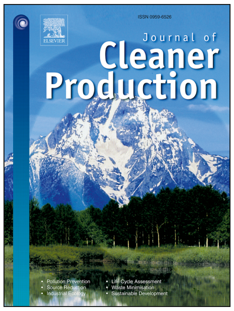

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Dynamics of material productivity and socioeconomic factors based on auto-regressive distributed lag model in China

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Abstract

Material productivity (MP), measured as economic output (such as Gross Domestic Product, GDP) per corresponding material input, is gained significant interest of becoming a widespread environmental sustainability indicator. The study of MP's dynamics is very important for policy-making on how to improve MP. This paper applies the auto-regressive distributed lag (ARDL) model to investigate the dynamic impacts of energy intensity for secondary industry (SEI), tertiary industry value added per GDP (TVA), trade openness (TO) and domestic extraction per capita (DEC) on MP in the case of China during the period from 1980-2010. The validated and robust results of the model confirm the existence of cointegration among the variables both in the long and short run. The impacts of selected socioeconomic factors can be summarized as follows: 1) In the long run, an SEI decrease driven by technology improvement is found to be the main driver of MP, and a 1% decrease in SEI results in an 0.432% increase in MP; 2) The magnitude of the impact of TVA on MP is higher over the short run than over the long run; 3) TO can reluctantly promote MP both in the long and short run; 4) DEC exhibits fundamentally different behaviors in the long and short run. DEC is not a strongly significant factor for MP, and the magnitude of the impact is very weak in the long run. However, it has the greatest negative impact on MP in the short run, as a 1% increase in DEC results in a 0.519% decrease in MP, which demonstrates that the marginal revenue of resource input has already dramatically declined. These insights from the study could be considerably helpful for sustainable resource

management and material productivity enhancement.

Keywords: material productivity, socioeconomic factors, ARDL (auto-regressive distributed lag), China

Acronyms

GDP	Gross Domestic Product
ARDL	Auto-regressive distributed lag
IDA	Index decomposition analysis
MFA	Material flow analysis
GCI	Growth competitive index
DMC	Domestic material consumption
EW-MFAcc	Economy-wide material flow accounting
ECM	Error correction model
UCB	Upper critical bound
LCB	Lower critical bound
SERI	Sustainable Europe Research Institute
NBS	National Bureau Of Statistics
VAR	Vector autoregression
T-Y	Toda-Yamamoto

Nomenclature

MP	Material productivity, US \$/ton
SEI	Energy intensity for secondary industry, 10000 ton of standard coal equivalent
TVA	Tertiary industry value added per GDP, %
TO	Trade openness, US \$
DEC	Domestic extraction per capita, ton/person

1. Introduction

The transformation and flow of natural resources function as the material foundation for the world economy as well as the link between human activities and environmental impacts [1]. However, since industrialization, natural resource consumption has risen sharply and thus has currently become a principal constraint to sustainable development. Meanwhile, excessive and insufficient material utilization lead to serious environmental issues such as climate change, air and water pollution, desertification, biodiversity loss and ecosystem degradation [2]. Material productivity (MP), measured as economic output (such as Gross Domestic Product, GDP) per corresponding material input, now becomes a widespread environmental sustainability indicator for the measurement and description of national material utilization efficiency in academia [3]. And it has to be acknowledged that material productivity also has the limitations similar to other efficiency indicators which may lead to the Jevons paradox [4, 5]. Nevertheless, as an integrated quantitative evaluating indicator, it has been as a popular topic that recently gained significant interest in societal and governmental documents [6-10]. Improving material productivity can create more economic benefits with less natural resources which to some extent could be an appropriate way to solve collisions between future increasing demand and limited natural resources [11].

There is no doubt that energy as the most significant type of natural resource has an extremely important strategic position in the national economy. Hashimoto et al. [12] have stated that reduction in energy intensity means that goods and services must be produced with less energy use and thus probably affected Japanese material productivity. Furthermore, a decline of energy intensity can partly characterize technological improvements in a broader sense [12,13]. Economic structure, which generates very different amounts of value added per ton of resource input, is another main factor in what might have changed national material productivity [11-16]. In addition to economic structure, Gilijum et al. [16] have also proposed that international trade and resource endowments play a major role in material productivity on the national level. In summarizing all of the available literature on examining the factors influencing material productivity [3, 11-18], previous studies have fallen into two categories. On the one hand, simple regression analysis has been used to elaborate on factors influencing material productivity based on cross-sectional data with a single time point mainly in developed countries [3, 11, 13-18]. On the other hand, index decomposition analysis (IDA) has been used to explain the influencing dynamics of Japanese material productivity [12]. IDA is a technique that emphasizes the decomposition of the indicator (for example, material productivity) into the different factors described in a series multiplication equation. No previous studies have focused on estimating the dynamic impacts among selected influencing factors on material productivity in China.

China, as the biggest emerging economy, has made remarkable achievements in social and economic development with its unprecedented consumption of natural resources since the initiated economic reforms in 1978 and, consequently, with a series of environmental issues. In 2008, China's total material consumption of 22.6 billion tons accounted for 32% of the world's total and made it by far the world's greatest consumer of primary materials, nearly fourfold the consumption of the USA, which was the second ranked consumer [19]. Therefore, it is urgent to change the economic growth pattern from high growth of high consumption to a more sustainable growth path. To accelerate the transformation, the Chinese government has already proposed improving material productivity by 15% over the period of 2011-2015 [10]. The improvement of material productivity in China also greatly promotes the world's efforts in resource conservation and environmental protection.

The main objective of this article is to investigate the long- and short-run impacts between material productivity and selected socioeconomic factors, such as energy intensity, economic structure, international trade and resource endowment in the case of China by using the auto-regressive distributed lag (ARDL) model over the period of 1980-2010. Compared to IDA, ARDL is preferable for examining dynamics of material productivity due to its following two advantages. First, ARDL, as an econometric tool, is relatively flexible in choosing explanatory variable. Second, it can quantify the long- and short-run impacts on material productivity. In the case of China, the selected time range reflects the rapid process of industrialization with a large consumption of natural resources and reveals typical emerging economies' developmental trajectories. There is no doubt that ARDL will be of vital importance during the transition of China's future development patterns through studying what drives material productivity during this period of time. Section 2 is the literature review. Section 3 describes the methodology and data; this section introduces the definition of material productivity, choice of explanatory variables, description of model and data sources. The empirical results are presented in section 4, and following are our conclusions and discussions.

2. Review of literature

Previous studies have focused on methodological foundations and accounting methods of Material Flow Analysis (MFA) [20-22]. Studies examining the factors influencing material productivity are few, and this topic is relatively under-researched. For the methodology, regression analysis is the main tool that has been used to elaborate on factors influencing material productivity. Van der Voet et al. [15] presented the first regression analysis to estimate the influences of socioeconomic variables on material productivity by using panel data from the EU. They stated that the differences in material productivity can be attributed in large part to income level (GDP per capita) and the structure of the economy. More recently, several authors [3, 11, 17, 18] also have suggested income level as a critical factor for a nation's material productivity due to associated technology improvements driven by economic development [23]. However, there is also an objection regarding income level as a factor for material productivity. They believe that income level can mask the effects of others [9]. Bleischwitz et al. [13, 14] have elucidated that energy use and economic structure are the main factors that have changed the EU's material productivity. Energy use has a high significance for resource use per capita as well as material productivity. The construction and service sectors also have an influence on the resource intensity of economies. In addition to economic structure, Gilijum et al. [16] have proposed that international trade and resource endowments play a major role in material productivity on the national level. Bleischwitz et al. [13, 14] and Wiedmann et al. [18] have identified that the growth competitiveness index (GCI) and population density are two additional influence factors, respectively. Gan et al. [11] have illustrated eighteen potential variables from six subgroups that could have affected material productivity and have demonstrated five significant factors, including income level, population density, economic structure, energy structure and raw material trade.

Index decomposition analysis (IDA) is another choice that can be used to explain the influencing dynamics of material productivity. Hashimoto et al. [12] have elucidated four factors that have changed Japanese material productivity by decomposition analysis. The analysis emphasizes decomposing resource-use intensity into the factors of recycling, induced material-use intensity, demand structure, and average propensity to import.

There are few studies on the dynamics of material productivity. Hence, this study conducted empirical analyses to explain the dynamic impacts of material productivity by considering the critical factors of energy intensity, economic structure, international trade and resource endowment, which will contribute to the need for research on the dynamics of material productivity.

3. Methodology and data

3.1 The definition of material productivity

The conception and notion of material productivity is relatively new, which illustrates the amount of economic value generated per ton of materials used[1]. When calculating a nation's material productivity, the numerator is quite easy to determine, that is, GDP. However, there are several indicators to measure resource input or use. In this study, the formula for material productivity is as follows:

$$MP = GDP / DMC \tag{1}$$

Domestic Material Consumption (DMC), which is defined as the total amount of materials directly used in an economy, is a major material flow indicator in the Economy-Wide Material Flow Accounting (EW-MFAcc) standard framework [20, 21]. It is calculated as domestic extraction, which measures the flows of materials that originate from the environment and physically enter the economic system for further processing or direct consumption, added to physical imports and subtracting physical exports. GDP/DMC is also the headline indicator of the EC's Roadmap to a Resource Efficient Europe[24].

3.2 The choice of potential explanatory variables

When choosing potential influencing factors, this study focus on variables that can represent

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[1] http://www.materialflows.net/glossary/mfa/

the current situation of the socioeconomic and technological system in China; in addition, these factors should affect national material consumption. At the same time, combined with previous research, this study includes factors from the following four categories:

- Technological progress: Technology improvement is a key factor in material productivity [3]. However, the measurement of the general status of scientific and technological progress in a nation is inconclusive. Several previous studies have suggested that GDP per capita[3, 11, 15, 17, 18], journal article publication (per 1000 persons), agricultural machinery (tractors per 100 square kilometers of arable land)[9] and total number of patent applications [25-27] might be appropriate to indicate national scientific and technological progress. In this article, we chose energy intensity for secondary industry (SEI) as the factor for two main reasons. First, there is a direct and strong connection between technological improvement and energy intensity (or efficiency). Technological improvement is crucial for promoting energy efficiency [28-30]. On the other hand, the chosen variable is more realistic and controllable than other variables for the current status of China over the study period. During the past few decades, China's GDP per capita increased by 12 times with an annual growth rate of nearly 9%, which is mostly attributed to a giant leap in industry and manufacturing. Therefore, energy intensity is appropriate for representing technological progress over the study period. To measure the relatively independent impact of technological improvement, we focus on energy intensity as a secondary industry, which excludes the impact of a drop in energy intensity resulting from structural adjustment from a secondary industry to a tertiary industry.
- Economic structure: Several authors have suggested that as the ratio of services and manufacturing rises in a national economy and, meanwhile, as the ratio of material-consuming agriculture and extractive industry declines, material productivity rises [31]. This implies that economic structure apparently has a significant effect on material productivity. Because Chinese secondary industry structure that is measured as the added value of a share of GDP only changed slightly from 47.9% in 1980 to 46.2% in 2010, in this study, we chose tertiary industry value added per GDP (TVA) to indicate the structure of the economy.

- International trade: There is also a vast body of studies investigating the impact of trade openness on economic growth in the long run [32]. On the one hand, trade openness can promote economic growth based on the comparative advantage of international specialization in the international market in the case of many nations. On the other hand, international trade can increase market competitiveness and thus improve efficiency of material utilization in local countries [33]. Furthermore, trade liberalization can promote the diffusion of technology from developed countries to less developed countries [34]. In this study, we incorporate trade openness (TO) into our empirical model to explore the nexus.
- Resource endowment and pressure: China's rapid economic growth during 1980-2010 is accompanied by huge consumption of natural resources from either domestic extraction or international trade. According to Sustainable European Resource Institute (SERI), China's domestic extraction was 227 hundred million tons in 2010, 3.7 times the volume of the US, which was the second largest county in resource extraction. High-speed development requires high resource input and conversely leads to resource pressure. In fact, there is a so-called phenomenon, the "curse of natural resources," in which countries rich in natural resources tend to show poorer growth than those with a relative scarcity of natural resources, that emerged in the late 20th century [35-37]. Although there is a question to whether natural resources are a curse for growth, the jury is still out [38], as a nation's DE, which can measure the abundance of its natural resources, should be an important factor for a nation's economic growth and thus its material productivity. In this study, domestic extraction per capital (DEC) is selected to represent the resource endowment and resource pressure of China.

3.3 The description of empirical model

The purpose of the present empirical investigation is to expose the relationship between material productivity and selected influencing factors in the case of China using annual data over the period of 1980-2010. Initially, unit root tests are used to check for the stationarity (or the order of integration) of data to avoid spurious regression, and the results of the unit root test will provide a basis for cointegration. This study employs the auto-regressive distributed lag (ARDL) bounds testing approach instead of other conventional cointegration methods, for example Engle and Granger (E-G) [39] and Johansen method [40]. E-G is a cointegration technique for bivariate analysis. Conversely, Johansen method is known as a system-based approach. This approach is more efficient than E-G approach as it offers multivariate analysis. Furthermore, the Johansen approach can reduce omitted lagged variables bias by including the lag in the estimation. However, this approach is also criticized because it is highly sensitive to the number of chosen lags [41]. Furthermore, it is also hard for interpretation when the model has more than one cointegration vector. More importantly, these approaches are only valid with the same order of integration. In the case of mixed orders of variables, the validity of both E-G and Johansen approach are challenged.

By comparison, the ARDL approach is preferable due to the following advantages [42]. On one hand, it is not strict in the integrating order of variables as long as no variable is stationary at order 2. On the other hand, Alfere [43] presented that this approach is superior and can provide consistent results for a small sample through Monte Carlo simulations. This method has been also commonly reported in recent literatures for examining the relationship among economic growth, energy emissions and other socioeconomic factors (such as income, trade and population) [44-48]. Furthermore, it has also been used in measurement for environmental quality related indicators (such as sandy desertification and deforestation) [49, 50].

The following is the basic mathematical representation of ARDL model.

$$Y_t = \alpha_0 + \alpha_T T + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=0}^{q} \gamma_j X_{t-j} + \mu_t \qquad (2)$$

Generally, the ARDL model can convert into an error correction model (ECM) which are presented below:

$$\Delta Y_t = \alpha_0 + \alpha_T T + \beta_Y Y_{t-1} + \gamma_X X_{t-1} + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \sum_{j=0}^{q} \gamma_j \Delta X_{t-j} + \mu_t \qquad (3)$$

We transformed the regression model by investigating variables in our case in logarithm linear functional form, which is specified as follows:

$$\ln MP_t = a_0 + a_1 \ln SEI_t + a_2 \ln TVA_t + a_3 \ln TO_t + a_4 \ln DEC_t + u_t \qquad (4)$$

Where MP is material productivity; SEI is energy intensity for secondary industry; TVA is territory value added per GDP; TO is trade openness; DEC is domestic extraction per capita; and the subscript t denotes the time period. a_0 is a constant, and u_t is a disturbance term supposed to be identically, independently and normally distributed. The constant parameters a_1, a_2, a_3 and a_4 are the elasticities of output with respect to SEI, TVA, TO and DEC, respectively. Eq. (4) describes the possible long-run equilibrium relationship between material productivity and selected variables. Furthermore, the short-run dynamic behavior of these variables also suggests that past changes in the variables, including useful information that can be used to predict future changes in output, here comprise material productivity. The short-run dynamics and the long-run equilibrium relationships of the ARDL model can be colligated into a dynamic unrestricted ECM where we can test the cointegration relationship. The ARDL version of the unrestricted ECM can be specified as follows:

$$\begin{aligned}\Delta\ln MP_t &= \lambda_0 + \lambda_t t + \lambda_{MP}\ln MP_{t-1} + \lambda_{SEI}\ln SEI_{t-1} + \lambda_{TVA}\ln TVA_{t-1} + \lambda_{TO}\ln TO_{t-1} + \lambda_{DEC}\ln DEC_{t-1}\\ &+\sum_{i=1}^{p}\lambda_i\Delta\ln MP_{t-i} + \sum_{j=0}^{q}\lambda_j\Delta\ln SEI_{t-j} + \sum_{k=0}^{r}\lambda_k\Delta\ln TVA_{t-k} + \sum_{l=0}^{s}\lambda_l\Delta\ln TO_{t-l} + \sum_{m=0}^{w}\lambda_m\Delta\ln DEC_{t-m} + \mu_t\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta\ln SEI_t &= \theta_0 + \theta_t t + \theta_{MP}\ln MP_{t-1} + \theta_{SEI}\ln SEI_{t-1} + \theta_{TVA}\ln TVA_{t-1} + \theta_{TO}\ln TO_{t-1} + \theta_{DEC}\ln DEC_{t-1}\\ &+\sum_{i=1}^{p}\theta_i\Delta\ln SEI_{t-i} + \sum_{j=0}^{q}\theta_j\Delta\ln MP_{t-j} + \sum_{k=0}^{r}\theta_k\Delta\ln TVA_{t-k} + \sum_{l=0}^{s}\theta_l\Delta\ln TO_{t-l} + \sum_{m=0}^{w}\theta_m\Delta\ln DEC_{t-m} + \mu_t\end{aligned} \tag{6}$$

$$\begin{aligned}\Delta\ln TVA_t &= \rho_0 + \rho_t t + \rho_{MP}\ln MP_{t-1} + \rho_{SEI}\ln SEI_{t-1} + \rho_{TVA}\ln TVA_{t-1} + \rho_{TO}\ln TO_{t-1} + \rho_{DEC}\ln DEC_{t-1}\\ &+\sum_{i=1}^{p}\rho_i\Delta\ln TVA_{t-i} + \sum_{j=0}^{p}\rho_j\Delta\ln MP_{t-j} + \sum_{k=0}^{r}\rho_k\Delta\ln SEI_{t-k} + \sum_{l=0}^{s}\rho_l\Delta\ln TO_{t-l} + \sum_{m=0}^{w}\rho_m\Delta\ln DEC_{t-m} + \mu_t\end{aligned} \tag{7}$$

$$\begin{aligned}\Delta\ln TO_t &= \sigma_0 + \sigma_t t + \sigma_{MP}\ln MP_{t-1} + \sigma_{SEI}\ln SEI_{t-1} + \sigma_{TVA}\ln TVA_{t-1} + \sigma_{TO}\ln TO_{t-1} + \sigma_{DEC}\ln DEC_{t-1}\\ &+\sum_{i=1}^{p}\sigma_i\Delta\ln TO_{t-i} + \sum_{j=0}^{q}\sigma_j\Delta\ln MP_{t-j} + \sum_{k=0}^{r}\sigma_k\Delta\ln SEI_{t-k} + \sum_{l=0}^{s}\sigma_l\Delta\ln TVA_{t-l} + \sum_{m=0}^{w}\sigma_m\Delta\ln DEC_{t-m} + \mu_t\end{aligned}$$

(8)

$$\Delta\ln DEC_t = \varsigma_0 + \varsigma_t t + \varsigma_{MP}\ln MP_{t-1} + \varsigma_{SEI}\ln SEI_{t-1} + \varsigma_{TVA}\ln TVA_{t-1} + \varsigma_{TO}\ln TO_{t-1} + \varsigma_{DE}\ln DEC_{t-1}$$
$$+\sum_{i=1}^{p}\varsigma_i\Delta\ln DEC_{t-i} + \sum_{j=0}^{q}\varsigma_j\Delta\ln MP_{t-j} + \sum_{k=0}^{r}\varsigma_k\Delta\ln SEI_{t-k} + \sum_{l=0}^{s}\varsigma_l\Delta\ln TVA_{t-l} + \sum_{m=0}^{w}\varsigma_m\Delta\ln TO_{t-m} + \mu_t$$

(9)

Where Δ is the differenced operator and μ_t is residual term in period t. Then, we can compute the F-statistic depending on the appropriate selection of lag length of the variables to compare with the critical bounds of Pesaran et al. [42] to test whether the long-run equilibrium relationship exists or not. The critical bounds generated by Pesaran et al. are two asymptotic critical values called the upper critical bound (UCB) and the lower critical bound (LCB). The null hypothesis of no long-run relationship between the variables in Eq. (4) is H_0: $\lambda_{MP} = \lambda_{SEI} = \lambda_{TVA} = \lambda_{TO} = \lambda_{DEC} = 0$ against the alternate hypothesis of long-run relationship H_1: $\lambda_{MP} \neq \lambda_{SEI} \neq \lambda_{TVA} \neq \lambda_{TO} \neq \lambda_{DEC} \neq 0$. We should compute the value of F-statistic in turn for Eq. (5)-(9), i.e., $F_{\ln MP}$(lnMP|lnSEI, lnTVA, lnTO, lnDEC), $F_{\ln SEI}$(lnSEI|lnMP, lnTVA, lnTO, lnDEC), $F_{\ln TVA}$(lnTVA|lnSEI, lnMP, lnTO, lnDEC), $F_{\ln TO}$(lnTO|lnSEI, lnTVA, lnMP, lnDEC), $F_{\ln DEC}$(lnDEC|lnSEI, lnTVA, lnTO, lnMP). The rules of decision of cointegration are as follows: if the computed F-statistic is more than UCB, then we conclude there is cointegration between the variables. If the computed F-statistic is less than LCB, then there is no cointegration among the variables. The decision of integration is inconclusive if the computed F-statistic is between LCB and UCB. It is worth mentioning that the critical value of Pesaran et al. [42] is not appropriate for a small sample. Therefore, we have adopted the lower and upper critical bounds of Narayan [51].

Once it is confirmed that a long-run relationship exists among the variables, in the next step, we should move to estimating the impacts among the variables. Taking an example of material productivity as dependent variables, the long- and short-run dynamic equations can be specified as follows:

$$\ln MP_t = \alpha_0 + \alpha_T T + \sum_{i=1}^{p}\alpha_i \ln MP_{t-i} + \sum_{j=0}^{q}\alpha_j \ln SEI_{t-j} + \sum_{k=0}^{r}\alpha_k \ln TVA_{t-k} + \sum_{l=0}^{s}\alpha_l \ln TO_{t-l} + \sum_{m=0}^{w}\alpha_m \ln DEC_{t-m} + \mu_t \qquad (10)$$

$$\Delta \ln MP_t = \beta_0 + \beta_T T + \sum_{i=1}^{p}\beta_i \Delta \ln MP_{t-i} + \sum_{j=0}^{q}\beta_j \Delta \ln SEI_{t-j} + \sum_{k=0}^{r}\beta_k \Delta \ln TVA_{t-k} + \sum_{l=0}^{s}\beta_l \Delta \ln TO_{t-l} + \sum_{m=0}^{w}\beta_m \Delta \ln DEC_{t-m} + \eta_1 ECT_{t-1} + \mu_t \qquad (11)$$

Where Δ is the differenced operator and μ_t are residual terms and are assumed to be identically, independently and normally distributed. η_1 is the coefficient of error correction term (ECT), defined as:

$$ECT = \ln MP_t - \alpha_0 - \alpha_T T - \sum_{i=1}^{p}\alpha_i \ln MP_{t-i} - \sum_{j=0}^{q}\alpha_j \ln SEI_{t-j} - \sum_{k=0}^{r}\alpha_k \ln TVA_{t-k} - \sum_{l=0}^{s}\alpha_l \ln TO_{t-l} - \sum_{m=0}^{w}\alpha_m \ln DEC_{t-m} \qquad (12)$$

ECT_{t-1} is the lagged residual term generated from the long-run relationship. The long-run relationship can be further validated by the statistical significance of ECT_{t-1}. The estimator of ECT_{t-1} also demonstrates the speed of convergence rate from the short run towards the long-run equilibrium path.

3.4 Data sources

This article employs annual data for China over the period from 1980 to 2010. The data on DMC and domestic extraction are from Sustainable Europe Research Institute (SERI) [52]. The data on energy consumption for secondary industries is from the China Energy Statistical Yearbook [53]. The data on secondary and tertiary industry value added per GDP are from the

National Bureau of Statistics (NBS) in China [54]. In addition, this study considers trade openness (TO), which is measured as the sum of the proportion of real exports and imports in GDP, and the data can be obtained from World Bank [55]. Finally, the data on GDP and population are also from World Bank [55]. All of our data using a model can be directly obtained from the above-mentioned authorities or can be simply calculated, as, for example, SEI.

4. Empirical results

4.1 Unit root tests and lag selection

Prior to testing for cointegration, this study applies augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Dickey-Fuller generalized least squares (DF-GLS) and the KPSS unit root tests to test the order of integration. The assumption of ARDL bounds testing requires that all variables should be integrated at purely order 0, purely order 1 or mutually cointegrated. Therefore, it is necessary to test the integrating order of all variables before applying ARDL bounds testing; otherwise, the calculation of the F-statistic of ARDL becomes invalid [56]. The results of the unit root test are shown in Table 1, which shows that the logarithmic form of all variables, whether they are with Intercept or Intercept and trend, are at the non-stationary level. However, these variables become stationary after considering the first difference, which is confirmed by the vast majority of our unit root test approaches. Thus, all variables are indicated at order 1.

Table 1

Results of ADF, PP, DE-GLS and KPSS unit root tests with Intercept and Intercept and trend

	Variables	ADF	PP	DF-GLS	KPSS
Level (Z_t)					
Intercept	lnMP	-1.701	-1.762	0.675	1.59
	lnSEI	-0.954	-0.868	0.046	1.07
	lnTVA	-2.086	-1.988	-0.152	1.47
	lnTO	-1.622	-2.012	-0.714	1.43
	lnDEC	0.943	1.257	1.308	1.12
Intercept and	lnMP	-1.022	-0.713	-0.890	0.271

trend	lnSEI	-1.871	-1.510	-2.233	0.148
	lnTVA	-2.335	-1.705	-1.445	0.245
	lnTO	-2.202	-2.092	-1.956	0.156
	lnDEC	-1.657	-1.165	-1.915	0.146
1st difference (Z_t)					
Intercept	Δ lnMP	-4.069***	-4.069***	-4.140***	0.399
	Δ lnSEI	-2.915*	-3.360**	-3.347***	0.133
	Δ lnTVA	-3.438**	-3.672**	-3.814***	0.258
	Δ lnTO	-4.737***	-4.737***	-4.235***	0.221
	Δ lnDEC	-2.593	-3.370**	-2.512**	0.271
Intercept and trend	Δ lnMP	-4.435***	-4.435***	-4.544***	0.0928
	Δ lnSEI	-2.898	-3.304*	-3.393**	0.105
	Δ lnTVA	-4.140**	-3.946**	-4.080***	0.0511
	Δ lnTO	-4.792***	-4.792***	-4.929***	0.0521
	Δ lnDEC	-2.797	-3.421*	-3.680**	0.0906

(***), (**) and (*) indicate significance at the 1%, 5% and 10% level, respectively.

Lag selection is very important for the ARDL approach to cointegration. This study uses Schwarz information criterion to choose the optimum lag length. The results of lag length are reported in Table 2, which indicates that lag 1 is appropriate.

Table 2

Selection criteria of lag order of variables for the ARDL approach

Lag	LogL	LR	FPE	AIC	SC	HQ
0	118.105	NA	2.1e-10	-8.07893	-7.84103	-8.0062
1	292.455	348.7	5.1e-15	-18.7468	-17.3194^{a}	-18.3104^{a}
2	321.196	57.482	4.8e-15^{a}	-19.014	-16.3972	-18.214
3	351.721	61.049^{a}	5.6e-15	-19.4086^{a}	-15.6023	-18.245

LR: sequential modified LR test statistic (each test at the 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion.

[a] indicates lag order selected by the criterion.

4.2 Hypothesis test of the model

This study applies a diagnostic and stability test to check the model. The values of R^2 and Adjusted R^2 are 0.9985 and 0.9980, respectively, which means the model is well fitted. Table 3 reports the results of the diagnostic test of the ARDL model, showing that no serial correlation is found. Our empirical exercise also reveals that there are no problems of normality, functional error or heteroscedasticity.

Fig. 1 is the CUSUM (cumulative sum) and CUSUMQ (cumulative sum of squares) from a recursive estimation of the model. It shows that the model is stable, as the residuals are within the critical bounds at the 5% significance level.

Table 3

Diagnostic tests of the ARDL approach (1,0,1,0,1)

	T-statistic	p-value
A: Serial correlation CHSQ(1)	0.0057	0.941
B: Functional form CHSQ(1)	0.726	0.404
C: Normality CHSQ(2)	2.019	0.364
D: heteroscedasticity CHSQ(1)	0.398	0.533

A: Lagrange multiplier test of residual serial correlation

B: Ramsey's RESET test using the square of the fitted values

C: Based on a test of skewness and kurtosis of residuals

D: Based on the regression of squared residuals on squared fitted values

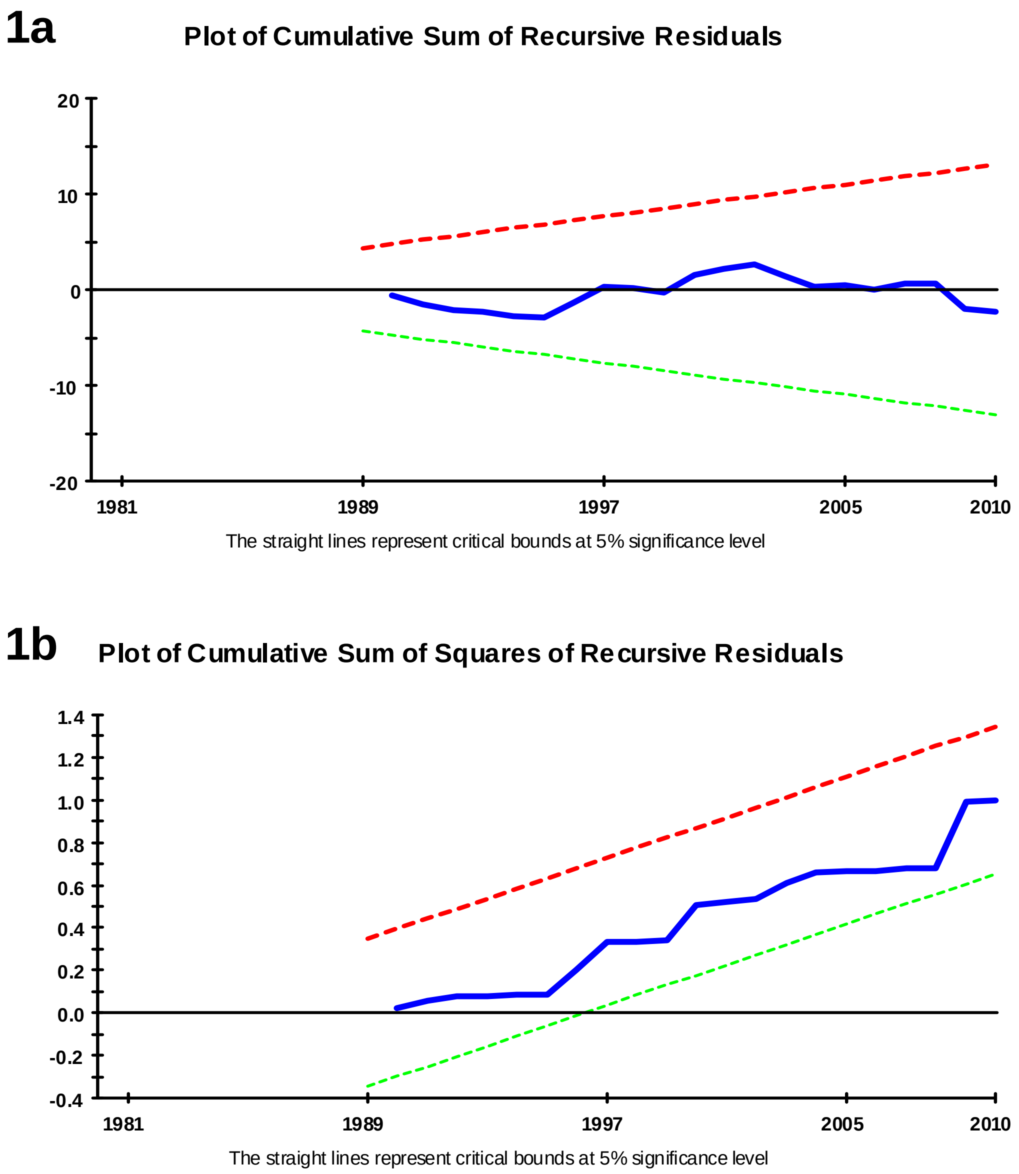

Fig. 1 Stability test of the ARDL model (1,0,1,0,1)

4.3 ARDL bounds test for cointegration

This study uses a Wald joint significance test (F-statistic) to examine the cointegration relationship. The results of the ARDL bounds testing and critical value according to Narayan [51] are reported in Table 3. The empirical evidence indicates that our computed F-statistics for $F_{\ln MP}$(lnMP|lnSEI, lnTVA, lnTO, lnDEC), $F_{\ln SEI}$(lnSEI|lnMP, lnTVA, lnTO, lnDEC), $F_{\ln TVA}$(lnTVA|lnSEI, lnMP, lnTO, lnDEC), $F_{\ln TO}$(lnTO|lnSEI, lnTVA, lnMP, lnDEC) and $F_{\ln DEC}$(lnDEC|lnSEI, lnTVA, lnTO, lnMP) are 5.2694, 1.3884, 1.70, 3.91 and 2.9635, respectively. For MP as a dependent variable, the value of F-statistics is larger than the upper bound critical value at the 5% significance level. It rejects the null hypothesis of no cointegration, which means that there is a long-run relationship among the variables when MP is a dependent variable. Nevertheless, when SEI, TVA and DEC are considered dependent variables, respectively, the calculated F-statistic falls below the lower bound critical value, implying the non-existence of a cointegration relationship. Conversely, when TO is considered a dependent variable, the computed F-statistic falls between the lower and the upper bound critical values; hence, the existence of a cointegration relationship is inconclusive at the 5% significance level.

Table 4

Results of the ARDL bounds test (equation (5)-(9))

Dependent variables	SBC Lag length	F-statistics	Outcome
F_{lnMP} (lnMP|lnSEI, lnTVA, lnTO, lnDEC)	1,0,1,0,1	5.2694**	Cointegration
F_{lnSEI} (lnSEI|lnMP, lnTVA, lnTO, lnDEC)	1,1,1,0,1	1.3884	No cointegration
F_{lnTVA} (lnTVA|lnSEI, lnMP, lnTO, lnDEC)	1,1,0,1,1	1.7000	No cointegration
F_{lnTO} (lnTO|lnSEI, lnTVA, lnMP, lnDEC)	1,1,1,1,1	3.9100	Inconclusive
F_{lnDEC} (lnDEC|lnSEI, lnTVA, lnTO, lnMP)	1,0,1,0,1	2.9635	No cointegration[2]
Critical value	I(0)	I(1)	
1% level	4.768	6.670	
5% level	3.354	4.774	
10% level	2.752	3.994	

(***), (**) and (*) indicate significance at the 1%, 5% and 10% level, respectively.

4.4 Long-run and short-run coefficients

After identifying a cointegration relationship among variables, this study proceeds to estimate the marginal impacts of SEI, TVA, TO and DEC on MP in the long and short run. Table 4 addresses long-run marginal impacts of the determinants of MP. Table 4 reveals a negative

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[2] At the 5% significance level

relationship between SEI and MP at the 1% significance level. It indicates that a 1% decline in SEI spurs a rise in MP of 0.432%, while everything else remains constant. The impact of TVA on MP is positive and is statistically significant at the 5% significance level. Everything else is constant, while a 1% increase in TVA causes a rise in MP of 0.226%. The relationship between TO and MP is positive and is statistically significant at the 1% significance level. The 0.148% rise in MP is stimulated by a 1% increase in TO, while everything else remains constant. Additionally, there is a weak long-run relationship between DEC and MP. The elasticity of DEC of MP is only 0.051 and is statistically significant at the 10% significance level, which implies that economic growth patterns through high material input are not sustainable in the long term.

Table 5

Long-run coefficients using the ARDL approach (1,0,1,0,1) selected based on Schwarz Bayesian Criterion; the dependent variable is lnMP.

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
lnSEI	-0.432***	0.040	-10.889[0.000]
lnTVA	0.226**	0.095	2.374[0.027]
lnTO	0.148***	0.041	3.597[0.002]
lnDEC	0.051*	0.027	1.886[0.073]
C	3.780***	0.259	14.614[0.000]

(***), (**) and (*) indicate significance at the 1%, 5% and 10% level, respectively.

Table 5 reports the results of the short dynamics of SEI, TVA, TO and DEC on MP. Over a short span of time, all variables contribute to material productivity significantly at the 1% level. A 1% decrease in SEI and DEC lead to a 0.236% and 0.519% increase in MP, respectively. Similarly, a 1% increase in TVA and TO lead a 0.341% and 0.081% increase in MP, proving that the marginal impact of exorbitant domestic extraction leads to a larger decrease in MP. Thus, it is urgent to change the economic growth pattern from high resource input to a more sustainable growth path, such as raising energy efficiency, accelerating structural adjustment and enlarging opening transactions. The negative and highly statistically significant estimate of ECM(-1) implies that 54.7% changes in material productivity are corrected by deviations in the short run towards the long-run equilibrium path for each year. In this model, short-run deviations in material productivity take 30 years to converge to the long-run equilibrium path.

Table 6

Error correction representation for ARDL (1,0,1,0,1) selected based on Schwarz Bayesian Criterion; the dependent variable is △lnMP.

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
△lnSEI	-0.236***	0.037	-6.366[0.000]
△lnTVA	0.341***	0.073	4.664[0.000]
△lnTO	0.081***	0.018	4.461[0.000]
△lnDEC	-0.519***	0.081	-6.389[0.000]
ECM(-1)	-0.547***	0.083	-6.582[0.000]

*** indicates significance at 1% level.

4.5 Toda-Yamamoto Granger causality analysis

This study applies the Toda-Yamamoto approach [57] based on the vector autoregression (VAR) model at various levels to investigate the direction of the causal relationship between these variables. The reason that I chose the T-Y approach based on the VAR model to test for Granger causality instead of a VECM Granger causality approach [58] depends on the following two aspects. First, the former approach is more appropriate for a small sample, especially when cointegration is a long-run phenomenon. On the other hand, the practice of pretesting for cointegration can result in severe over-rejections of the noncausal null, whereas overfitting (which is the T-Y approach chosen in our empirical case) results in better control of the Type I error probability with often little loss in power [59]. The causality between SEI, TVA, TO, DEC and MP, which would help policy makers in formulating a relative policy to improve material productivity for the long run, has already been proposed as an anticipated target in the Outline of the Twelfth Five-Year Plan for National Economic and Social Development [10]. Table 9 presents the empirical evidence causality relationships among these variables. The results suggest that a bidirectional causal relationship is found between TO and MP, DEC and MP, in the case of China over the study period of 1980-2011. This shows that MP has an extraordinarily distinct feedback to TO and DEC, combining the short- and long-run impacts of these two variables. The improvement of TO leads to an increase in MP, and MP can re-promote TO. Conversely, high domestic extraction leads to a decrease in material productivity in the short run and vice versa. Thus, it provides an effective “Forced” mechanism for China to accelerate the transformation of development patterns. There are also many unidirectional causalities when MP, TO and DEC are considered dependent variables. The most notable unidirectional causality is found running from SEI to MP because the variable has the largest (-0.432) negative impact on material productivity in the long run and also shows a stronger causal relationship compared to other variables. This implies that the government must concentrate more on launching a comprehensive energy policy and exploring new sources of improving energy efficiency. R&D and foreign direct investment activities should be encouraged in energy sectors. Structural adjustment should also be paid attention by the Chinese government for its relative strong short-run impacts (0.341) and causal relationship with material productivity.

Table 7

Results of the Toda-Yamamoto Granger causality test

Dependent variables	Direction of causality				
	lnMP	lnSEI	lnTVA	lnTO	lnDEC
lnMP	-	38.8177***	30.9349***	9.1432***	39.5099***
lnSEI	0.5010	-	0.4469	1.2650	0.8782
lnTVA	4.2325	0.5392	-	2.1086	1.4112
lnTO	13.5901***	9.8407**	14.1257***	-	1.5355
lnDEC	10.3885**	9.3986**	13.0056***	15.6127***	-

(***) and (**) indicate significance at the 1% and 5% level, respectively.

5. Conclusions and future research

The present study applied the auto-regressive distributed lag (ARDL) model to investigate the marginal impacts of four socioeconomic factors on material productivity in the long and short run in the case of China during the period of 1980-2010. The validity and robustness of model results were assessed through diagnostic tests, stability tests and the Gregory-Hansen cointegration test under the assumption of structural breaks. The T-Y approach based on vector autoregression (VAR) model at various levels was used to examine the direction of causal relationship between these variables.

Our empirical results confirmed the existence of a long-run cointegration relationship among these variables and have produced several interesting findings.

- Energy intensity for secondary industry (SEI) is a significant factor for material productivity both in the long and short run. Furthermore, it has the most remarkable impact on material productivity in the long run, as a 1% decrease in SEI results in a 0.432% increase in MP. It has proven that an energy intensity decrease driven by technological improvements enables better use of raw materials, which contributes to higher material productivity. Additionally, a very strong unidirectional causality from SEI to MP is found. Bleischwitz et al. reported that energy use has a high significance for resource use per capita as well as material productivity. This study also found that energy intensity has a direct link to material productivity. Therefore, it can be concluded that some synergies exist between climate and resource policies. This implies that the government must concentrate more on launching a comprehensive energy policy and exploring new sources of improving energy efficiency. R&D and foreign direct investment activities should be encouraged in energy sectors to promote technological improvements.
- Tertiary industry value added per GDP (TVA) also increases material productivity both in the long and short run. The magnitude of its impact on MP is higher over the short run than over the long run. Thus, this implies that structural adjustment of increasing tertiary industry proportion in our case should be paid more attention by the Chinese government in the short term. However, it should be paid attention to the transfer of industries from the focal country to other neighbouring countries in the process of structural adjustment. Recent studies have shown that the high material productivity in industrialized countries often comes at the expense of industrial relocation to neighbouring countries with laxer environmental regulation or cheaper labour costs [60-62]. Hence, it is necessary to strengthen international or regional cooperation, and jointly improve the material productivity.

- Trade openness (TO) is also a significant factor for material productivity, but the magnitude of its impact is weak both in the long and short run. It is worth mentioning that there is a bidirectional causal relationship between TO and MP. This demonstrates that the improvement of TO leads an increase in MP and that MP can re-promote TO. Trade openness produces rebound effects in material productivity. Thus, the government should enlarge opening transactions appropriately.
- Last but not least, domestic extraction per capita (DEC) has an extraordinarily distinct impact on material productivity in the long and short run. It is not a strongly significant factor for MP, and the magnitude of its impact is very weak. However, it has the greatest negative impact on material productivity in the short run, as a 1% decrease in DEC leads to a 0.519 increase in MP. This implies that the marginal impact of exorbitant domestic extraction leads to a dramatic decrease in material productivity. Therefore, it is urgent to change economic growth patterns from the past path of high resource input to a more sustainable growth path, such as raising energy efficiency, accelerating structural adjustment and enlarging opening transactions. There is also a bidirectional causal relationship between DEC and MP. The Chinese government has already proposed improvement of material productivity by 15% in 2011-2015. The proposed anticipated target provides an effective “Forced” mechanism for China to accelerate the transformation of development patterns.

The current study chose macroeconomic indicators of economic system based on the existing literature and theoretical framework, and constructed an econometric model to study on the impacts of China’s material productivity. It can be augmented to investigate the impacts of microcosmic behaviors on material productivity by agent-based modelling. There are many theoretical models would be probably suitable for further research in an agent-based setting [63, 64].

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