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Is urbanization eco-friendly? An energy and land use cross-country analysis

X. Long [a], Xi Ji [a,*], S. Ulgiati [b,c]

[a] School of Economics, Peking University, Beijing 100871, PR China
[b] Department of Science and Technology, Parthenope University of Naples, 80143 Naples, Italy
[c] School of Environment, Beijing Normal University, Beijing, PR China

HIGHLIGHTS

- Ecological effects of urbanization are estimated.
- Ecological footprint is used to represent the integrated change related to energy and land use.
- Static and dynamic STIRPAT models are employed for regression.
- The reasons for the ecological protection effect of urbanization are analyzed.
- The heterogeneity of urban structure and function across income levels is discussed.

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ABSTRACT

Urbanization imposes complicated and heterogeneous impacts on ecosystems. With the purpose of reflecting the comprehensive influence of urbanization on the ecosystem, we choose the ecological footprint to represent the ecosystem's integrated change and distinguish low-income, middle-income and high-income countries to reflect the nonlinear impact. This paper uses both static and dynamic STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) models to analyze 72 countries at different income levels during the 1980–2008 period. The results show that the overall ecological elasticity of urbanization at the global level is negative. Specifically, results suggest urbanization, associated to increased income, to have eco-friendly potential in terms of decreased ecological footprint. To explain such results, this paper answers two questions: Why does urbanization show ecological protection effects? Why does a more pronounced protection effect seem associated to increased income levels? Improved market mechanism, increased resource use efficiency as well as increased environmental awareness in urban areas associated to increased income levels are likely to support an eco-friendly urbanization process. Burden-shift to low-income countries also needs to be taken into account, in order to avoid policies that increase wellbeing locally at the expenses of far-away areas.

1. Introduction

Currently, urbanization is proceeding worldwide, particularly in developing countries. In 2014, there were 3.9 billion people living in urban areas, representing 54% of the total population; this will increase to 66% in 2050 (UN, 2014). Large-scale urbanization has spurred global economic development. In 2011, 80% of global GDP originated from urban areas, and 600 urban cities contributed to 60% of the global GDP (Mckinsey Global Institute, 2011). However, resource consumption and environmental degradation were largely noted because population concentration would undoubtedly lead to a severe change in the ecosystem (Ji, 2015). In particular, energy scarcity, along with environmental problems, has seriously hindered global development (Ji and Long, 2016). Moreover, agricultural land was transforming to construction land in the process of urbanization. Angel et al. (2005) estimated that the average transformation rate from 1990 to 2000 was 3.2%, which was higher than that of the urban population (2.25% in the same period). Because of population swell and land expansion, interference caused by urbanization was unavoidable (Li et al., 2010). Cities accounted for two-thirds energy consumption and over 70% carbon dioxide emission in 2006 (IEA, 2008). Since

* Corresponding author.
E-mail address: jixi@pku.edu.cn (X. Ji).

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urbanization will remain a central theme worldwide in future decades, particularly in developing countries, it is meaningful to analyze urbanization's impact on the ecosystem.

Urbanization's impact on the ecosystem is complicated and varied. In order to include energy and other natural resources as well as environmental services, this paper uses ecological footprint as an indicator that can integrate various resource consumption and environmental impacts. William Rees and Mathis Wackernagel proposed the measurement of human demands on ecosystems (Rees, 1992; Wackernagel, 1994); this is defined as the quantity of biologically productive land and sea area necessary to supply the resources a human population consumes and to assimilate the associated waste. Ecological footprint is composed of six types of land: cropland, grazing land, fishing ground, forest land, carbon uptake land and built-up land. Carbon uptake land, which is receiving more and more attention since global warming, is regarded as the land necessary to absorb the anthropic carbon emissions. Therefore, the ecological footprint provides us with an account to measure human's impact on the ecosystem. In addition, the ecological effect of urbanization was not identical across low-, middle- and high-income countries (Poumanyvong et al., 2012). Income level has a significant impact on resource utilization, technological level and resident lifestyle, thus making the ecological effect of urbanization heterogeneous across income levels.

Because of lack of suitable data and still insufficiently developed theory and methodology, existing studies suffer from simplification, homogeneity and localization. Firstly, most of them only focus on a single environmental indicator (e.g., carbon emissions) or a single natural resource (e.g., energy). A single environmental effect of urbanization only reflects a specific environmental impact caused by urbanization, whereas urbanization's influence on the ecosystem is diverse and complex. Secondly, “homogeneity”[1] is one of the most common hypotheses in existing studies, which prevents the identification of “heterogeneity” of urbanization across income levels. Third, regarding the research scope, most studies use a specific country or area as an investigated case; thus, results are not sufficiently discussed at global level. Therefore, this paper contributes to the existing knowledge in three different ways. The first novelty is to focus on comprehensive ecological impacts by means of ecological footprint as an evaluation method. The use of ecological footprint is justified by the relatively high comprehensiveness of this indicator, capable to capture at the same time the upstream and downstream demand for resources (land and energy, in particular), needed for production processes as well as for pollution abatement. In spite of still existing uncertainties, ecological footprint database is large enough to allow statistical treatment and partial uncertainty removal. The second novelty is to consider the “heterogeneity” of the ecological effect of urbanization across income levels using both the static and dynamic models. The third novelty is to evaluate the ecological effect of urbanization on a global scale.

In this paper, we define the ecological effect of urbanization as the comprehensive impact of urbanization on the ecosystem, which can be categorized into the ecological protection effect and the ecological degradation effect. The ecological effect of urbanization is a synthesized result of these two aspects. We distinguish the income level to evaluate the ecological effect of urbanization based on panel data using data from 72 countries from 1980 to 2008, to explore the influence mechanism of urbanization under different structures and functions.

[1] The “Homogeneity” hypothesis indicates an identical impact of urbanization on the ecosystem regardless of income level, which means evaluating the relation between urbanization and the ecological variable without distinguishing income level in the regression model; in addition, the regression result of the coefficient of urbanization is regarded as a result for all income level countries.

The next sections are organized as follows: Section 2 summarizes theoretical background and relevant literature. Section 3 presents the methodology, data and regression procedure; Section 4 shows the regression results; Section 5 discusses the implications of regression results; and Section 6 draws conclusions and proposes suggestions on urbanization for policy makers.

2. Literature review

2.1. Existing studies on single environmental effects of urbanization

Existing studies mainly focus on urbanization's impact on a single environmental indicator or a single natural resource, defined as a single environmental effect of urbanization in this paper. Among these studies, the impact on the energy consumption and carbon emissions is the main research field (Jones, 1991; Parikh and Shukla, 1995; Cole and Neumayer, 2004; Wei et al., 2006; Wei et al., 2007; York, 2007). Most studies showed that urbanization would accelerate the energy demand and greenhouse gas emissions. For example, Jones (1991) proposed that urbanization increased the energy demand on transportation and agriculture; Parikh and Shukla (1995) analyzed the relation between urbanization, energy consumption and the greenhouse effect in developing countries and concluded that when the urbanization rate increased by 10%, the energy consumption per capita would increase by 4.7%, and the carbon dioxide emission per capita would increase by 0.3%. Cole and Neumayer (2004) verified the positive relation between carbon dioxide emissions and urbanization using data in 86 countries from 1975 to 1998 and similarly concluded that when the urbanization rate increased by 10%, carbon dioxide emissions would increase by 7%. In contrast, some researchers believed that urbanization had a scale effect because it could increase public infrastructure's usage efficiency, adjust the economic structure and reduce the commuting distance, thus decreasing energy consumption (Liddle, 2004; Chen et al., 2008). Furthermore, some studies focused on the “heterogeneity” of urbanization's energy effect. For example, Fan et al. (2006) used the STIRPAT model to recognize CO_2 emission factors at different income levels over the 1975–2000 period and observed an inverse U-shape for the urbanization impact. Poumanyvong and Kaneko (2010) realized most studies' tacit approval of the homogeneity of urbanization across income levels, and they found that urbanization in low-income countries would reduce energy consumption, whereas urbanization in middle-income and high-income countries would promote energy consumption. Ji and Chen (2015) concluded that the energy-saving effect of urbanization follows a U-shaped path across different stages of urbanization in China. Martinez-Zarzoso and Maruotti (2011) focused on the “heterogeneity” of urbanization's impact on CO_2 emissions as well, using the Bayesian Information Criterion (BIC) and the Integrated Completed Likelihood (ICL) to distinguish.

In addition, researchers have studied the impact of urbanization on land resources, forest resources, water resources and biodiversity. First, Carlson and Arthur (2000), Leitão and Ahern (2002) and Deng et al. (2009) explored the changes in land area and land use patterns in the process of urbanization. Wei and Zhang (2006) illustrated a negative relation between the urbanization rate and cultivated land area, which helped to prove that the shrinkage of the agricultural area was one feature of urbanization. Second, studies showed that urbanization would impose pressure on forest resources because forest areas were becoming tourist attractions (Ode and Fry, 2006; Atmiş et al., 2007). Third, urbanization has an influence on water volume and water quality. Hubacek et al. (2009) explained the relation between urbanization and water footprint and discussed how urbanization affected water's sustainable development in China. Ren et al. (2003) discovered a positive relation between urbanization and water quality degradation in Shanghai from 1947 to 1996. Fourth, urbanization, which is a process of remodeling the natural environmental, may inevitably affect biodiversity. Patterson et al. (2003) and Pauchard et al. (2006) regarded urban sprawl as a process of creating an opportunity for non-native species by replacing native species. Similarly, McKinney (2006) illustrated that biological homogenization resulted from urban expansion because the same “urban-adaptable” species became increasingly widespread and locally abundant in urban areas.

2.2. Existing studies on the ecological effect of urbanization

Indeed, the ecological effect of urbanization is various and integrated; therefore, it is not sufficient to solely focus on a single environmental effect (Ulgiati et al., 2006). However, currently, there is a limited quantity of research that studies the ecological effect of urbanization, and this research includes two approaches. One adopts various environmental indicators to represent the ecological change. The Pressure-State-Response (PSR) model is an example, which was proposed by Rapport and Friend (1979) and then promoted by the OECD and UNEP. This model has been used to estimate the impact of urbanization on ecological security and air quality (Bai and Tang, 2010; Wang et al., 2013). The other approach chooses an indicator to directly reflect the comprehensive change in the ecosystem, among which, the ecological footprint is one frequently used indicator (Solís-Guzmán et al., 2013). Jorgenson (2003) estimated the impacts of the world-system position on the ecological footprint and concluded that urbanization was one significant factor for the ecological footprint. Jia et al. (2009) used the STIRPAT and PLS methods to identify major drivers of the ecological footprint in Henan, China, and showed urbanization was one of the drivers. Hubacek et al. (2009) simulated the evolution process of social and economic factors including urbanization in China to predict the ecological footprint in the future. These studies believed that urbanization always accelerated the demand for natural resources because organizations and firms commandeered limited natural resources.

3. Methods

3.1. Model

This paper uses the STIRPAT model to regress. The STIRPAT model is based on IPAT identity and ImPACT identity. IPAT identity is often used to evaluate the impact of human activities on the environment (York et al., 2003), and it specifies that environmental impact (I) is driven by three factors: population (P), affluence (consumption or output per capita, A) and technology (environmental impact per consumption or per output, T); thus, I=PAT. Furthermore, Waggoner and Ausubel (2002) decomposed technology (T) into consumption per output (C) and environmental impact per consumption (T); thus, ImPACT identity is I=PACT. In contrast to IPAT and ImPACT, STIRPAT is not an accounting equation but a stochastic model used to test hypotheses empirically (York et al., 2003). The original and logarithmic forms of STIRPAT are as follows, respectively:

$$I_i = aP_i^b A_i^c T_i^d e_i \tag{1}$$

$$\log I = lna + b(\,lopP)+c(\,\log A)+lne \tag{2}$$

where I is environmental impact, P is population, A is Affluence, T is technology, a is a coefficient, and e is error term. Technology (T) is always included in the error term (York et al., 2003).

The STIRPAT model is always used in empirical analysis to examine the drivers of environmental or ecological impacts. The logarithmic form facilitates estimation and hypothesis testing (York et al., 2003). Because of the logarithmic form, the coefficients of independent variables should be interpreted as elasticities. Ecological elasticity is defined as the proportional change in ecological impacts caused by change in any driver.

Because STIRPAT is a simplified model, we can refine it by adding other necessary variables. First, affluence level and population are considered to be two main driving factors of ecological and environmental impact. York et al. (2003) and Dietz et al. (2007) concluded that affluence and population had a large impact on ecological and environmental change. Second, economic structure and technological level are discussed as well. It is widely believed that services is more environmentally friendly than industry, hence dematerialization of economy will change ecological footprint (York et al., 2003). Researchers hold different opinions towards technological level. Bicknell et al. (1998) proposed that technological level should be taken into consideration when calculating ecological footprint, while Costanza (2000) thought people were always blindly optimistic about the positive impact of technology, and suggested analyzing the impact of technology objectively. Accordingly, we choose economic structure, technological level, affluence level and population as independent variables in our model (Table 1), with urbanization included in the population factors. Compared with the original STIRPAT model, our extended version including economic structure, technology and urbanization allows more driving factors to be examined simultaneously.

Economic structure refers to the sectorial structure of economy, corresponding to GDP sector composition. Three main sectors are considered: agriculture, industry and services. Since industry structure and service structure are always used as representatives for structural change in empirical modeling. Therefore, we choose industry structure as one explanatory variable in regression, and in order to do a robustness check, we include service structure in another regression, which excludes industry structure, to check whether there is any big difference between the two regressions.

We use both static model and dynamic model to estimate. Most existing studies employ static STIRPAT model for panel data. Static

Table 1
Summary of variables.

Variable		Indicator	Definition	Unit
Dependent variable	Ecosystem change	Ecological footprint	Total ecological footprint caused by domestic consumption	Global hectare
Structure	Economic structure	Share of industry	Industry, value added (% of GDP)	Percent
		Share of services	Services, value added (% of GDP)	Percent
Technology	Efficiency of energy use	Energy Intensity	Energy use per $1000 GDP (constant 2005 PPP)	Kilogram of oil equivalent per $1000
Affluence	Economic scale	GDP per capita	–	Current US$
Population	Population size	Total population	–	Number
	Population structure	Urbanization	Ratio of urban population to total population	Percent

model has the assumption that there is no lag effect between independent and dependent variables. On the contrary, dynamic model allows for the lag effect, especially when technology effect is involved. However, an *endo*geneity problem exists in dynamic modeling. This study uses both static and dynamic models to explore the impact of urbanization on ecological footprint in order to be able to draw a comparison between results achieved through different procedures in so assessing their robustness and acceptability.

The regression equation of static model is:

$$lnEF_{it} = a_0 + a_1(lnIND_{it}) + a_2(lnEI_{it}) + a_3(lnGDPPC_{it}) + a_4(lnP_{it}) + a_5(lnURB_{it}) + e_{it} \tag{3}$$

$$lnEF_{it} = a_0 + a_1(lnSV_{it}) + a_2(lnEI_{it}) + a_3(lnGDPPC_{it}) + a_4(lnP_{it}) + a_5(lnURB_{it}) + e_{it} \tag{4}$$

The regression equation of dynamic model is:

$$lnEF_{it} = a_0 + \beta lnEF_{i,t-1} + a_1(lnIND_{it}) + a_2(lnEI_{it}) + a_3(lnGDPPC_{it}) + a_4(lnP_{it}) + a_5(lnURB_{it}) + e_{it} \tag{5}$$

$$lnEF_{it} = a_0 + \beta lnEF_{i,t-1} + a_1(lnSV_{it}) + a_2(lnEI_{it}) + a_3(lnGDPPC_{it}) + a_4(lnP_{it}) + a_5(lnURB_{it}) + e_{it} \tag{6}$$

where *EF* is the ecological footprint; *IND* is industry, value added (% of GDP); *SV* is services, value added (% of GDP); *EI* is energy intensity; *GDPPC* is GDP per capita; *P* is total population; *URB* is urbanization rate; a_0 is constant term; β, a_1, a_2, a_3, a_4, a_5, a_6 are coefficients; *e* is error term.

Coefficients from Eqs. (3) and (4) refer to the percentage change in *lnEF* in response to a 1% change in independent variables. Since the share of industry, share of services and urbanization are already in percentage form, the interpretation of their coefficients is not straightforward. However, York et al. (2003), Poumanyvong and Kaneko (2010), and Martínez-Zarzoso and Maruotti (2011) all indicated that these variables should also be in logarithmic form to keep consistency with other variables. The elasticities of the three variables should be interpreted as the percentage change in *lnEF* in response to a 1% change in their percentage values, which also have economic meaning.

3.2. Data

Our regression is based on balanced panel data including 72 countries or areas from 1980 to 2008 (2088 observations). The data on ecological footprint originate from the Global Footprint Network,[2] and data on other variables originate from the World Bank.[3] Furthermore, we categorized 72 countries as low-income, middle-income and high-income groups (Table 3) using the criterion of the World Bank (Table 2).

Table 4 presents the descriptive data analysis.

This study first regresses the entire 72-countries group and then regress three subsets, according to the following steps:

*Step 1: Test unit root. We test whether the panel data are stationary to avoid spurious regressions. Two different but commonly quoted unit root tests are used: the Levin-Lin-Chu ADF test (Levin et al., 2002) and the Fisher-PP test (Maddala and Wu, 1999; Choi, 2001). The null hypothesis assumes there is a unit-root process. The LLC test examines the null of a common unit root for all cross-sectional units, while the Fisher-PP test examines the null of individual unit roots (Martínez-Zarzoso and Maruotti, 2011). The tests results (Table 5) show that all the variables are stationary at 1% or 5% significance level.

*Step 2: Regression methods selection. (1) For static model, we should choose one method from the fixed effects (FE) method, the random effects (RE) method and the pooled OLS method. We use an *F*-test to choose from fixed effects and pooled OLS regression and then use the Lagrange Multiplier test to choose from random effects and pooled OLS regression. Furthermore, we use the Hausman test to choose from fixed effects and random effects. Test results show that fixed effects method should be used for static model. (2) For dynamic model, there are two ways to correct the *endo*geneity bias: difference GMM (difference Generalized Method of Moments) proposed by Arellano and Bond (1991) and system GMM proposed by Blundell and Bond (1998). The problem of difference GMM is that lagged levels are poor instruments if the variables are close to a random walk. The system GMM is proposed to address the problem.

*Step 3: Test multicollinearity with Variance Inflation Factor (VIF). If $0 < \text{VIF} < 10$, there is no multicollinearity; if $10 \le \text{VIF} < 100$, there is multicollinearity; if $\text{VIF} \ge 100$, there is strong multicollinearity (Freund and Wilson, 2006; Jia et al., 2009). Results show that there is no multicollinearity for any independent variable (Tables 6a and 6b).

*Step 4: Test heteroskedasticity by means of the Modified Wald statistic for groupwise heteroskedasticity for fixed effects method in static model.[4] Results show that there is heteroskedasticity for all groups (all, low-income, middle-income and high-income).

*Step 5: Test serial correlation: (1) For static modeling, we test the serial correlation using a Wooldridge test (Drukker, 2003). Results suggest that there is no serial correlation for the low-income group, whereas there is serial correlation for the entire group, middle-income group and high-income group; (2) For dynamic modeling, Arellano and Bond (1991) and Blundell and Bond (1998) suggested the prerequisite for GMM is that there is no second-order serial correlation in the first-differenced residuals. The second-order serial correlation is tested using Arellano-Bond test. Results show that there is no second-order serial correlation in all groups.

Table 2
Income level classified by GNI (US$ per capita).

Low-income	Middle-income	High-income
Less than 1556.7	Between 1556.7 and 9385.0	More than 9385.0

Since data are from year 1980–2008, we choose our classification criterion in 1995. We merged lower-middle-income into low-income and middle-upper-income into middle-income to simplify the explanation.

In the static model, we should choose a way to correct standard errors. There are two variance estimators: robust and cluster. The cluster option can address both the heteroskedasticity and serial correlation, and the robust option only deals with heteroskedasticity (Hoechle, 2007). Two test steps show that the entire group, middle-income group and high-income group have both heteroskedasticity and serial correlation problems in both regression with industry share and regression with service share, while low-income group only has heteroskedasticity problem in both regression with industry share and regression with service share. Therefore, the robust

[2] Available online: http://www.footprintnetwork.org/en/index.php/GFN/.
[3] Available online: http://data.worldbank.org/.
[4] There is no need to test the heteroskedasticity for GMM method.

Table 3
Income groups.

Income level	Country
Low-income (23 countries)	Albania, Bangladesh, Benin, Bolivia, Cameroon, China, Congo, Congo Democratic Republic of, Egypt Arab Rep., Ghana, Honduras, India, Indonesia, Kenya, Mozambique, Nepal, Nigeria, Pakistan, Philippines, Senegal, Sri Lanka, Togo, Zambia
Middle-income (24 countries)	Algeria, Botswana, Brazil, Bulgaria, Chile, Colombia, Cuba, Dominican Republic, Ecuador, Gabon, Hungary, Iran Islamic Rep., Jordan, Malaysia, Malta, Mexico, Morocco, Panama, Saudi Arabia, South Africa, Thailand, Tunisia, Turkey, Venezuela RB
High-income (25 countries)	Australia, Austria, Belgium, Brunei Darussalam, Canada, Cyprus, Denmark, Finland, France, Germany, Iceland, Ireland, Italy, Japan, Korea, Rep., Luxembourg, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, United Kingdom, United States

Table 4
Descriptive data analysis.

Variables	Obs	Mean	Std. dev.	Min	Max
lnEF	2088	17.432	1.619	13.167	21.753
lnIND	2088	3.438	0.329	1.867	4.441
lnSV	2088	3.953	0.275	2.677	4.437
lnEI	2088	4.930	0.489	3.934	7.266
lnGDPPC	2088	8.372	1.629	4.955	11.382
lnP	2088	16.526	1.706	12.171	20.986
lnURB	2088	3.989	0.475	1.807	4.605

Table 5
Panel unit root tests.

Variable	Levin, Lin & Chu test		Fisher-PP test	
	Statistic (Adjusted)	Prob.	Statistic (Inverse chi-squared)	Prob.
lnEF	-1.867	0.031**	184.345	0.009***
lnIND	-2.252	0.012**	188.577	0.008***
lnSV	-8.520	0.000***	318.408	0.000***
lnEI	-10.552	0.000***	400.332	0.001***
lnGDPPC	-15.321	0.000***	849.219	0.000***
lnP	-11.293	0.000***	611.025	0.000***
lnURB	-25.254	0.000***	1439.122	0.000***

[a]Newey-West bandwidth selection using Bartlett kernel.
[b]Automatic selection of lags based on SIC: 0 to 10 (maximum lags).
[c]*** and ** denotes rejection of the null hypothesis of nonstationary at 1% and 5% significance level respectively.

Table 6a
Test results of multicollinearity (VIF value) when using share of industry sector as independent variable.

	Static model				Dynamic model			
	All	Low	Middle	High	All	Low	Middle	High
L. lnEF					7.01	7.34	7.31	8.08
lnGDPPC	2.95	3.47	1.76	1.43	8.59	4.15	2.71	1.95
lnIND	1.13	1.83	1.22	1.13	1.16	1.85	1.21	1.29
lnURB	3.12	1.75	1.54	1.26	3.15	1.78	1.53	1.43
lnEI	1.15	1.93	1.05	1.23	1.55	2.14	1.47	2.03
lnP	1.10	1.31	1.07	1.07	1.70	1.27	1.01	1.99
Average VIF	1.89	2.06	1.33	1.22	3.86	3.09	2.54	2.80

[a]*L. lnEF* refers to last-period *lnEF*.
[b]All: Entire group. Low: Low-income group. Middle: Middle-income group. High: High-income group.

Table 6b
Test results of multicollinearity (VIF value) when using share of service sector as independent variable.

	Static model				Dynamic model			
	All	Low	Middle	High	All	Low	Middle	High
L. lnEF					7.18	8.17	7.97	8.81
lnGDPPC	3.39	2.81	1.57	1.28	8.71	3.42	2.49	1.95
lnSV	1.55	1.16	1.11	1.34	1.59	1.15	1.10	1.48
lnURB	3.01	1.70	1.57	1.48	3.00	1.72	1.56	1.48
lnEI	1.14	2.13	1.04	1.23	1.59	2.33	1.45	2.02
lnP	1.12	1.07	1.08	1.21	1.33	1.44	1.88	1.22
Average VIF	2.04	1.77	1.27	1.31	3.90	3.04	2.74	2.83

[a]*L. lnEF* refers to last-period *lnEF*.
[b]All: Entire group. Low: Low-income group. Middle: Middle-income group. High: High-income group.

variance estimator is used for low-income group, and the cluster variance estimator is used for the other groups.

4. Results

The regression results for static model are shown in Table 7a and the regression results for dynamic model are shown in Table 7b. In both static model and dynamic model, we use share of industry sector as a measure of structural change first, and then use share of service sector as a measure of structural change as a robustness check.

The results in Table 7b indicate that the null hypothesis of AR (2) test is accepted for all groups in dynamic model, which means there is no second-order serial autocorrelation in the first-differenced residuals. The coefficient estimations in dynamic model are unbiased. Meanwhile, the Hansen test shows that there is no over-identifying problem using GMM method.

A number of important findings are presented by the regression results.

When using the share of industry sector as a measure of structural change:

1. The estimated coefficient of lagged ecological footprint is positive and statistically significant for all groups. The elasticity is 0.533 for the entire group. The elasticity of lagged ecological footprint is highest for high-income group (0.590), indicating a moderate degree of persistence. The generation of ecological footprint is a dynamic and cumulative process.
2. The coefficient of urbanization is significantly negative in both static and dynamic models for all groups except low-income group. In static model, the coefficient of urbanization for the entire group is -0.167, which means that if the urbanization rate increases by 1%, the ecological footprint will decrease by 0.167%. In dynamic model, the coefficient for the entire group is -0.107, which represent short-run elasticity of urbanization.
3. Regarding the elasticity of urbanization in low-income, middle-income and high-income groups, results show that the elasticity is more negative in higher income group, no matter in static model or in dynamic model. In static model, the coefficient is insignificant in low-income countries but is significant in middle- and high-income countries, -0.462 and -0.553, respectively. In dynamic model, the coefficient is also insignificant in low-income countries, while significantly negative in middle-

Table 7a
Regression results for static model.

	Static model (FE)							
	All		Low		Middle		High	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lnIND	0.095***		0.071		0.209***		-0.094**	
	(0.018)		(0.062)		(0.034)		(0.046)	
lnSV		-0.134***		-0.114**		-0.261***		0.178***
		(0.022)		(0.049)		(0.038)		(0.058)
lnEI	0.378***	0.368***	0.274***	0.252***	0.334***	0.319***	0.454***	0.438***
	(0.021)	(0.022)	(0.063)	(0.066)	(0.041)	(0.041)	(0.040)	(0.039)
lnGDPPC	0.520***	0.535***	0.395***	0.422***	0.577***	0.613***	0.565***	0.563***
	(0.016)	(0.017)	(0.046)	(0.042)	(0.032)	(0.032)	(0.034)	(0.034)
lnP	0.964***	0.953***	0.839***	0.839***	1.204***	1.217***	0.792***	0.781***
	(0.025)	(0.025)	(0.086)	(0.085)	(0.053)	(0.052)	(0.068)	(0.066)
lnURB	-0.167***	-0.115***	-0.003	0.020	-0.462***	-0.426***	-0.553***	-0.559***
	(0.038)	(0.038)	(0.098)	(0.093)	(0.081)	(0.081)	(0.138)	(0.142)
Constant	-4.379***	-3.623***	-1.301	-0.776	-7.739***	-6.561***	-0.601	-0.973
	(0.335)	(0.339)	(1.132)	(1.206)	(0.597)	(0.609)	(1.046)	(0.916)
Number of obs	2088	2088	667	667	696	696	725	725
R-squared (within)	0.744	0.745	0.781	0.782	0.789	0.792	0.660	0.663

[a] L. *lnEF* refers to last-period *lnEF*.
[b] All: Entire group. Low: Low-income group. Middle: Middle-income group. High: High-income group.
[c] t statistics in parentheses
[d] Statistical significance is indicated by: ***P < 0.01, **P < 0.05, *P < 0.1

Table 7b
Regression results for dynamic model.

	Dynamic model (System GMM)							
	All		Low		Middle		High	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
L. lnEF	0.533***	0.529***	0.471**	0.466**	0.471***	0.464***	0.590***	0.591***
	(0.019)	(0.019)	(0.183)	(0.118)	(0.033)	(0.032)	(0.030)	(0.030)
lnIND	0.058***		0.041		0.150***		-0.044	
	(0.015)		(0.030)		(0.031)		(0.037)	
lnSV		-0.104***		-0.066		-0.210***		0.017
		(0.019)		(0.047)		(0.035)		(0.050)
lnEI	0.159***	0.147***	0.150**	0.139**	0.116***	0.096**	0.186***	0.177***
	(0.020)	(0.020)	(0.063)	(0.059)	(0.039)	(0.039)	(0.035)	(0.034)
lnGDPPC	0.252***	0.266***	0.219**	0.238***	0.320***	0.351***	0.267***	0.268***
	(0.017)	(0.017)	(0.082)	(0.082)	(0.034)	(0.034)	(0.032)	(0.032)
lnP	0.435***	0.431***	0.438**	0.443**	0.607***	0.623***	0.270***	0.285***
	(0.029)	(0.028)	(0.172)	(0.173)	(0.062)	(0.062)	(0.061)	(0.059)
lnURB	-0.107***	-0.077**	-0.003	0.009	-0.222***	-0.191**	-0.304***	-0.306**
	(0.034)	(0.034)	(0.061)	(0.055)	(0.077)	(0.077)	(0.116)	(0.119)
Constant	-1.839***	-1.287***	-0.680	-0.390	-3.678***	-2.730***	0.804	0.349
	(0.306)	(0.308)	(0.682)	(0.699)	(0.602)	(0.604)	(0.853)	(0.750)
Number of obs	2016	2016	644	644	672	672	700	700
AR (2)- chi square	0.600	0.600	0.720	0.720	0.580	0.580	0.520	0.520
prob > chi square	(0.754)	(0.754)	(0.573)	(0.573)	(0.785)	(0.785)	(0.872)	(0.872)
Hansen test-chi square	39.120	39.330	10.230	10.520	15.230	15.540	15.850	15.920
prob > chi square	(0.630)	(0.643)	(0.548)	(0.572)	(0.683)	(0.688)	(0.692)	(0.697)

[a] *L. lnEF* refers to last-period *lnEF*.
[b] All: Entire group. Low: Low-income group. Middle: Middle-income group. High: High-income group.
[c] t statistics in parentheses
[d] Statistical significance is indicated by: ***P < 0.01, **P < 0.05, *P < 0.1

income and high-income countries (-0.222 and -0.304, respectively), and more negative in high-income countries.

4. In both static and dynamic models, the energy intensity, GDP per capita and total population have impacted the ecological footprint positively. The three factors all impose pressure on the ecosystem, which is most pronounced in middle-income or high-income countries. For the entire group, the coefficient of industry share is significantly positive.
5. All the coefficients in dynamic model are smaller than those in static model, when comparing the absolute value, due to adding the lagged ecological footprint in dynamic model. The coefficient of industry share for high-income countries even becomes insignificant after taking the lagged ecological footprint into consideration. It is probably because of the lack of dynamism in the static model. Since the generation of ecological footprint is a dynamic and cumulative process, it is influenced by previous

factors, especially by previous technology because the effects of technology usually last for a long time. In static model, the effects of previous factors are ignored, which may confound the parameter estimates since previous factors are always positively correlated with current factors. This is the possible reason that the coefficients in static model are larger than the coefficients in dynamic model. Therefore, the parameters in dynamic model are more meaningful.

When using the share of service sector as a measure of structural change, similar conclusions can be drawn, including: (1) The estimated coefficient of lagged ecological footprint is positive and statistically significant for all groups; (2) The coefficient of urbanization is significantly negative in both static and dynamic models for all groups except low-income group; (3) The coefficient is insignificant in low-income countries but is significantly negative in middle- and high-income countries, and more negative in high-income countries; (4) The energy intensity, GDP per capita and total population have impacted the ecological footprint positively; (5) All the coefficients in dynamic model are smaller than those in static model, when comparing the absolute value. The only difference between the models using industry share and the models using service share is that the coefficients are not exactly the same. However, the minor difference does not matter since we do not care about the specific size of parameters, instead, we care about the difference among different income groups.

But it is not enough to just look at the size of parameters of urbanization for heterogeneity analysis, so we need to confirm that the difference in coefficient of urbanization is statistically significant among different income groups. We use dummy variables to do the t-test for the significant difference between parameters. Since the impact of urbanization is insignificant in low-income group, we only need to test if there is significant difference between the impact of urbanization in middle-income group and the impact of urbanization in high-income group. For both static and dynamic model, we test the difference using industry share and service share separately.

Table 8
Test results for difference between parameters.

	Static model		Dynamic model	
L. lnEF			0.537***	0.537***
			(0.022)	(0.022)
lnIND	0.145***		0.093***	
	(0.026)		(0.022)	
lnSV		-0.161***		-0.139***
		(0.031)		(0.027)
lnEI	0.396***	0.413***	0.150***	0.152***
	(0.029)	(0.028)	(0.026)	(0.026)
lnGDPPC	0.568***	0.578***	0.286***	0.295***
	(0.023)	(0.023)	(0.023)	(0.023)
lnP	1.095***	1.079***	0.467***	0.456***
	(0.039)	(0.039)	(0.042)	(0.041)
lnURB	-0.603***	-0.580***	-0.360***	-0.325***
	(0.126)	(0.132)	(0.115)	(0.115)
lnURB × *dm*	0.290**	0.335***	0.250**	0.271**
	(0.126)	(0.125)	(0.110)	(0.109)
dm	-1.112**	-1.281**	-1.073**	-1.172**
	(0.532)	(0.528)	(0.466)	(0.460)

[a] *L. lnEF* refers to last-period *lnEF*.
[b] t statistics in parentheses
[c] Statistical significance is indicated by: ***P < 0.01, **P < 0.05, *P < 0.1
[d] The null hypothesis of AR (2) test is accepted in dynamic model. The Hansen test shows that there is no over-identifying problem using GMM method.

$$lnEF_{it} = a_0 + a_1(lnIND_{it}) + a_2(lnEI_{it}) + a_3(lnGDPPC_{it}) + a_4(lnP_{it}) + a_5(lnURB_{it}) + a_6(lnURB_{it}) \times (dm) + a_7(dm) + e_{it} \tag{7}$$

$$lnEF_{it} = a_0 + a_1(lnSV_{it}) + a_2(lnEI_{it}) + a_3(lnGDPPC_{it}) + a_4(lnP_{it}) + a_5(lnURB_{it}) + a_6(lnURB_{it}) \times (dm) + a_7(dm) + e_{it} \tag{8}$$

$$lnEF_{it} = a_0 + \beta lnEF_{i,t-1} + a_1(lnIND_{it}) + a_2(lnEI_{it}) + a_3(lnGDPPC_{it}) + a_4(lnP_{it}) + a_5(lnURB_{it}) + a_6(lnURB_{it}) \times (dm) + a_7(dm) + e_{it} \tag{9}$$

$$lnEF_{it} = a_0 + \beta lnEF_{i,t-1} + a_1(lnSV_{it}) + a_2(lnEI_{it}) + a_3(lnGDPPC_{it}) + a_4(lnP_{it}) + a_5(lnURB_{it}) + a_6(lnURB_{it}) \times (dm) + a_7(dm) + e_{it} \tag{10}$$

where dm is a dummy variable, which equals to 1 for middle-income countries and 0 for high-income countries. If the parameter of $(lnURB_{it}) \times (dm)$ is significant, the difference between middle-income group and high-income group is statistically significant.

Fixed effect method is used for static model and system GMM is used for dynamic model.

As shown in Table 8, the parameter of cross term $lnURB \times dm$ is significant at 1% or 5% significance level in both static and dynamic model; therefore, the difference between middle-income group and high-income group is statistically significant.

Hence, urbanization showed an ecological protection effect, which was more pronounced in higher-income countries.

5. Discussion

As we have noted above, urbanization seems to generate an overall ecological protection effect since the elasticity of urbanization for the entire group is negative, whether in static model or dynamic model. Moreover, the ecological protection effect appears to be more pronounced in high-income countries as the elasticity is more negative in high-income countries, whether in static model or dynamic model. Therefore, we attempt to answer two questions: Why does urbanization show an ecological protection effect, and why does it seem to be more pronounced at the higher income level?

5.1. Why does urbanization show an ecological protection effect?

Some studies showed that urbanization led to increased energy use and carbon dioxide emissions, particularly in some countries where cities consumed the largest fractions of energy because of many large-scale firms and industrial activities centralized in urban areas, such as cities in China (Zhang and Lin, 2012) and in the Middle East and North African region (Al-mulali et al., 2013). However, in some European cities, industrial facilities have been transferred outside of city boundaries (Nijkamp and Perrels, 2014). Furthermore, energy is only an aspect of environmental impact. Consensus is still far to be reached about how to assess a comprehensive impact of urbanization on environment or ecosystem.

The ecological effect of urbanization is the synthesized result of the protection and degradation effects. As shown in Tables 7a and 7b, the elasticity of urbanization is −0.167 and −0.107 in static model and dynamic model respectively (using industry share as a measure of structural change). Since ecological footprint is used as an indicator of comprehensive ecological effect, a negative elasticity indicates that the ecological protection effect of urbanization outweighs its ecological degradation effects, which makes urbanization exhibit an ecological protection effect.

The concept of urbanization is not only demographic and spatial, but also social and economic. From the demographic and spatial perspectives, urbanization might lead to ecological degradation (e.g. slow recovery of forests). From the social and economic perspectives, urbanization aggregates a large trade network, thus expanding the market size without increasing the land area. The expansion of market size is expected to promote labor division, reduce transaction and transportation costs and, consequently, realize economies of scale and the ecological protection effect.

5.2. *Why does the protection effect seem more pronounced in higher income level countries?*

There are two relations between income level and ecological footprint. One is how income level, as an independent variable, affects the ecological footprint directly, which shows positive elasticity (0.520 in static model and 0.252 in dynamic model with industry share) in Tables 7a and 7b. Income level has directly negative impact on ecosystem. Another relation is how income level affects the ecological effect of urbanization, that is, the ecological effect of urbanization under different income levels. Our focus is the latter; therefore, the following part will answer the question: how does the income level influence the urban structure and function, thereby influencing the ecological effect of urbanization?

According to Tables 7a and 7b, the coefficients of urbanization are positive but insignificant in low-income group, significantly negative in middle-income group and more significantly negative in high-income group, whether in static model or dynamic model. Although the coefficients are different between static and dynamic models, they both illustrate the same conclusion, that is, the ecological protection effect seems to be more pronounced in higher income countries.

How does income level affect urbanization so as to make the ecological protection effect of urbanization more pronounced in higher income countries? In general, the income level may both boost the urbanization rate and optimize the urban structure and function. First, high-income cities always possess rich opportunities and superior public services, which is likely to entice people from rural areas to transfer to urban areas, boosting the urbanization rate. Second, the market mechanism, resource integration ability and globalization might be well improved in high-income cities; these adjust and optimize the urban structure and function.

5.2.1. *Improve market mechanism*

In a perfect market, the value of the ecosystem contains not only the direct use value but also the indirect, spiritual and long-term values, although these are difficult to measure. Using the carbon uptake land as an example, it is the productive land and sea area required to sequester carbon dioxide emissions; thus, it is not a real existing land type, which makes its value difficult to measure because its value contains both the economic costs and the environmental costs caused by carbon dioxide emissions.

As the income level increases, the market mechanism, particularly in highly urbanized areas, is expected to be gradually improved. Accordingly, the value of the ecosystem tends to be fully evaluated by internalizing the indirect costs of utilizing the ecosystem, and the ecological value may be endowed with economic scarcity, which will increase the price and then restrain the demand and pressures on ecosystem.

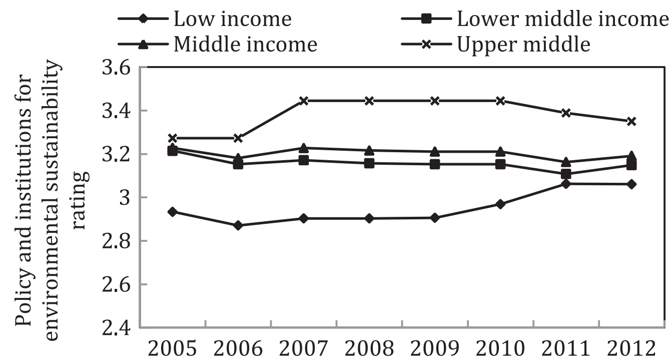

Fig. 1. Policy and institutions for environmental sustainability rating in low-income, lower-middle-income, middle-income and upper-middle-income countries. High-income countries are not included in the rating system in the World Bank. 1=lowest, 6= highest.

5.2.2. *Enhance resource utilization efficiency*

Cities are expected to become greener with higher resource utilization efficiency as a result of economic development. Cities in which industrial agglomeration occurs are likely to be much more positively influenced by the resource utilization efficiency than rural areas. Therefore, economic development may promote resource utilization efficiency and then enhance the ecological protection effect of urbanization.

In addition, the resource recycling industry might become an emerging industry because of economic development. The resource recycling industry is currently dominated by high-income countries, which accounts for 70% of the global resource recycling industry (Respect Marketing Research Inc, 2011).

5.2.3. *Increase environmental awareness*

The environmental awareness of both government and urban residents may increase because of economic development.

Regarding government, economic development could ensure its strong fiscal capacity to formulate environmental policy, implement environmental protection and improve regulatory mechanisms. This may play a significant role in the urban development pattern. The Policy and Institutions for Environmental Sustainability Ratings showed a strong relation between the environmental policy score and income level: the higher the income level was, the higher the score was (Fig. 1).

Taking a specific country for example, in 2013, Luxembourg, the richest country in Europe with the highest GDP per capita, invested 1.2% of GDP and 2.6% of total government expenditure on environmental protection. In contrast, Croatia, one of the poorest countries in Europe with the lowest GDP per capita, only invested 0.4% of GDP and 0.9% of total government expenditure on environmental protection (Eurostat, 2015). Such phenomenon can be seen in many countries (Eurostat, 2015).

The gap of ecological policy between urban and rural areas may exist. Taking China as an example, government expenditure spending on cities' environmental infrastructure (including sewage treatment facility) over the period from 1998 to 2007 accounted for 51.68% of the total government environmental protection expenditure (China Environment Yearbook, 2009). Sewage treatment rates in urban areas are 35-59 times higher than treatment rates in rural areas in 2007 (China Urban-Rural Construction Statistical Yearbook, 2007).

Regarding residents, a high-income level may lead people to focus on sustainable development, particularly for urban residents, who have a higher requirement for environmental quality after their material living conditions have been improved. Furthermore, as market participants, they could use market mechanisms to impose pressure on firms to force them to implement a green transformation by preferring eco-friendly goods and rejecting eco-unfriendly goods.

5.2.4. Promote economic globalization

The urbanization process is viewed as the theatre of economic globalization. First, economic globalization facilitates the labor division across countries and adjusts the economic structure in high-income countries. Consequently, some high-income countries tend to invest greatly in high-tech and high value-added industries. Evidence supports the reallocation of energy-intensive industries to low-income countries (Copeland and Taylor, 2003). Second, natural resources, as a main production input, are relocated worldwide because of economic globalization; this is called “resource globalization”, which is realized through resource transactions, resource leases, resource exploration and the assignment of exploitation rights. Hence, economic globalization, which occurs mainly in the urbanization process, has reallocated eco-unfriendly industries from high-income cities to low-income cities; therefore, economic globalization has a positive impact on the ecological effect of urbanization in high-income countries.

The improved effect of urbanization in high-income countries is therefore only one side of the coin. While the increased attention to environmental protection may have boosted local efficiency in resource use, investments on environmental technologies, improved infrastructures and market dynamics (e.g. online shopping), the transfer of high-energy industries and the increased pressure on resource extraction in low-income countries generates a burden shift. The increasing environmental awareness and education investments associated to urban systems are expected to orient production and consumption towards increased recycling of mineral resources, increased use of renewable energy, increased recycling and better treatment of municipal solid waste and wastewater, so that the indirect pressure on surrounding regional areas and low-income countries is decreased. Furthermore, the increased awareness of the impacts generated in far-away areas should lead high-income countries to more environmental friendly behavior and economic strategies in those areas where impacts are heavier (e.g. the European Union has forbidden any disposal of WEEE, Waste Electric and Electronic Equipment, outside of the EU, requiring them to be treated, recycled and disposed of internally). In so doing, increasing urbanization-driven wealth and welfare in high-income countries would also translate into actually increased wellbeing and environmental protection in low-income areas.

6. Conclusion and policy implications

Based on panel data that include 72 countries during the period from 1980 to 2008, the STIRPAT model is used to evaluate the impact of urbanization on the ecological footprint. When compared with existing studies, this paper provides interesting improvements. First, instead of focusing on a single environmental effect of urbanization, we use the ecological footprint as an indicator to reflect the comprehensive impact of urbanization on the ecosystem directly. Second, we emphasize the “heterogeneity” of the ecological effect of urbanization across income groups by dividing the entire group into low-income, middle-income and high-income groups. Third, we measure the effects of urbanization at the global level, instead of estimating the ecological effects of urbanization in only one country.

The results show the following: (1) the estimated coefficient of lagged ecological footprint is significantly positive for all groups. The generation of ecological footprint is a dynamic and cumulative process; (2) at the global level: the ecological elasticity of the urbanization rate is negative; (3) in low-income group: the elasticity is insignificant; and (4) in middle-income and high-income groups: the elasticity is negative, and it is more negative in high-income group. Therefore, we can conclude that urbanization shows an ecological protection effect, which is more pronounced in higher-income countries.

To explain the results, we answer two questions: why does urbanization show an ecological protection effect, and why does the protection effect seem more pronounced where the income level is higher?

For the first question, we think the reason is that the urbanization is a process where economies of scale and industry agglomeration are promoted. For the second question, we propose a specific influence mechanism of the income level on the ecological effect of urbanization: a high-income level is expected to improve market mechanisms in cities, enhance resource utilization efficiency, increase government's and urban residents' environmental awareness and promote economic globalization. Consequently, urbanization is not only urban population swell and urban land expansion but also the optimization of urban structure and functions, thus making its ecological protection effect more pronounced. For this to happen, policies to prevent burden-shift from high-income to low-income areas or countries need to be enforced.

Besides, the difference of results between static model and dynamic model suggests that ignoring the effects of previous factors may confound the parameter estimates. Therefore, dynamic model can give us more meaningful results than static model, especially when we are analyzing environmental impacts since some factors, such as technology and capital, always play a role in long-term environmental change. Hence, when we are examining the effects of environmental policies, we should not only consider the short-term effects, but also the long-term effects.

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