the some differences in cross-sectional estimations, the Asian panel data, overall, yield negative impact of urbanization on energy intensity. The latter output indicates that the urbanization path increases the energy productivity in Asian panel models. Within this scope, the paper presents some policy proposals related to the reduction of energy intensity in Asia.

1. Introduction

Urbanization is an important indicator of development together with industrialization and modernization [1–6]. The share of cities in GDP increases year by year, and the World Bank [7] points out that the share of cities in GDP is 80% in the world. This output shows the importance of urbanization clearly. Economists evaluate the increase in the share of cities in GDP as a success for the path of wealth and welfare and are pleased with this increase [8], since the urbanization is occurred along with the social and economic transformations that correspond to development in growing economies. A transition process begins from the agricultural-based economy to the industry and service-based economy and, hence, the labour force in rural areas is transferred to urban areas [8,9]. As a result of this transformation, people in rural areas migrate to urban areas and the population of cities increases [3]. As an important indicator of this transformation, the population in urban areas increased from 1.52 billion to 3.29 billion between 1957 and 2007 [10]. This development process denominated as urbanization leading to major changes in the use of natural resources and energy [11]. The increase in economic activities in urban areas especially brings about great increases in energy demand [12]. IEA [13] remarks that 67% of world energy consumption was city-based in 2006 and this figure will reach 69% in 2015. This enormous energy consumption in urban areas induces three main concerns on a

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global scale.

The first concern is about sustainability of energy sources. Accordingly, a large part of the world energy consumption is provided by fossil energy sources, such as oil, coal, and natural gas, and these non-renewable energy sources are likely to drain away in near future. Chapman [14] denotes that, according to the Peak Oil Theory, oil production through conventional methods has reached the maximum level and almost the half of world oil reserves is consumed. This case is considered an important issue for oil [14]. There exist some evidences supporting this theory. For example, the oil explorations decreased beginning from the mid-1950s and it is expected that the oil production in 2050 will be 70% as much as the maximum production level [15]. In a similar way, Dincer [16] remarks that coal and natural gas will drain away in the future. When one considers the shares of urban areas in world energy demand, it is clear that urban areas have an important role about the arising concern.

The second concern is about energy security and energy dependency, namely the risk about providing energy demand of urban areas. Within this scope, energy security is defined as a safe and elastic energy system that provides required energy for life, economic and social activities, and defense at reasonable prices [17]. In short, energy security is associated with the issues based on energy supply disruption and price shocks [18–20]. This concern arises because of the unbalanced distribution of energy sources across countries and causes dependence of foreign energy for some countries. Therefore, providing energy security is especially important for countries that import energy [21]. Energy security takes part at the top of political agendas of many countries on a national and international basis [22,23].

The third concern is about global warming and thus climate change. For instance, over the period 2000–2010, average land surface temperature is higher than previous periods' averages and it is forecasted that global temperature will increase by 4–6° Celsius if this trend [24]. The rise in greenhouse gas emissions, particularly in CO_2, induces global warming [25,26]. According to IEA [27], CO_2 intensity in the atmosphere has grown by 40% since the industrial revolution. The increasing fossil fuel consumption, such as oil, coal, and natural gas, led to such a rapid increase [28,29]. Therefore, urban areas and urban energy consumption have a critical role about increment in global warming and climate change. Hence urban areas induce many local and global environmental problems [30]. Within this scope, Wang et al. [31] point out that many environmental problems stem from the relationships among urbanization, energy consumption, and CO_2 emissions. Some recent papers yield that there is a relationship between the urbanization process and CO_2 emissions [32–36].

Overall, one may claim that the concerns given above refer to an augmentation in energy demand of urban areas. Therefore, some sustainable policies are required to minimize the effects of potential problems that might occur through urbanization process.

What is the motivation of this paper? It can be argued that, in general, as other things are given, the relevant successful policies are expected to decrease energy intensity (the ratio of energy consumption divided by GDP). From this point of view, a question becomes meaningful: "Does the urbanization process affect energy intensity? Or one might ask if urbanization process can influence the energy productivity (defined as the ratio of output divided by energy consumption)?" The purpose of this paper, then, is to reveal an answer to either 1st or later question above. Within the scope of this purpose, the paper examines the relationship between urbanization and energy intensity using environmental Kuznets curve (EKC) model for 10 Asian countries over the period 1990–2012 by employing the augmented mean group (AMG) estimator developed by Eberhardt and Bond [37].

How our paper contributes to the literature on urbanization and energy economics lies in following four points:

i) Sadorsky [38] remarks that the work of Jones [39,40] is the first paper investigating the relationship between urbanization and energy intensity. This work, however, provides potential reader/researcher with limited information and empirical evidence about how urbanization affects energy intensity. Our paper aims at revealing more efficient empirical evidence through a consistent estimation methodology and through a well-defined function.
ii) The related available literature mainly focuses on relationship between energy consumption and urbanization (see e.g., [6], [40–43]). Our paper, unlike other papers, specifically considers the nexus between energy intensity and urbanization. Energy intensity is an important indicator of energy productivity as Liu and Xie [44] point out. Proskuryakova and Kovalev [45] yield as well that energy intensity and energy efficiency are equivalent measures about energy performances of countries.
iii) In the energy economics literature, most of the papers, which conduct panel data analysis, assume that the countries are homogeneous and there is no cross-sectional dependence among countries. Therefore, the findings of these papers are valid for whole panel data of all countries in general. Our paper, on the other hand, considers the possibility that the individual countries might be heterogeneous.

The heterogeneity among panel countries is an important issue in panel estimation. Hence, the relevant group might follow heterogeneity and there might exist cross-sectional dependence among countries. Therefore, some recent papers criticize homogenous panel data analyses and the assumption of cross-sectional independence [46]. Thus our paper employs the AMG estimator proposed by Eberhardt and Bond [37] considering cross-sectional dependence and heterogeneity.

iv) Besides the AMG estimator, the paper employs the dynamic analyses through cointegration and causality models to obtain more reliable output. The relevant tests are to examine the significant relationships (if exist) among variables for both short-term and long-term considering the serial correlation, heterogeneity or cross-sectional dependence.
v) To the best of our knowledge, our paper is the first paper searching urbanization-energy intensity nexus for Asian countries.

This paper considers specifically the Asian data set since (a) currently, the annual urbanization rate is 1.5% in Asia and (b) the Asian countries have the highest annual rates of urbanization, and 53% of the world urban population lives in Asia [47]. Besides, with regard to 2010 data, 31% of total world energy consumption is executed by Asian countries, energy demand of Asian countries increase more quickly than that of other continents over 1990–2010 [48]. As a result of this major energy consumption, with reference to 2012 data, Asia is responsible for about 38% of energy-based CO_2 emissions, and CO_2 emissions of China, India, Japan, and South Kore are especially prominently high [27]. (c) In the last 20 years, while there is a sharp increase in urbanization, energy intensity has a tendency to decrease in the Asian countries with regard to the World Bank data.

A research to detect whether urbanization and energy intensity are correlated and/or whether the increase in urbanization has a role in the decrease in energy intensity may provide researchers and policy makers some important policy implications.

Eventually, following the motivations through (i) to (iv), the empirical findings of this paper reveal that there exists bidirectional causality between urbanization and energy intensity. Upon this output, in conclusion, this paper suggests that policy makers follow some policy implications of this work to struggle with global warming and climate change.

The rest of the paper is organized as follows: Section 2 presents the theoretical framework. The related empirical literature is given in Section 3. Section 4 reveals model and data. Econometric methodology is presented in Section 5. Estimation results are reported in Section 6. Finally, Section 7 provides potential researcher with a summary of the main findings and some policy proposals.

2. Theoretical framework

Urbanization is characterized as a development and modernization process which includes social, economic, ecologic, and demographic transformations. As Poumanyvong et al. [49] remark, these transformations increase the population and economic activities in urban areas, enlarge residential areas, and change land usage and land cover. Also, relevant transformations affect human behaviors and change consumption patterns [49] and influence energy use through different channels [39–41,50]. Regarded channels might be classified under four groups.

The first channel is that urbanization affects energy consumption by promoting production in urban areas [51]. As a result of increases in economic activities, new technologies and industries show up and production structure is changed in urban areas. The change in production structure induces migration from rural areas to urban areas and labor force in rural areas is transmitted to industry and services in urban areas [50]. In conclusion, a transition process occurs from the agricultural sector in which energy intensity is low to industrial sector in which energy intensity is high [38].

The second channel explores inner city mobility and transportation. Increasing economic activities in urban areas enhance passenger mobility and raise inner city transportation [49,50]. Urbanization increases demand for individual motorized transportation and the level of inner city private transportation [52]. Therefore, traffic and the number of motor vehicles increase in urban areas. Besides, raw materials are transported from rural areas to urban areas to supply the increasing raw material demand of urban areas [38,51]. As a result, these developments affect energy demand. As more than half of oil is used in the transportation sector on a global scale in 2005, one may state clearly that the demand for energy of the transportation sector is considerably high [49].

The third channel is associated with infrastructure expenditures required by the urbanization process as infrastructure expenditures require energy [50]. Urban areas require road networks, sewages, cleaning and drainage systems, communication networks, office buildings, and electrical grids [40]. Additionally, inner city clusters and increases in multi-storey buildings arise in urban areas because of land shortages [41]. For these reasons, urbanization increases infrastructure demand and construction activities [38]. As Costa et al. [53] and Hong et al. [54] denote, construction activities account for 40% of global energy demand. Since construction activities require cement and steel [40], demand for cement and steel, which have high energy intensity, increase [38]. On the other hand, shadow activities in the construction sector enhance along with urbanization, and energy is usually utilized inefficiently in illegal houses [51]. For these reasons, construction activities and infrastructure expenditures make upward pressure on energy intensity.

The fourth channel exhibits the effects of urbanization on consumer behaviors. Urbanization affects consumer needs and life styles of households [51]. Urbanization and economic development make people who live in urban areas wealthier and thus consumption structures of people change by including more energy-intensive products [38]. For example, along with urbanization, demand for refrigerators, microwave ovens, air conditioners, and private cars, which require more energy, increase [39,55]. Besides, urban households are more subject to commercial products and services compared with rural households [50]. Generally, commercial production in urban areas requires more energy than that in rural areas [39].

Based on explanations above, as a result of urbanization, one can argue that changes in consumers' needs and behaviors have potential impact on urban energy demand directly.

3. Literature review

Since the seminal paper of Kraft and Kraft [56], the relationship between energy and economic growth has become an essential research interest [57], and the energy economics literature has expanded through enormous and useful modelling studies [11]. However, there exists still limited evidence about the effects of urbanization, which is an important factor of economic development, on energy consumption though there has been an increase in papers investigating urbanization-energy consumption nexus lately. One observes from the literature of urbanization-energy consumption nexus that the first systematic paper of Jones [39,40] conducts cross-sectional analysis and examines the effects of urbanization, income, the share of industry in GDP, and population intensity on energy consumption and energy intensity for 59 developing countries in 1980. According to the findings, urbanization, income, the share of industry in GDP, and population intensity have significant and positive effects on energy consumption and energy intensity. Parikh and Shukla [41] investigate the effects of urbanization on energy consumption for 78 developed and developing countries over the period 1965–1987 by employing panel data analysis and yield that urbanization has positive effects on energy consumption. In addition to these papers, some others confirm the positive relationship between urbanization and energy consumption [12,31,49,58–63]. On the contrary, some papers find that energy demand is negatively related to urbanization [64–67]. On the other hand, in literature, some papers employing a panel data obtain mixed results. For instance, Poumanyvong and Kaneko [10], who use a panel data set covering the period 1975–2010 for 99 countries, yield that urbanization decreases energy demand in low-income economies while urbanization increases energy demand in middle-income and high-income countries. Al-Mulali et al. [35] search a panel data model for the period 1980–2008 and obtain that urbanization negatively affects energy demand in some countries while urbanization has positive effects on energy demand in some countries. Finally, some papers use causality analysis to investigate urbanization-energy demand nexus. Al-Mulali et al. [62], Wang et al. [31] and Solarin and Shahbaz [68] find bidirectional causality between urbanization and energy demand and confirm the feedback hypothesis. Liu [43], Mishra et al. [61], and Shahbaz et al. [63] yield that there is a unidirectional causality from urbanization to energy consumption in both short and long runs. Additionally, Salim and Shafiei [11] and Ghosh and Kanjilal [6] do not reach a causal relationship between urbanization and energy consumption and thus confirm the neutrality hypothesis.

One observes, as well, from the literature that papers in general mainly focus on the relationship between urbanization and energy consumption. In fact, as explained in Section 2, energy demand is expected to increase as long as urban areas expand. Therefore, one may argue that whether or not energy is used more productively in growing urban areas is more important. Only a few papers consider the relationship between urbanization and energy intensity. For instance, the pioneer paper of Sadorsky [38] examines the relationship between urbanization and energy intensity for 76 developing countries over 1980–2010 and yields mixed results about the relationship. Liu and Xie [44], examining the relationship between urbanization and energy intensity in China for the period 1978–2010, find that there is a bidirectional nonlinear causal relationship between variables. Another paper, Elliott et al. [51], investigating the relationship between urbanization and energy intensity obtain mixed results about the relationship between urbanization and energy intensity. Ma [55] studies the effects of urbanization on energy intensity, coal intensity, and electricity intensity in China. According to the empirical findings, while urbanization does not have any effect on coal intensity, it has positive effects on energy intensity and electricity intensity. We may summarize the evidence-based literature of urbanization and energy consumption/energy intensity nexus in Table 1.

4. Model and data

This paper employs an environmental Kuznets curve (EKC) model to investigate the effects of urbanization on energy intensity in Asian countries. Within this scope, the relevant initial function is defined as below:

$$EI = f\,(Y, Y^2, URB, RUR) \tag{1}$$

where EI, Y, Y^2, URB, RUR refer to energy intensity, GDP per capita, the square of GDP per capita, urbanization, and ruralization, respectively. Ruralization is the control variable in this function. All variables are used in natural logarithmic forms as is denoted in Equation (2). Hence the problems regarding the dynamic features of the data set are eliminated and more consistent empirical results are obtained [46]. Based on these explanations, the model used in the paper is specified as below:

$$lnEI_{it} = \beta_{0i} + \beta_{1i}lnY_{it} + \beta_{2i}(lnY)^2_{it} + \beta_{3i}lnURB_{it} + \beta_{4i}lnRUR_{it} + \varepsilon_{it} \tag{2.1}$$

where EI is the ratio of primary energy supply divided by GDP measured at 2011 purchasing power parity, Y is GDP per capita (constant 2005 prices in USD), Y^2 is the square of GDP per capita, URB refers to people living in urban areas and RUR refers to people living in rural areas. The data set used in this paper includes 10 Asian countries (Bangladesh, China, India, Indonesia, Malaysia, Nepal, Philippines, South Korea, Thailand and Vietnam). The annual data cover the period 1990–2014 and are extracted from Ref. [69].

According to the EKC hypothesis, energy intensity increases in the first stages of economic growth because of the usage of more energy (scale effect). Then, a structural transformation begins in the economy along with continuing growth (structural effect) and energy intensity decreases due to the development of clean Technologies (technological effect). Therefore, if $\beta_1 > 0$ and $\beta_2 < 0$, the EKC hypothesis prevails between energy intensity and income and thus economic growth stimulates energy productivity by reducing energy intensity.

The effects of urbanization and ruralization on energy intensity are determined by β_3 and β_4, respectively. Accordingly, statistically significant and positive β_3 indicates that urbanization increases energy intensity while statistically significant and negative β_3 indicates that urbanization decreases energy intensity. Besides, statistically significant and positive β_4 indicates that ruralization increases energy intensity while statistically significant and negative β_4 indicates that ruralization decreases energy intensity.

Beyond the tests of EKC hypothesis, one might need also to observe the effects of other potential variables on energy intensity. Therefore, later, this paper employs as well the additional explanatory/control variables into the model, and, thusly, the regarding model becomes as follows.

$$lnEI_{it} = \alpha_{0i} + \alpha_{1i}lnY_{it} + \alpha_{2i}lnURB_{it} + \alpha_{3i}lnRUR_{it} + \alpha_{4i}lnEXP_{it} + \alpha_{5i}lnREN_{it} + \alpha_{6i}lnNONREN_{it} + \varepsilon_{it} \tag{2.2}$$

where lnEXP, LnREN and LnNONREN denote the natural logarithms of export, renewable energy consumption and nonrenewable energy consumption, respectively.

5. Estimation methodology

When one examines the relationships in a panel data model, he/she must consider the possibility of two important issues. The first issue is cross-sectional dependence which means a shock that affects one country may also affect other countries in the panel data model through high degree of globalization and possible cooperation among countries. The Monte Carlo experiments performed by Pesaran [70] exhibit the substantial bias and size distortions if cross-sectional dependence is ignored. The second concern is slope heterogeneity. The slope coefficients may not be homogeneous across the sample of countries as countries differ in their development stages and technology levels [71]. Granger [72] remarks the null hypothesis that some variable causes another variable for all units in the panel is very strong. Besides, the homogeneity assumption can mask country-specific characteristics [73].

Based on the discussions above, testing for cross-sectional dependence and slope homogeneity is an important step in a panel data model. We therefore start by examining whether there are cross-sectional dependence and heterogeneity across the countries.

5.1. Preliminary analysis: cross-sectional dependence and homogeneity tests

To test for cross-sectional dependence, Breusch and Pagan [74] propose the Lagrange multiplier (LM) test statistic. To compute the LM test, the following panel data model in Equation (3) is estimated:

$$y_{it} = \alpha_i + \beta_i x_{it} + \varepsilon_{it} \quad \text{for } i = 1, 2, \ldots, N; \ t = 1, 2, \ldots, T \tag{3}$$

where i is the cross section dimension, t is the time dimension, x_{it} is kx1 vector of explanatory variables, α_i and β_i are respectively the intercepts and slope coefficients. The LM test is calculated as follows:

$$LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{\rho}_{ij}^2 \sim \chi^2_{N(N-1)/2} \tag{4}$$

where $\widehat{\rho}_{ij}$ is the sample estimate of pairwise correlation of the residuals obtained from individual ordinary least squares (OLS) estimation of Equation (3). The null hypothesis of no cross-sectional dependence ($H_0: Cov(\varepsilon_{it}\varepsilon_{jt}) = 0$ *for all* $t,\ i \neq j$) is tested against the alternative hypothesis of ($H_1: Cov(\varepsilon_{it}\varepsilon_{jt}) \neq 0$ *for at least one pair of* $i \neq j$).

Pesaran [75] states that this test is not applicable when N is large. For large panels where $T \to \infty$ first and then $N \to \infty$, Pesaran [75] proposes the scaled version of the LM test as given in Equation (5):

Table 1
Literature on the relationship between urbanization and energy consumption/energy intensity.

Paper	Period	Country	Methodology	Results
Jones [39,40]	1980	59 developing countries	Cross-sectional analysis	positive
Parikh and Shukla [41]	1965–1987	78 countries	Pooled OLS, Fixed effects (FE)	positive
Imai [58]	1980–1993	9 countries	Weighted OLS	positive
Lariviere and Lafrance [64]	1999	Canada	Cross-sectional analysis	negative
Holtedahl and Joutz [59]	1956–1995	Taiwan	VAR, Cointegration	positive
Liddle [65]	1960–2000	23 OECD countries	OLS	negative
York [60]	1960–2000	14 European Union countries	Prais-Winsten (PW) regression model	positive
Ewing and Rong [66]	1940–2000	The United States	OLS	negative
Mishra et al. [61]	1980–2005	9 Pacific Island countries	Panel cointegration and causality	positive U→EC (LR) U→EC (SR)
Liu [43]	1978–2008	China	Cointegration and causality	U→EC (LR) U→EC (SR)
Poumanyvong and Kaneko [10]	1975–2005	99 countries	OLS, FE, PW regression model	Negative (low income countries) positive (middle and high income)
Shahbaz and Lean [12]	1971–2008	Tunisia	Cointegration and causality	positive U→EC (LR) EC→U (SR)
Poumanyvong et al. [49]	1975–2005	92 countries	FE, Generalized method of moments (GMM)	positive
Al-Mulali et al. [35]	1980–2008	9 region (multi-country model)	Fully modified ordinary least squares (FMOLS)	positive (84% of the countries)
Al-Mulali et al. [62]	1980–2009	MENA countries	Panel cointegration and causality	positive U↔EC (LR) U→EC (SR)
Solarin and Shahbaz [68]	1971–2009	Angola	Cointegration and causality	U↔EC (LR) U↔EC (SR)
Wang et al. [31]	1995–2011	China (province-level)	Panel cointegration, Dynamic OLS, causality	positive U→EC (SR) U↔EC (LR)
Salim and Shafiei [11]	1980–2011	29 OECD countries	Panel cointegration and causality, GMM	no relationship
Shahbaz et al. [63]	1970–2011	Malaysia	ARDL and causality	positive U→EC (LR)
Sadorsky [67]	1971–2008	18 emerging countries	Panel ARDL	negative
Ghosh and Kanjilal [6]	1971–2008	India	Cointegration and causality	no relationship
Sadorsky [38]	1980–2010	76 countries	Pooled OLS, FE, Mean group (MG)	Mixed results
Liu ve Xie [44]	1978–2010	China	Non-linear cointegrating and causality	U↔EI
Elliott et al. [51]	1997–2010	China (province-level)	FE, MG, AMG	Mixed results
Ma [55]	1986–2011	China (province-level)	Correlated effects mean group (CCEMG) and AMG	positive (energy and electricity intensity) No relationships (coal intensity)

Notes:
1- U, EC, and EI indicate urbanization, energy consumption, and energy intensity, respectively.
2- Arrows show the existence of a causal relationship and its direction (U→EC: causal relationship from U to EC; EC→U: causal relationship from EC to U; U↔EC: bidirectional causal relationship between variables).
3- LR and SR depict long run and short run respectively.
4- Positive (negative) result indicates that as urbanization intensifies, the energy consumption/energy intensity will increase (decrease).

$$CD_{lm} = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T\hat{\rho}_{ij}^2 - 1 \right) \sim N(0,1) \qquad (5)$$

where CD depicts the statistic to be tested under the null hypothesis of no cross-sectional dependence. CD test may present substantial size distortions when N is large and T is small. Pesaran [75] develops a test for panels where T → ∞ and N → ∞ in any order. This test is based on pairwise correlation coefficients rather than their squares used in the LM test as given in Equation (6):

$$CD = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \sim N(0,1) \qquad (6)$$

Pesaran et al. [76] denote that the CD test will lack power in certain situations where the population average pair-wise correlations are non-zero. Therefore, for large panels where T → ∞ first and then N → ∞, Pesaran et al. [76] suggest a bias adjusted version of the LM test that uses the exact mean and variance of the LM statistic. Equation (7) reveals the bias-adjusted LM test:

$$LM_{adj} = \sqrt{\left(\frac{2}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{\upsilon_{Tij}^2}} \sim N(0,1) \qquad (7)$$

where k is the number of regressors, μ_{Tij} and υ_{Tij}^2 are respectively the exact mean and variance of $(T-k)\hat{\rho}_{ij}^2$.

To test for slope homogeneity, Pesaran and Yamagata [77] follow delta ($\tilde{\Delta}$) tests. The null hypothesis of slope homogeneity (H_0: $\beta_i = \beta$ for all i) is tested against the alternative hypothesis of slope heterogeneity (H_1: $\beta_i \neq \beta$ for a non-zero fraction of pair-wise slopes for $i \neq j$). When the error terms are normally distributed, the $\tilde{\Delta}$ tests are valid as (N, T) → ∞ without any restrictions on the relative expansion rates of N and T. To produce $\tilde{\Delta}$ tests, firstly, the following modified version of Swamy [78] test is calculated:

$$\tilde{S} = \sum_{i=1}^{N} \left(\hat{\beta}_i - \tilde{\beta}_{WFE} \right)' \frac{X_i' M_\tau X_i}{\tilde{\sigma}_i^2} \left(\hat{\beta}_i - \tilde{\beta}_{WFE} \right) \qquad (8)$$

where

$$\tilde{\sigma}_i^2 = \frac{\left(y_i - X_i\widehat{\beta}_i\right)' M_\tau \left(y_i - X_i\widehat{\beta}_i\right)}{(T-k-1)} \tag{9}$$

and where M_τ is an identity matrix of order T and $\widehat{\beta}_{WFE}$ is the weighted fixed effect pooled estimator defined as

$$\tilde{\beta}_{WFE} = \left(\sum_{i=1}^{N} \frac{X_i' M_\tau X_i}{\tilde{\sigma}_i^2}\right)^{-1} \sum_{i=1}^{N} \frac{X_i' M_\tau y_i}{\tilde{\sigma}_i^2} \tag{10}$$

Under the null hypothesis with the condition that the error terms are normally distributed, (N, T) → ∞, and so long as $\sqrt{N}/T \to 0$, the standard dispersion statistic is defined as follows:

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \tag{11}$$

The small sample properties of the $\tilde{\Delta}$ test can be improved under the normally distributed errors by using the following mean and variance bias adjusted version of $\tilde{\Delta}$ as is in Equation (12).

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{iT})}{\sqrt{Var(\tilde{z}_{iT})}}\right) \tag{12}$$

where

$$E(\tilde{z}_{iT}) = k, \quad Var(\tilde{z}_{iT}) = \frac{2k(T-k-1)}{T+1} \tag{13}$$

5.2. CADF unit root test

Pesaran [79] produces a panel unit root test allowing cross-section dependence and heterogeneity. He extends the standard Dickey Fuller (DF) (or augmented Dickey Fuller (ADF)) regressions with the cross-section averages of the lagged levels and first differences of the individual series rather than basing the unit root tests on deviations from the estimated factors. Thus new asymptotic results are obtained both for the individual cross-sectionally augmented ADF (hereafter CADF) statistics and for their simple averages. The small sample properties of the tests are explored through Monte-Carlo experiments, and the simulations indicate that CADF panel unit root tests have satisfying size and power even though N and T are relatively small.

When y_{it} is the observation on the i_{th} cross-section unit at time t and is generated with regard to the simple dynamic linear heterogeneous panel data model, CADF test statistic is defined as follows:

$$y_{it} = (1-\Phi_i)\mu_i + \Phi_i y_{i,t-1} + u_{it}, \quad i = 1,\dots,N; \; t = 1,\dots T, \tag{14}$$

where initial value, y_{i0}, has a given density function with a finite and mean variance. The error term, u_{it}, has the single-factor structure

$$u_{it} = \gamma_i f_t + \varepsilon_{it} \tag{15}$$

where f_{it} is the observed common effect, and ε_{it} is the individual-specific error.

Pesaran [79] denotes that it is available to writer Equation (14) and Equation (15) as below:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i f_t + \varepsilon_{it} \tag{16}$$

where $\alpha_i = (1-\Phi_i)\mu_i$, $\beta_i = -(1-\Phi_i)$ and $\Delta y_{it} = y_{it} - y_{i,t-1}$. The null hypothesis of a unit root, Φ_i, is expressed as follows:

$$H_0\colon \beta_i = 0 \text{ for all i} \tag{17}$$

The alternative hypothesis is as

$$H_1\colon \beta_i < 0,\ i = 1,2,\dots,N_1,\ \beta_i = 0,\ i = N_1+1, N_1+2,\dots,N \tag{18}$$

Pesaran [79] builds on our test of the unit root hypothesis, Equation (17), on the t-ratio of the ordinary least squares (OLS) estimate of b_i $(\widehat{b}_i)$ in the following CADF regression:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta\bar{y}_t + e_{it} \tag{19}$$

This t-ratio, t_i(N, T), is computed as below:

$$t_i(N,\,T) = \frac{\Delta y_i' \overline{M}_w y_{i,-1}}{\widehat{\sigma}_i\left(y_{i,-1}' \overline{M}_w y_{i,-1}\right)^{1/2}} \tag{20}$$

Pesaran [79] also calculates cross-sectionally augmented IPS (CIPS) statistic through the average of individual CADF test statistics for the whole panel. CIPS statistic is as follows:

$$CIPS(N,\,T) = t - bar = N^{-1}\sum_{i=1}^{N} t_i(N,\,T) \tag{21}$$

where t_i(N, T) is the CADF statistic for the ith cross—section unit (see Pesaran [79] for further information about notations).

5.3. Westerlund [80] cointegration test

Westerlund [80] considers the following data generating process:

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it} \tag{22}$$

$$x_{it} = \delta_i x_{i,t-1} + \varepsilon_{it} \tag{23}$$

If $\delta_i = 1$, the variable x is not stationary and if $\delta_i < 1$, the variable is stationary. The disturbance term u_{it} conforms the following set of equations allowing for cross-sectional dependence:

$$u_{it} = \lambda_i' F_t + e_{it} \tag{24}$$

$$F_{jt} = \rho_j F_{jt-1} + w_{jt} \tag{25}$$

$$e_{it} = \varphi_i e_{it-1} + \upsilon_{it} \tag{26}$$

where F_t represents a k-dimensional vector of common factors F_{jt} with j = 1, …,k, and λ_i is a conformable vector of factor loadings. By considering $\rho_j < 1$ for all j, we assure that F_t is stationary. While the null hypothesis is $H_0\colon \varphi_i = 1$ for all i, the alternatives are $H_1^p\colon \varphi_i = \phi$ and $\phi < 1$ for all i and $H_1^g\colon \varphi_i < 1$ for at least some i.

Westerlund [80] suggests estimating the differenced model defined in Equation (27):

$$\Delta u_{it} = \lambda_i' \Delta F_t + \Delta e_{it} \tag{27}$$

by utilizing the OLS residuals $\{\widehat{u}_{it}\}$ and employing the principal components method. Westerlund [80] estimates $\{e_{it}\}$ as

$\widehat{e}_{it} = \sum_{j=2}^{t} \Delta\widehat{e}_{it}$. Then, he applies Choi's [81] Durbin-Hausman test to $\{\widehat{e}_{it}\}$. Let the OLS estimator of φ_i from each time series be $\widehat{\varphi}_i$ and the corresponding instrumental variable estimator be $\tilde{\varphi}_i$. The pooled counterparts are described as $\widehat{\varphi}$ and $\tilde{\varphi}$. The Durbin-Hausman test statistics can be obtained as follows:

$$DH_g = \sum_{i=1}^{N} \widehat{S}_i \left(\tilde{\varphi}_i - \widehat{\varphi}_i\right)^2 \sum_{t=2}^{T} \widehat{e}_{it-1}^2 \tag{28}$$

$$DH_p = \widehat{S}_N \left(\tilde{\varphi} - \widehat{\varphi}\right)^2 \sum_{i=1}^{N} \sum_{t=2}^{T} \widehat{e}_{it-1}^2 \tag{29}$$

where $\widehat{S}_i = \widehat{\omega}_i^2 / \widehat{\sigma}_i^4$, $\widehat{S}_N = \widehat{\omega}_N^2 / \widehat{\sigma}_N^4$, and $\widehat{\omega}_i^2$ and $\widehat{\sigma}_i^2$ are the short and long-run variance estimators, respectively using the OLS residuals from regressing $\{\widehat{e}_{it}\}$ on $\{\widehat{e}_{it-1}\}$, $\widehat{\omega}_N^2 = \frac{1}{N}\sum_{i=1}^{N} \widehat{\omega}_i^2$, and $\widehat{\sigma}_N^2 = \frac{1}{N}\sum_{i=1}^{N} \widehat{\sigma}_i^2$. The test statistic DH_g is used for the alternative hypothesis of H_1^g and DH_p is used for H_1^p.

5.4. Augmented mean group estimator

Eberhardt and Bond [37] adopts the following empirical model for i = 1, …,N and t = 1, …T:

$$y_{it} = \beta_i' x_{it} + u_{it} \quad u_{it} = a_i + \lambda_i' f_t + \varepsilon_{it} \tag{30}$$

$$x_{mit} = \pi_{mi} + \delta_{mi}' g_{mt} + \rho_{1mi} f_{1mt} + \ldots + \rho_{nmi} f_{nmt} + v_{mit} \tag{31}$$

where m = 1, …,k and $f_{.mt} \subset f_t$

$$f_t = \varphi' f_{t-1} + \varepsilon_t \text{ and } g_t = \omega' g_{t-1} + \varepsilon_t \tag{32}$$

where x_{it} represents a vector of observable covariates, f_t and g_t are unobserved common factors, and λ_i denotes country-specific factor loadings.

Eberhardt and Bond [37] introduce the AMG estimator which accounts for cross-sectional dependence by inclusion of a ‘common dynamic effect’ in the country regression. This variable is extracted from the time dummy coefficients of a pooled regression in first differences and stands for the levels-equivalent mean evolvement of unobserved common factors across all cross-section units. On condition that the unobserved common factors form part of the unit-specific cointegrating relation, the augmented unit regression model comprises the cointegrating relationship which is allowed to differ across countries:

$$\text{AMG} - \text{Stage(i)} \qquad \Delta y_{it} = b' \Delta x_{it} + \sum_{t=2}^{T} c_t D_t + e_{it} \quad \Rightarrow \widehat{c}_t \equiv \widehat{\mu}_t^{\circ} \tag{33}$$

$$\text{AMG} - \text{Stage(ii)} \qquad y_{it} = a_i + b_i' x_{it} + c_i t + d_i \widehat{\mu}_t^{\circ} + e_{it} \qquad \widehat{b}_{AMG} = N^{-1} \sum_{i=1}^{N} \widehat{b}_i \tag{34}$$

The first stage denotes a standard pooled first difference estimator regression with T-1 time dummies in first differences from which they obtain the time dummy coefficients which are redefined as $\widehat{\mu}_t^{\circ}$. In the second stage, this variable is included in each of the N standard unit regressions which also include linear trend terms to capture omitted idiosyncratic processes that develop in a linear fashion over time.

5.5. The short-run and long-run causality analyses

One might launch causality tests to examine the dynamic relationships among variables. A large number of works conducted the causality analyses in the literature of econometrics and economics since the seminal paper of Granger [82] on causality. These relevant works either conduct causality tests for time series analysis [83–87], or run the causality methods for panel data models [88–92]. To examine the causal relationships among variables, this paper employs not only the panel cointegration analyses based on the error correction model suggested by Pesaran et al. [93] for panel data models but also Dumitrescu and Hurlin [92] panel causality test. While the panel causality test based on the VECM presents both short- and long-run causal relationships, Dumitrescu and Hurlin [92] panel causality test exhibits the country-specific causality findings considering both cross-sectional dependence and heterogeneity.

5.5.1. Panel analyses based on the error correction

One might observe intensively, within the relevant literature, the panel cointegration analyses based on error correction (ec) and/or vector error correction (VECM) [93] and several applications of panel-EC-VECM that depict the short-run and long-run dynamics within the panel data [94–97]. The Panel Pooled Mean Group (PMG) model based on error correction mechanism has been followed in the literature profoundly. The PMG is set up by using ARDL model with error correction term and lagged variables. To examine the long-run and short-run relationships between variables, the PMG might be considered efficient model as is given in Pesaran et al. (1999). Following the ARDL cointegration model, Pesaran et al. (1999) develop the PMG model to estimate short-run and long-run parameters through heterogeneous cross-sections. Then, in the model, all estimations are allowed to differ across individual units within the panel data.

$$\Delta Y_{it} = \vartheta_i n_{it} + \sum_{J=0}^{q-1} \theta_{ij}' \Delta X_{it-j} + \sum_{J=1}^{p-1} \gamma_{ij} \Delta Y_{it-j} + e_{it} \tag{35}$$

$$n_{it} = \delta Y_{it-1} - \beta' X_{it} \tag{36}$$

where Y_{it} represents dependent variable, X_{it} is (k × 1) vector of explanatory variables, θ_{ij} denotes coefficient vectors (k × 1), γ_{ij} depicts the coefficients of lagged variables, Δ denotes lag operator, n_{it} is the error correction term, β exhibits long-term coefficients and ϑ denotes adjustment coefficients.

If the coefficient of error correction term is negative and less than 1 in absolute value, then the system will not be explosive and will return to long-run equilibrium. Thereby, in this case, one might observe the explanatory variables' short run and long run impacts on the dependent variable.

5.5.2. Dumitrescu and Hurlin [92] panel causality test

Dumitrescu and Hurlin [92] develop a panel causality test that is based on the individual Wald statistics and that regards cross-sectional dependence and heterogeneity. They first consider the following models:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t} \tag{37}$$

$$x_{i,t} = \delta_i + \sum_{k=1}^{K} \theta_i^{(k)} x_{i,t-k} + \sum_{k=1}^{K} \lambda_i^{(k)} y_{i,t-k} + \varepsilon_{i,t} \tag{38}$$

For simplicity, the individual effects α_i and δ_i are assumed to be fixed in the time dimension. Initial conditions ($y_{i,-K}, \ldots, y_{i,0}$) and ($x_{i,-K}, \ldots, x_{i,0}$) of both individual processes yi, t and xi, t are given and observable. They presume that the panel is balanced and lag orders K are identical for all cross-section units of the panel. Additionally, they allow the autoregressive parameters $\gamma_i^{(k)}$ and $\theta_i^{(k)}$ and the regression coefficients slopes $\beta_i^{(k)}$ and $\lambda_i^{(k)}$ to differ across cross section units.

They test the Homogeneous Non Causality (HNC) hypothesis considering heterogeneity of the causal relationships. Under the alternative, they examine a subgroup of individuals for which there is no causal relationship and a subgroup of individuals for which there is a causal relationship. For instance, in order to test whether x Granger causes y, the null hypothesis of HNC is stated as the following:

$$H_0 = \beta_i = 0 \quad \mathit{\Lambda}\mathrm{i} = 1, \ldots, \mathrm{N} \tag{39}$$

as $\beta_i = (\beta_i^{(1)}, \ldots, \beta_i^{(K)})'$. Besides, β_i can differ across groups under the alternative (model heterogeneity). They also allow some of the individual vectors β_i to be equal to 0 (non-causality assumption). They assume there are $N_1<N$ individual processes with no causality from x to y under H_1. It follows that their test is not a test of non-causality assumption against causality from x to y for all the individuals in a panel data model. They can observe causality for some units under the alternative:

$$\begin{aligned} H_1 &: \beta_i = 0 \quad \mathit{\Lambda}\mathrm{i} = 1, \ldots, \mathrm{N}_1 \\ &\beta_1 \neq 0 \quad \mathit{\Lambda}\mathrm{i} = \mathrm{N}_1 + 1, \ \mathrm{N}_1 + 2, \ldots, \mathrm{N} \end{aligned} \tag{40}$$

where N_1 is unknown and meets condition $0 \leq N_1/N < 1$. The rejection of the null hypothesis with $N_1 = 0$ indicates that x Granger causes y for all the cross section units of the panel while the rejection of the null hypothesis with $N_1 > 0$ indicates that the causal relationship is heterogeneous. This means that the causal relationships are different from one individual to another. Within this framework, they propose to use the average of individual Wald statistics associated with the test of the non-causality hypothesis for units i = 1, …, N. The average statistic $W_{N,T}^{Hnc}$ associated with the null HNC hypothesis is calculated as follows:

$$W_{N,T}^{Hnc} = \frac{1}{N} \sum_{\mathrm{i}=1}^{N} W_{i,T} \tag{41}$$

where $W_{i,T}$ denotes the individual Wald statistics for the ith cross section unit.

Allow one to remark by Z_i the (T,2K + 1) matrix $Z_i = [e{:}Y_i{:}X_i]$, where e stands for a (T, 1) unit vector, and by $\theta_i = (\alpha_i\ \gamma_i'\ \beta_i')'$ the vector of parameters of the model. The rest for the HNC hypothesis can now be expressed as $R\theta_i = 0$ where R stands for a (K,2K + 1) matrix with $R = [0{:}I_K]$. The Wald statistic $W_{i,T}$ corresponding to the individual test H_0: $\beta_i = 0$ is described for each i = 1, …, N as

$$W_{i,T} = \widehat{\theta}_i' R' \left[\widehat{\sigma}_i^2 R \left(Z_i' Z_i\right)^{-1} R'\right]^{-1} R\widehat{\theta}_i = \frac{\widehat{\theta}_i' R' \left[R\left(Z_i'Z_i\right)^{-1} R'\right]^{-1} R\widehat{\theta}_i}{\widehat{\varepsilon}_i'\widehat{\varepsilon}_i \Big/ (T - 2K - 1)} \tag{42}$$

where $\widehat{\theta}_i$ denotes the estimate of parameter θ_i that is obtained under the alternative hypothesis, and $\widehat{\sigma}_i^2$ stands for the estimate of the variance of the residuals. This Wald statistic can also be described as below:

$$W_{i,T} = (T - 2K - 1)\left(\frac{\tilde{\varepsilon}_i' \Phi_i \tilde{\varepsilon}_i}{\tilde{\varepsilon}_i' M_i \tilde{\varepsilon}_i}\right), \qquad i = 1, \ldots, N \tag{43}$$

Under the null hypothesis of non-causality, each individual Wald statistic converges to a chi-squared distribution with K degrees of freedom for T → ∞:

$$W_{i,T} \to \chi^2(K), \quad \mathit{\Lambda}\mathrm{i} = 1, \ldots, \mathrm{N} \tag{44}$$

When Wald statistic is greater than the critical values, then the null hypothesis of no causality can be rejected.

6. Estimation results

The results of Table 2 indicate that the null hypothesis of no cross-sectional dependence is rejected at 1% level of significance. This output implies that a shock occurring in one Asian country may be transmitted to other Asian countries. Table 2 explores, as well, that the results from the slope homogeneity tests reject the null hypothesis of slope homogeneity and thus support country-specific heterogeneity.

Table 3 Depicts the results of the CADF unit root test. As seen from the table, the results of this test are mixed for countries.

The results of the CADF unit root test for countries in Table 3 indicate that i) energy intensity is stationary at level for Bangladesh and is stationary at first difference for Malaysia and Vietnam, ii) GDP per capita is stationary at level for six out of ten countries (Bangladesh, China, India, Indonesia, Nepal, and Philippines) and becomes stationary at first difference for Thailand, iii) The square of GDP per capita is stationary at level for five out of ten countries (Bangladesh, China, India, Indonesia, and Philippines) and appears stationary at first difference for only Thailand, iv) urbanization is stationary at level for five out of then countries (Bangladesh, China, Indonesia, Thailand, and Vietnam) and reaches stationarity at first difference for only Philippines), v) ruralization variable is stationary at level for Bangladesh, China, and Indonesia and is stationary at first difference for South Korea, India, and Thailand. When one examines the findings obtained from the CADF unit root test for the panel through CIPS statistics, he/she observes that all variables are stationary at first differences. Therefore, the cointegration relationship among variables and, if this relationship exists, the cointegration coefficients for these variables can be investigated.

Table 4 illustrates the output of Westerlund [80] cointegration test. As seen, tests statistics are highly greater than critical values. Hence the null hypothesis of no cointegration can be rejected at 1% level significance for both test statistics. In other words, the findings of the cointegration test indicate that there is a long-run relationship among energy intensity, GDP per capita, the square of GDP per capita, urbanization, and ruralization for 10 Asian

Table 2
Cross-sectional dependence and heterogeneity tests.

Test	Statistic	p-value
Cross-sectional dependence tests		
LM	45.34	0.45
CD_{LM}	0.03	0.48
CD	2.71[a]	0.00
LM_{adj}	24.08[a]	0.00
Homogeneity tests		
$\tilde{\Delta}$	10.04[a]	0.00
$\tilde{\Delta}_{adj}$	10.99[a]	0.00

Note:
[a] Denotes 1% statistical significance.

countries during the period 1990–2012. The next stage is to estimate the long-run parameters of independent variables. Table 5 presents the results of the AMG estimator.

The results can be classified under three groups:

(a) Findings for the relationship between energy intensity and GDP per capita

The EKC hypothesis is valid in China, Indonesia, and Nepal. Accordingly, an increase in GDP per capita first leads to an increase in energy intensity and then leads to a decrease in energy intensity after GDP per capita reaches a threshold. Therefore, the findings indicate that economic growth decreases energy intensity in the long run in these three countries. There is a U-shaped relationship between energy intensity and GDP per capita in India, Malaysia, and Philippines. Accordingly, an increase in GDP per capita first leads to a decrease in energy intensity and then leads to an increase in energy intensity after GDP per capita reaches a threshold. Therefore, the findings indicate that economic growth increases energy intensity in the long run in these three countries. GDP per capita does not have statistical significant effects on energy intensity in Bangladesh, South Korea, and Thailand. The findings for these three countries indicate that economic growth does not affect energy intensity. Finally, there seems to be a linear and positive relationship between energy intensity and GDP per capita in Vietnam. Accordingly, economic growth increases energy intensity in Vietnam in the long run.

(b) Findings for the relationship between energy intensity and urbanization

Urbanization affects energy intensity negatively in China and India in the long run. According to this, the acceleration of urbanization increases energy productivity in these countries. This finding indicates that the increase in urban population stimulates new processes that use energy more productive. In Malaysia, Nepal, Philippines, South Korea, Thailand, and Vietnam, urbanization affects energy intensity positively. This output implies that the urbanization process has negative effects on energy productivity. On the other hand, the findings show that the urbanization process has no statistically significant effects on energy intensity in Bangladesh and Indonesia.

Table 4
Westerlund [80] cointegration test.

Test statistics		Critical values		
DH_g	DH_p	1%	5%	10%
42893.92[a]	58.66[a]	2.33	1.64	1.28

Note:
[a] Illustrates 1% statistical significance.

Table 5
Cointegration coefficients obtained from AMG estimator.[a]

Country	lnY	$(\ln Y)^2$	lnURB	lnRUR
Bangladesh	−4.96 (0.44)	0.39 (0.42)	−0.36 (0.54)	0.83 (0.35)
China	13.02[b] (0.00)	−0.97[b] (0.00)	−3.28[b] (0.00)	−14.13[b] (0.00)
India	−7.28[b] (0.00)	0.52[b] (0.00)	−1.68[d] (0.07)	3.31[c] (0.04)
Indonesia	5.80[c] (0.06)	−0.45[c] (0.03)	0.10 (0.62)	−4.60[b] (0.04)
Malaysia	−40.38[b] (0.00)	2.37[b] (0.00)	1.53[b] (0.00)	7.40[b] (0.00)
Nepal	7.24[d] (0.09)	−0.67[d] (0.06)	0.83[b] (0.00)	−3.48[b] (0.00)
Philippines	−13.12[b] (0.00)	0.92[b] (0.00)	6.78[b] (0.00)	−5.64[b] (0.00)
South Korea	6.28 (0.15)	−0.35 (0.11)	2.10[c] (0.03)	0.99 (0.15)
Thailand	−9.36 (0.12)	0.59 (0.13)	0.67[b] (0.00)	1.45[b] (0.00)
Vietnam	3.79[d] (0.09)	0.26 (0.16)	1.20[b] (0.00)	−2.30 (0.14)

Notes:
[a] Values in parentheses are prob. values.
[b] Illustrates 1% statistical significance.
[c] Illustrates 5% statistical significance.
[d] Illustrates 10% statistical significance.

(c) Findings for the relationship between energy intensity and ruralization

In China, Indonesia, Nepal, and Philippines, ruralization affects energy intensity negatively in the long run. In other words, the increase in rural population decreases energy intensity in these countries. Ruralization affects energy intensity positively in India, Malaysia, and Thailand in the long run. This finding shows that the increase in rural population increases energy intensity in these countries. Besides, the findings indicate that ruralization has no statistical significant effects on energy intensity in Bangladesh, South Korea, and Vietnam. That is to say, there is not a relationship between ruralization and energy intensity in these countries.

The results of the PMG tests based on the error corrections are reported in Table 6. Accordingly, there exist long run impacts of

Table 3
CADF unit root test [a,b].

Country	Test statistic									
	lnEI	ΔlnEI	lnY	ΔlnY	$(\ln Y)^2$	$\Delta(\ln Y)^2$	lnURB	ΔlnURB	lnRUR	ΔlnRUR
Bangladesh	−5.14[c]	−2.19	−4.33[d]	−0.98	−4.39[d]	−1.42	−4.92[d]	−3.83[e]	−5.62[c]	−2.21
China	−1.90	−3.25	−4.24[d]	−4.54[d]	−4.24[d]	−4.30[d]	−6.20[c]	−3.56[e]	−6.69[c]	−2.06
India	−1.64	−2.60	−4.71[d]	−2.99	−5.60[c]	−2.68	−3.22	−1.55	0.32	−4.29[d]
Indonesia	−3.39	−2.11	−4.18[d]	−3.04	−4.19[d]	−3.23	−7.01[c]	−4.16[d]	−4.44[d]	−2.52
Malaysia	−2.61	−4.32[d]	−1.88	−3.00	−3.43	−3.21	−3.30	−3.36	−1.31	−2.05
Nepal	−1.76	−2.81	−4.19[d]	−2.16	−1.51	−2.59	−0.96	−3.53	−1.40	−1.64
Philippines	−2.80	−2.13	−4.45[d]	−2.31	−4.41[d]	−4.09[d]	−3.41	−4.56[d]	−2.92	−2.28
South Korea	−1.77	−3.25	−2.38	−2.64	−2.36	−1.98	−2.67	−0.71	−2.73	−4.79[d]
Thailand	−1.96	−1.46	−3.24	−5.02[c]	−1.18	−5.26[c]	−5.12[c]	−3.51	−0.82	−3.63[e]
Vietnam	−2.96	−3.76[e]	−3.27	−2.50	−1.15	−2.50	−4.77[d]	−3.09	−0.78	−3.32
Panel (CIPS)	−2.59	−2.79[e]	−3.69[c]	−2.93[d]	−3.25[c]	−3.12[d]	−4.16[c]	−3.19[c]	−2.64	−2.88[e]

Notes:
[a] 1%, 5%, and 10% critical values for individual units are −4.97, −3.99, and −3.55, respectively. 1%, 5%, and 10% critical values for the whole panel are −3.15, −2.92, −2.74, respectively. Critical values are obtained from Pesaran [79].
[b] Δ is the first difference operator.
[c] Illustrates 1% statistical significance.
[d] Illustrates 5% statistical significance.
[e] Illustrates 10% statistical significance.

explanatory variables on energy intensity, except the regressor export variable. Hence one may claim that the possible significant determinants of energy intensity are income, urbanization, ruralization, renewable and nonrenewable energy consumption, respectively. Table 6 long-run output confirms, in general, the cointegration coefficients obtained from AMG estimator given in Table 5.

In the short run, however, the dynamic regressors of income, urbanization, export and nonrenewable are found significant to explain the change in energy intensity.

One might need to compare the output of the dynamic PMG analyses based on the error correction (Table 6) with the error correction from dynamic OLS, in which additional explanatory and deterministic variable(s) are employed, with 1 lead and 1 lag under the heterogeneous variance structure (Table 7).

Table 7 reveals (i) the long run estimations by adding the differenced leads and lags into cointegration equation to correct the serial correlation and endogeneity of $\varepsilon_{i,t}$ from OLS, and, (ii) the relevant short run estimations.

In Table 7, the independent variables of lnY, lnURB, lnRUR, lnEXP, lnREN, lnNONREN denote the logarithms of GDP per capita, urbanization, ruralization, export, renewable energy consumption, and, non-renewable energy consumption, respectively. The dependent variable is denoted by the logarithm of energy intensity (lnEI). Additionally, the dynamic OLS panel model estimations in Table 7 employs the deterministic variable of the logarithm of import (lnIMP) since the import is assumed to be necessary to sustain the production and consumption patterns within the individual countries. Thusly, we conducted the dynamic OLS estimations (i) to observe if it is possible, by employing other possible relevant explanatory variables, to confirm Table 6 output which reveals the significant causality from urbanization and ruralization to energy intensity, and, (ii) to detect the direction of causality from independent variables to dependent variable of lnEI.

Upon the results of Table 7, one may claim, in the long run, that the GDP, urbanization and renewable energy usage increase the energy productivity by diminishing the energy intensity, and, that the ruralization, export, and the consumption of non-renewable energy sources increase the energy intensity within the panel for the period 1990–2014. Table 7 output exhibits, as well, that, in the short run, the GDP and the usage of renewables have significant impact on energy intensity variable.

Then, for instance, 1% increase in urbanization index will lead to 2.80% decline in energy intensity, as, e.g. 1% increase in nonrenewable consumption will cause to 0.27% increase in energy intensity in the long run.

The error correction, the short run deviation(s) from the cointegrating equilibrium, hence, is the deviation from log run (cointegrating) equilibrium in previous period (t-1). The estimated value of error correction, then, depicts the speed of adjustment to access the long-run (cointegration) equilibrium at current period.

Considering the short run deviations from the long run, one might explore that the energy intensity does respond significantly to the changes in GDP (ΔlnY) and renewable energy consumption (ΔlnREN) in the short run.

Let one observe, by coincidence, that the error correction term (e_{t-1}) of Bangladesh in 1997 is equal to −0.011433. It means that energy intensity of Bangladesh is below its long run equilibrium by 0.011433 units in 1997, and, the next year, in 1998, the energy intensity will increase by 0,009409 units ($= -0.823 \times$ - 0.011433) to restore its long-run equilibrium.

Let us follow another example. The error correction term (et-1) of Malaysia in 2013 is 0.006822. It indicates that the energy intensity of Malaysia is above its long run equilibrium by 0.006822 units in 2013, and, in following year, in 2014, the energy intensity will decrease by 0,005614 units ($= -0.823 \times 0.006822$) to recover the cointegrating equilibrium.

Tables 6 and 7, on the other hand, differ from each other in terms of the significance of GDP on energy intensity. As Table 6 exhibits that the panel GDP has no statistical influence on energy intensity, Table 7 results in significant impact of GDP on energy intensity in panel of 10 countries within absolute values.

Although dynamic OLS yields the estimations by correcting the serial correlation and endogeneity of $\varepsilon_{i,t}$ from OLS, it does not consider the cross-sectional dependence. Therefore, we run specifically the Dumitrescu and Hurlin [92] panel causality tests in which the individual country-specific causalities are considered for the period 1990–2014. Table 8 reveals that (i) the panel causalities from energy intensity variable to GDP, export, and, nonrenewable energy consumption variables are found insignificant, (ii) there exist significant estimations of panel causalities from energy intensity to urbanization, ruralization, and, renewable energy consumption, (iii) All variables in the model have significant statistics on energy intensity. Then, one may claim that (a) GDP, urbanization, ruralization, export, renewable and nonrenewable energy usages might be considered the determinants of energy intensity

Table 6
PMG analyses based on the error correction (short-run and long-run estimations).[a]

Dependent variable: ΔlnEI						
Variables						
Long-run[b]	lnY	lnURB	lnRUR	lnEXP	lnREN	lnNONREN
	−0.74[c] (0.00)	−6.34[c] (0.00)	1.68[c] (0.00)	−0.01 (0.22)	−0.20[c] (0.00)	0.20[c] (0.00)
Short-run[b]	ΔlnY	ΔlnURB	ΔlnRUR	ΔlnEXP	ΔlnREN	ΔlnNONREN
	0.07 (0.70)	−88.88[d] (0.06)	−178.74 (0.11)	0.00 (0.85)	0.53 (0.66)	−1.22[d] (0.07)
	ΔlnY_1	ΔlnURB_1	ΔlnRUR_1	ΔlnEXP_1	ΔlnREN_1	ΔlnNONREN_1
	0.15[d] (0.09)	33.90 (0.35)	64.65 (0.46)	−0.04[d] (0.07)	0.37 (0.54)	3.62 (0.15)
Constant	12.87[c](0.00)					
Trend	0.03[c] (0.00)					
Error Correction	−0.55[c] (0.00)					

Notes:
[a] The dependent variable's lag = 1, regressors' lag = 2.
[b] Exhibits the t statistics and prob-values in parentheses.
[c] Illustrates 1% statistical significance.
[d] Illustrates 10% statistical significance.

Table 7
Dynamic OLS tests based on the EC (short-run and long-run estimations).

Dependent variable: ΔlnEI						
Variables						
Long-run[a,b]	lnY	lnURB	lnRUR	lnEXP	lnREN	lnNONREN
	−0.91[c] (0.00)	−2.80[c] (0.00)	5.11[c] (0.00)	0.26[c] (0.00)	−0.27[e] (0.08)	0.27[d] (0.03)
Short-run[b]	ΔlnY	ΔlnURB	ΔlnRUR	ΔlnEXP	ΔlnREN	ΔlnNONREN
	−0.35[c] (0.00)	0.16 (0.71)	−0.62 (0.27)	−0.01 (0.74)	−0.09[c] (0.00)	0.02 (0.71)
Constant	−0.008 (0.221)					
Error Correction	−0.823[d] (0.047)					

Notes:
[a] The deterministic variables in cointegrating (long-run) equation are constant and lnIMP (logarithm of import), respectively.
[b] Exhibits the t statistics and prob-values in parentheses.
[c] Illustrates 1% statistical significance.
[d] Illustrates 5% statistical significance.
[e] Illustrates 10% statistical significance.

within Asian panel data, (b) panel variables of GDP, urbanization, ruralization, export, renewable energy consumption and nonrenewable energy consumption can forecast well the future values of panel energy intensity variable.

One might need to observe, specifically, as well, the country specific results. Table 9 exhibits the individual output of Dumitrescu and Hurlin [92] panel Granger causality tests in heterogeneous panel data models.

The panel data reveals significant causality from GDP (lnY) to energy intensity (lnEI) as shown in Table 8. As for the cross section units, 5 out of 10 countries' data (Bangladesh, China, Indonesia, Malaysia, and South Korea) yield influences of GDP on energy intensity. The data for India, Nepal, Philippines, Thailand and Vietnam, on the other hand, do not reject the null of no causality (Table 9).

Following the cross section estimates (Table 9), one observes that the urbanization process (lnURB) seems to be significant on energy intensity (lnEI) in Bangladesh, China, Nepal, Philippines, South Korea and Thailand. The urbanization variable, on the other hand, depicts insignificant influences on energy intensity indexes of India, Indonesia, Malaysia, and, Vietnam. The ruralization (lnRUR) provides, also, the significant impulses on energy intensity in the same cross-sections of the panel. The null hypothesis of no causality cannot be rejected for India, Indonesia, Malaysia, and, Vietnam data. The countries of Bangladesh, China, Nepal, Philippines, South Korea and Thailand, on the other hand, follow the path in which the variance of ruralization variable can explain that of energy intensity variable. The overall panel estimations of 10 Asian countries explore that the energy intensity level is affected by urbanization and ruralization levels (Table 8).

The variables of export, renewable and nonrenewable energy consumption are considered other possible potential determinants of energy intensity in this paper. As the panel observation exhibits the significant effect of export on energy intensity (Table 8) some specific country level analyses differ from the panel output. In Bangladesh, China, Philippines, South Korea and Thailand, there exists statistically significant links between export and energy intensity. The same bidirectional causality does not appear in India, Indonesia, Malaysia, Nepal and Vietnam (Table 9).

The renewable and nonrenewable energy consumption seems to have significant influence on energy intensity in panel observation (Table 8). As in the urbanization and ruralization case in which they both have significant impacts on energy intensity in the same cross sections, the renewables and non-renewables similarly show the same influences on energy intensity in the same countries except Malaysia. While Bangladesh, China, Nepal, Philippines and Thailand yield the causality from these energy sources to energy intensity, the Malaysia case presents the causality from nonrenewable usage to energy intensity index but non causality from renewables to lnEI.

7. Conclusion and policy implications

The energy intensity is defined as the ratio of energy usage to GDP, or the level of energy usage needed to produce one unit of GDP. Hence, the energy intensity stands for the energy productivity in the economies of the countries.

Therefore the administrators and/or policy makers need to optimize the energy intensity level which is the function of several factors. The possible potential factors might be the market size of the economies (GDP), the industrialization level of the economies that might be represented also by GDP and/or the level of squared GDP of the economies, the regional or international comparative advantages within the industrial production process that is

Table 8
Dumitrescu and Hurlin [92] panel causality tests.[a]

Panel	Null hypothesis (no causality)					
	lnEI→lnY	lnY→lnEI	lnEI→lnURB	lnURB→lnEI	lnEI→lnRUR	lnRUR→lnEI
	3.41 (0.14)	6.14[b] (1E-06)	5.55[b] (4E-05)	7.91[b] (2E-12)	5.87[b] (7E-06)	7.82[b] (5E-12)
Panel	lnEI→lnEX	lnEX→lnEI	lnEI→lnREN	lnREN→lnEI	lnEI→lnNONREN	lnNONREN→lnEI
	3.12 (0.28)	5.12[b] (4E-03)	4.58[b] (0.00)	4.51[b] (0.00)	2.95 (0.38)	4.17[c] (0.02)

Notes:
[a] Wald Statistic: The values in parentheses are prob-values.
[b] Illustrates 1% statistical significance.
[c] Illustrates 5% statistical significance.

Table 9
Dumitrescu and Hurlin [92] panel causality test (country-specific causality).[a]

Country	Null hypothesis (no causality)					
	lnY→lnEI	lnURB→lnEI	lnRUR→lnEI	lnEX→lnEI	lnREN→lnEI	lnNONREN→lnEI
Bangladesh	29.90[b] (0.00)	19.81[b] (0.00)	19.42[b] (0.00)	9.58[b] (0.00)	23.41[b] (0.00)	9.65[c] (0.02)
China	6.70[d] (0.08)	20.63[b] (0.00)	18.77[b] (0.00)	5.13[d] (0.07)	8.06[c] (0.04)	10.09[c] (0.01)
India	2.90 (0.40)	5.33 (0.14)	3.77 (0.28)	1.17 (0.55)	0.11 (0.98)	0.17 (0.98)
Indonesia	8.85[c] (0.03)	4.96 (0.17)	5.85 (0.11)	4.44 (0.10)	3.30 (0.34)	2.30 (0.51)
Malaysia	6.57[d] (0.08)	0.80 (0.84)	0.45 (0.92)	0.58 (0.74)	4.26 (0.23)	7.93[c] (0.04)
Nepal	2.82 (0.41)	7.13[d] (0.06)	8.42[c] (0.03)	0.53 (0.76)	7.21[d] (0.06)	7.76[d] (0.05)
Philippines	1.64 (0.64)	12.08[b] (0.00)	12.36[b] (0.00)	8.17[c] (0.01)	8.23[c] (0.04)	7.43[d] (0.06)
South Korea	1.41[c] (0.01)	13.13[b] (0.00)	13.30[b] (0.00)	16.88[b] (0.00)	2.24 (0.52)	2.31 (0.51)
Thailand	1.98 (0.57)	6.95[d] (0.07)	6.55[d] (0.08)	6.31[c] (0.04)	6.55[d] (0.08)	9.30[c] (0.02)
Vietnam	2.62 (0.45)	1.52 (0.67)	1.53 (0.67)	4.05 (0.13)	1.16 (0.76)	2.28 (0.51)

Notes:
[a] Wald Statistic: The values in parentheses are prob-values.
[b] Illustrates 1% statistical significance.
[c] Illustrates 5% statistical significance.
[d] Illustrates 10% statistical significance.

depicted by the export level or export volume of the countries, the composition of energy consumption (renewables and nonrenewables) of the industries and households, and, some leading socioeconomic and/or demographic factors such as urbanization and ruralization indexes of the regions or national economies, and, other potential factors such as the structural changes in technologies and/or regime shifts occurred in socioeconomic factors. Later two factors might be captured implicitly by the dynamics of economic and socioeconomic variables in the short-run and long-run.

This paper, thusly, employs the economic variables (the GDP, the squared GDP, export, renewable energy consumption and nonrenewable energy consumption) and socioeconomic/demographic variables (the urbanization and ruralization paths) to be able to capture the movements or variance of the energy intensity levels in panel data of 10 Asian countries. The Asian panel data includes the countries of Bangladesh, China, India, Indonesia, Malaysia, Nepal, Philippines, South Korea, Thailand and Vietnam, respectively. The paper, then, reveals its output through the dynamic estimations of panel and cointegration models. The output comprises both panel and cross sectional impacts of urbanization on energy intensity throughout the estimations of the regarding models in which other economic and socioeconomic control variables are monitored as well.

The short run and long run cointegration and/or causality relationships between the urbanization and energy intensity is of interest to this paper due to (i) observed relatively prominent changes in socioeconomic variable of urbanization, and, (ii) the relatively considerable changes in energy intensity, and, (iii) the relative importance of energy intensity that might change greatly the production costs of commodities and services of transportation, tourism, telecommunication, mining, construction and manufacturing sectors.

This section, next, exposes the subsections of (7.1) the summary statistics of estimated models, (7.2) the executive summary, and, (7.3) some policy implications, respectively.

7.1. The summary statistics of estimated models

The paper investigates the effects of urbanization on energy intensity for 10 Asian countries by utilizing annual data covering the period 1990–2014. After conducting cross-sectional dependence and heterogeneity tests, the paper employs unit root and cointegration tests. Thus, the paper performs the AMG estimator developed by Eberhardt and Bond [37], Dumitrescu and Hurlin [92] panel causality tests and panel causality test based on the error correction model suggested by Pesaran et al. [93] for panel data models. This paper follows ruralization variable as well as control variables within the relevant models and yields that there happens to be a long-run relationship between energy intensity, GDP per capita, the square of GDP per capita, urbanization, and ruralization in 10 Asian countries.

This paper, later, employs other control variables of export, renewable energy consumption and nonrenewable energy consumption. The all estimations can be summarized within below subsections of A, B, C and D.

A- The empirical findings obtained from cointegration analyses through augmented mean group (AMG) estimations can be summarized under three classifications:

(a1) Energy intensity is negatively related to urbanization in China and India and is positively related to urbanization in Malaysia, Nepal, Philippines, South Korea, Thailand, and Vietnam. Besides, urbanization has no effects on energy intensity in Bangladesh and Indonesia. These findings indicate that urbanization either negatively effects energy intensity or has no effect on energy intensity in some Asian countries.

(a2) While the EKC hypothesis prevails in China, Indonesia, and Nepal, there is a U-shaped relationship between energy intensity and GDP per capita in India, Malaysia, and Philippines. Besides, there exists a linear and positive relationship between energy intensity and GDP per capita in Vietnam while GDP per capita does not affect energy intensity in Bangladesh, South Korea, and Thailand.

(a3) Energy intensity is negatively related to ruralization in China, Indonesia, Nepal, and Philippines and is positively related to ruralization in India, Malaysia, and Thailand. Besides, ruralization has no effects on energy intensity in Bangladesh, South Korea, and Vietnam.

B- The empirical findings throughout panel Granger causality tests based on the VECM and Dumitrescu and Hurlin [92] panel causality tests:

The findings of the panel Granger causality test based on the VECM show that there exists causality from GDP per capita, urbanization, and ruralization to energy intensity in the long run. Besides, in the short run, (i) there is unidirectional causal relationship running from urbanization to energy intensity and ruralization to energy intensity, and (ii) there exists unidirectional causal relationship from energy intensity to GDP per capita and from ruralization to GDP per capita.

C- The results from Dumitrescu and Hurlin [92] panel causality tests can be classified under six sub-groups.

(c1) There is unidirectional causality from GDP per capita and energy intensity in the panel.

(c2) There exists a bidirectional causal relationship between urbanization and energy intensity within panel.

(c3) There happens to be bidirectional causality between ruralization and energy intensity in panel.

(c4) There is unidirectional causality from export to energy intensity in the panel.

(c5) Bidirectional causality relationship appears between renewable usage and energy intensity in panel.

(c6) As nonrenewable consumption has the impact on energy intensity, the energy intensity does not cause the change in nonrenewable usage (unidirectional causality) in the panel.

D- The output from Dumitrescu and Hurlin [92] panel cross-section causality tests can be classified under six sub-groups:

(d1) Bangladesh, China, Indonesia, Malaysia, and South Korea yield significant influences of GDP on energy intensity. The data for India, Nepal, Philippines, Thailand and Vietnam, on the other hand, do not reject the null of no causality from income to energy intensity.

(d2) The urbanization variable is significant on energy intensity in Bangladesh, China, Nepal, Philippines, South Korea and Thailand whereas, it does not reveal insignificant effect on energy intensity index variable of India, Indonesia, Malaysia, and, Vietnam.

(d3) The ruralization variable is found significant on energy intensity in Bangladesh, China, Nepal, Philippines, South Korea and Thailand.

(d4) The change in export causes energy intensity to change in Bangladesh, China, Philippines, South Korea and Thailand. The same causality does not happen in India, Indonesia, Malaysia, Nepal and Vietnam.

(d5) The renewable energy consumption variable seems to be able to explain the variance of energy intensity in Bangladesh, China, Nepal, Philippines and Thailand whereas it has no explanatory power on energy intensity in India, Indonesia, Malaysia, South Korea and Vietnam.

(d6) There exists causality from nonrenewable energy consumption to energy intensity in Bangladesh, China, Malaysia, Nepal, Philippines and Thailand. The same data, on the other hand, does not depict causality from nonrenewables to energy intensity India, Indonesia, South Korea and Vietnam.

7.2. The executive summary

(i) The purpose of this paper is to investigate mainly the impact of urbanization on energy intensity through 10 Asian countries' panel data analyses for the period 1990–2014. All panel estimations are in favor of significance of urbanization process on energy intensity in the long run.

(ii) The urbanization variable has also significant influences on energy intensity in the short- run.

(iii) Although there exist some empirical cross-sectional differences, the 10 Asian countries' panel data, eventually, reveal that the urbanization path increases the energy productivity by diminishing the energy intensity both in the long-run and short-run.

7.3. Some policy implications

In today's world, the risk of depletion of fossil energy sources (the Peak Oil Theory), energy safety, global warming, and climate change are among the most considerable concerns. Increasing energy demand of urban areas underlies these concerns. For this reason, sustainable urbanization policies that consider mainly energy productivity are very important to manage successfully the urbanization process.

As indicated in Section 1, (i) Asian countries have the greatest annual rates of urbanization in the World, (ii) they consume 31% of total world energy, (iii) energy demand of Asian countries has been increasing more quickly than that of other continents, and (iv) Asia is responsible for about 38% of energy-based CO_2 emissions [47,48,98]. Therefore, with regard to policies to mitigate the negative impacts of the environmental issues stemming from fossil energy requirements, researchers specifically need to observe closely the Asian countries' energy consumption pattern today and in the future. Thus, this paper reveals some relevant policy proposals.

Urbanization is a development indicator that shows up along with industrialization and modernization. Economically, the urbanization processes of Asian countries indicate a success. However, along with this process, energy demand of Asia that depends on fossil sources increases rapidly. Therefore, with regard to economic development, this is an important constraint within the scope of sustainability. From this point of view, the main policy proposal of the paper might be that Asian countries might need to implement policies considering energy productivity in the urbanization and development processes. These policies should mitigate energy demand stemming from the urbanization process and several incentive mechanisms should be deployed. These mechanisms should force urban production to be more innovator and should guide producers to use more modern and eco-friendly technologies [50,51]. As a result of these mechanisms, more modern, flexible, and safe sources will be utilized in industrial and commercial areas [39].

Buildings use energy in urban areas and various implementations considering energy productivity have been developed in the buildings. For instance, green building codes like Leadership in Energy & Environmental Design (LEEDS) certificates that have been developed recently can decrease energy intensity in buildings [38]. A similar system has been implemented in California since mid-1970s. Some measures including building codes and appliance standards are applied to increase energy productivity in California. As a result of these measures, while energy consumption per capita doubled in the US, energy consumption per capita did not change in California during the following years [21]. One may follow similar measures to show the possible decrease in energy intensity for Asian countries.

The transportation sector increases energy demand and greenhouse gas emissions in urban areas. As Akisawa and Kaya [99] remark, this sector depends on fossil fuels. For this reason, sustainability of transportation sector in urban areas becomes more important [100]. Therefore, if some renewables, e.g. biomass-based fuels, are utilized in highway vehicles via various incentive mechanisms, some potential favorable outcome might appear in terms of environment and climate change. Oil-based fuels can be substituted especially by biofuels due to production facility, usage and storage features, and the success in decreasing greenhouse gas emissions of biofuels [101]. One observes that as Indonesia, Malaysia, the Philippines, Thailand, China, and India produce more biofuels than other countries do [102], they also aim at following considerable national development goals, strategies, incentives, and policies for their energy usages. Additionally, biomass sources might be employed in electricity generation and heating. Therefore, the usage of biomass sources in urban areas is regarded important in terms of sustainable policies.

Finally, the increase in demand for energy as a result of the urbanization process may increase environmental concerns in the

Asian countries in the future. In literature, there are some papers that reveal renewable energy consumption can decrease CO_2 emissions [103,104]. Therefore, As Bilgili et al. [103] and Bilgili [105] remark, policy makers in the Asian countries may follow (i) demand side management (DSM) strategies for renewables and non-renewables to improve customer service in consumption of energy [106–109], (ii) subsidies for low emitting renewables [110], (iii) subsidies for R&D for renewables [111], (iv) policies for fair and easy access to electricity obtained from renewable sources [112], and (v) some tax incentive policies as carried out by Energy Policy Act (EPACT) for the period 1992–2011 in the US [113]. In conclusion, these subsidies/incentives for renewable energy consumption may increase environmental quality in the Asian countries.

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