Long-term Relationship among the Generation of Municipal Solid Waste, Urbanization, Affluence and Prosperity of Tertiary Industry

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Abstract
Because of the ever fast improvement in people’s living standard and prosperity of city lives, how to effectively manage the MSW problems becomes the key for the sustainable development of China’s cities. This work uses the STIRPAT model to identify the different roles of population, people’s affluence, urbanization and prosperity of tertiary industry in contributing to the growth of MSW in China. The final results have shown that among all the factors, the prosperity of tertiary industry and increase in urbanization are identified as the most sensitive factors that contribute to the growth of MSW in China, and the urbanization is the only factor that negatively contribute to the growing MSW. By carefully analyzing the developing trends of population, people’s affluence, urbanization and tertiary industry in the future, it has been found that the generation of MSW is anticipated to continue growing, and encourage on efficiently classifying MSW after it generated and reusing them is one of the most important way for reducing the negative environmental impacts of mass MSW generation in cities.
Key words: MSW; URBANIZATION; STIRPAT

1. Introduction

With the rapid development of China’s economy, the urban citizen's living standard has been greatly improved, which also caused serious environmental problems. Among all these problems, the rubbish Siege phenomenon is one of the most urgent problems that need to be solved in order to make the cities to be better. The reasons that lead to the increase of municipal solid wastes (MSW) cover many aspects, including the rapid growth in population, wealth and the development of related service industries like logistics, catering and tourism. All of these factors jointly contributed to the rapid growth of MSW. However, the effects of these factors vary in large detail, it is very necessary to make clear which factor is most important in order to effectively control the MSW.

In regarding to the factors that contributing to the growth of MSW, there are many researches. According to the summary of Rotchana[1], which was concluded based on the research of Buenrostro[2], Lebersorger[3] and Purcell[4], the factors that contributing to the generation of MSW can be basically divided into 2 groups, that is the socio-economic factors and demographic factors. The socio-economic factors mainly include income, gross domestic product, expenditure, tax, employment, unemployment, number of overnight stays per habitant of tourists and business travelers, energy consumption, etc. The demographic factors mainly include population, population density, number of households, urbanization, household size, age of people, education and attitude, number of rooms of a habitant, infant mortality rate, life expectancy at birth, etc. However, the importance of these factors varied a lot depending on the regions and models selected to research [5-7].STIRPAT (Stochastic impacts by regression on population, affluence, and technology) model is a model developed by York to simulate the long-term relationship between the environment, population, affluence and technologies. Currently, the STIRPAT model is widely used for forecasting the GHG emission and tracing its affecting factors [8-11]. Because the MSWs are also caused by people's activities, the STIRPAT model is also useful for examining the driving forces of MSWs, however, it is very hard to find researches that deal with this problem. Although the methods that used to forecast the development of MSWs can also be used to identify the factors that contribute to the growth of MSWs, such as correlation analysis, group comparison, single regression analysis, multiple regression analysis, time-series analysis, input–output analysis, and system dynamics [12], only by the multiple regression analysis or time-series analysis can clearly identify the different importance of different factors when the data is sufficient. The STIRPAT model is a kind of time-series analysis model, which is different from other time-series analysis model in that the STIRPAT model is based on the solid theory that from the macro perspective, the environment is mainly impacted population growth, affluence and technology, all the other factors can be regarded as a subgroups of population, affluence or technology.

So in this work, the STRIPAT model was used to track the factors that contributing to the generation of China's MSW, by regressing the long-term relationship between the generation of China's MSW and its impacting factors, we want to identify the importance of different factors in controlling the future growth of China's MSW. The following part of this work is constructed as: part 2 introduces the STRIPAT model; part 3 illustrates the data collecting and processing; part 4 explains the results and part 5 concludes the work.

2. Methodology

2.1 STIRPAT model

The STIRPAT model was developed based on the IPAT model. The philosophy of IPAT model is that the environment is impacted by the growth of population, income and technologies used for economy, and the equation that used to describe this relationship is [13]

$$I = P \times A \times T \quad (1)$$

where I is expressed as environment impacts, such as all kinds of pollutants and also including MSWs; P is expressed as population, A is expressed as affluence, such as GDP capita, real income and others, while T is expressed as technologies that generate the environment impacts, which usually represented by economic structure, energy intensity and so on. It can be clearly seen from equation (1) that in IPAT model, the effects of population, income and technologies on environment are the same, this may not suitable for the real situation, obviously, their effects are different. So Dietz and Rosa's developed the STIRPAT model [14] to examine the different importance of P, A and T on the change of environment impacts, which can be expressed as

$$I = aP^b A^c T^d e \quad (2)$$

where a is the constant of the model, b, c and d are the coefficients, and e is the model residual error term.

Furthermore, equation (2) can be transformed into

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e \quad (3)$$

From equation (3), it can be seen that the elasticity of P, A and T to I can be represented by b, c and d, which implies that every 1% increase in P, A and T can result in a%, b% and c% increase in I respectively.

2.2 MSW STIRPAT model

In our work, because we want to use the STIRPAT model to simulate the factors that contributing to the growth of MSWs in China, the variable of MSW disposed (MSWD) was used to represent the environment impacts, the urban citizen's per capita disposable income (UIP) was used to represent the affluence. In regarding to the technologies leading to the growth of MSWs, the urbanization rate (UR) and the share of tertiary industries in the overall economies (TS) were selected, so the STIRPAT model constructed to reflect the factors that influencing the growth of MSW was

$$\ln MSVD = a + b\ln P + c\ln UIP + d\ln UR + e\ln TS + f \quad (4)$$

where a is the constant in the model, f is the model's residual error.

3 Data collection and processing

3.1 Data collection

The historical period of the data is from 1980 to 2012. The data on MSW disposed, urban citizen's per capita disposable income in 2009-2012 was collected from *China Statistical Yearbook 2010-2013*, and the data on MSW disposed in 1980-2008 was collected from *China Compendium of Statistics 1949-2008*. The data on population, urbanization was collected from *China Statistical Yearbook 2013.*

3.2 Processing

3.2.1 Unit Root Test

Before regress the long-term equilibrium relationships among all the variables in equation (4), we need to test the stationary of the time series of each variable, and this is called unit root test. Only if all the time series passed the unit root test, the regressing results can be considered as the real long-term relationship. However, in most of the cases, the time series of most variables tested are not stationary, for these variables, there are still the possibilities to exist a long-term relationship among them if 1st differences of these series are stationary, that is they are integrated in the same order 1, $I(1)$. If this happens, the cointegration test need to be done to test if there are equations that can describe the long-term relationships among these variables, only if cointegration test passed, then the regressions results can be considered as the real long-term relationship.

Of all the unit root tests, ADF, DF-GLS and PP are the most commonly used methods to test the stationary of a time series, and we use the EViews 7 to do the unit root tests for our model, and the test results are shown in Table 1. From the table it can be clearly seen that, under the ADF and DF-GLS test scheme, the first differences of all the series are tested to be stationary. Although for the PP test, the level of P is tested to be stationary, however, the ADF and DF-GLS test results show that its 1st difference is stationary. Because theoretically, each unit root test method has its own disadvantages and advantages in regarding to variables with different features, it is difficult to say which one is superior to other ones, so in this work the results that most of the methods support are selected to judge the stationary of a variable, so we can conclude from table 1 that all the variables in our model are tested to be integrated of order 1, I(1).

3.2.2 Cointegration

Given that all the variables are integrated of the same order 1, I(1), the cointegration test should be done to check whether there are long-run relationships among the series. In regarding to the cointegration test, the Johansen test is used and the results are shown in Tab.2. From the results it can be clearly seen that there are at least 5 cointegration equations existing among ln*MSWD*, ln*UIP*, ln*UR* and ln*TS*, so they are cointegrated.

4. Results and Analysis

4.1 Regression results

Table 1. Unit roots tests results

Variables	ADF		DF-GLS		PP	
	Level	1st difference	Level	1st difference	Level	1st difference
ln*MSWD*	-2.069	-6.685*	-1.678	-4.599**	-0.436	-10.351*
ln*P*	-2.245	-2.834*	0.859	-2.665**	-7.760***	-
ln*UIP*	-1.984	-3.270*	- 0.543	-2.386**	-0.465	--2.883*
ln*UR*	- 3.548*	- 3.143**	0.204	- 2.870***	-0.472	-3.263**
ln*TS*	-2.031	-3.387***	-0.150	-3.983***	-0.193	-3.877***

* Statistical significance at the10% level; ** Statistical significance at the 5% level; *** Statistical significance at the 1% level

Table 2. Cointergration tests results

Hypothesized No. of CE(s)	T-Statistic	Prob.
None *	157.768	0.000
At most 1 *	32.183	0.000
At most 2*	12.788	0.000
At most 3 *	4.575	0.016
At most 4*	0.047	0.021

* Statistical significance at the 5% level

From the results of unit root tests and cointegration tests it can be seen that there are long-term equilibrium relationships among ln*MSWD*, ln*P*, ln*UIP*, ln*UR* and ln*TS*, so we need to use some kind of regression methods to simulate the equations. In this work, the FMOLS estimator was selected to regress the equations because it is superior to the OLS (Ordinary Least Square) estimator when dealing with small samples [15]. The estimation was done by the EViews 7, and the result of the long-relationship among ln*MSWD*, ln*P*, ln*UIP*, ln*UR* and ln*TS* was firstly obtained as

$$\ln MSWD = 0.750\ln P + 0.379\ln UIP - 1.156\ln UR + 1.663\ln TS$$

Adjusted R^2=0.986,DW=0.834 (5)

Although the value of adjusted R^2 is very near to 1, which means that the actual curve is greatly fitted by the estimating curve, the value of DW is far smaller than 2, which indicates that the residual error series is positive auto-correlated, so we need to correct the autocorrelation of residual error series in order to get an accurate estimation of the long term relationship, after we add the first and second lags of residual error into the model, we finally got

$$\ln MSWD = 0.751\ln P + 0.378\ln UIP - 1.190\ln UR + 1.721\ln TS$$

Adjusted R^2=0.991, DW=1.945 (6)

Eq.(6) shows that after adding the first and second lags of residual error into the model, the fitting effect was slightly improved and the autocorrelation of residual error series was well eliminated, so Eq. (6) can be considered as the long term relationship between ln*MSWD*, ln*P*, ln*UIP*, ln*UR* and ln*TS*.

4.2 Analysis

From Eq.(6) it can be seen that among all the factors that contributing to the growth of MSW in China, the effect of increase in share of tertiary industry in overall economy is most prominent, followed by the increase in urbanization, the effect of increase in population and urban citizen's per capita disposable income are much smaller than the other two factors. Meantime, although the increase in ratio of tertiary industry in overall economy, population and urban citizen's per capita disposable income positively contribute to the growth of MSW, the growth in urbanization negatively contributes to the growth of MSW.

4.2.1 Share of Tertiary Industry in Overall Economy

From Eq.(6) it can be seen that every 1% increase in the share of tertiary industry in overall economy will result in 1.721% increase in MSW, which means that the growth of MSW is very sensitive to the change of share of tertiary industry in overall economy. Fig.1 shows the developing trend of the share of tertiary industry in China's overall economy during 1980 and 2013, which increased from 21.60% in 1980 to 46.09% in 2013. The prosperity of the tertiary industry enriched people's lives in large detail, such as the increasing tourisms, entertainment, catering and so on. All of these consuming behaviors will result in the increase in MSWs. Although currently the tertiary industry has replaced the secondary industry to play the leading role in China's economy, the share of tertiary industry in overall economy is forecasted to grow much higher than current level, and this will further lead to the prominent increase in the overall MSW.

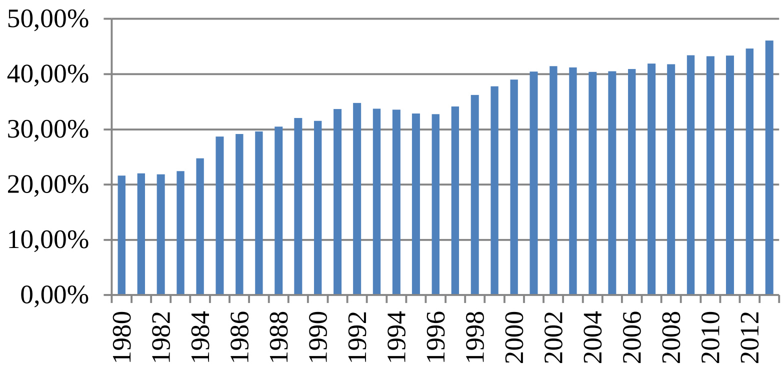

Figure 1. The share of tertiary industry in overall economy from 1980 to 2013

4.2.2 Urbanization

Among all the factors, urbanization is the only one factor that negatively contributes to the growth of MSW in China, and every 1% increase in the share of urbanization will result in 1.156% decrease in MSW, which also means the growth of MSW is very sensitive to the change of urbanization. However, compared to the effect of share of tertiary industry in overall economy, the effect of urbanization is much lower. The negative effects of urbanization on the growth of MSW can be explained by that the vast development of urban areas enhances the local government much more abilities to intensively publicize the necessaries to reduce MSW and thus improves the citizen's awareness of environmental protection. As Fig.2 indicates, the urbanization rate of China had greatly improved during 1980 to 2013, which was 19.39% in 1980 and 53.73% in 2013, while compared with the developed countries, the urbanization rate in China is very low, and in the future, it is anticipated that the urbanization rate in China will be further increased, and the negative effect on the generation of MSW will continue to exert, however, these negative effectives may be compensated by the large positive effects of increase in share of tertiary industry in overall economy.

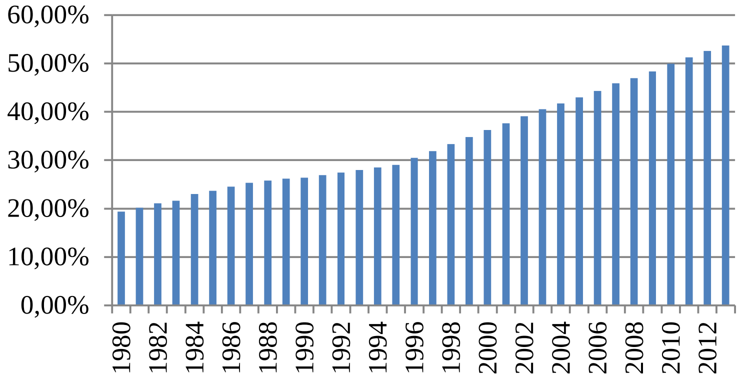

Figure 2. The change of urbanization rate from 1980 to 2013

4.2.3 Population

The growth of China's population positively contributes to the growth of MSW, however, the contribution is much lower compared with the change of share of tertiary industry in overall economy and urbanization rate, since every 1% increase in population will result in 0.75% increase in MSW. During the last few years, China's population had grown from more than 0.98 billion in 1980 to more than 1.36 billion in 2013, and in recent years the growth rate is much lower. It is anticipated that in the future, the growth of China's population will keep on a very low level and reach the peak in 2030s, so overall the population growth will not obviously increase the generation of MSW in China.

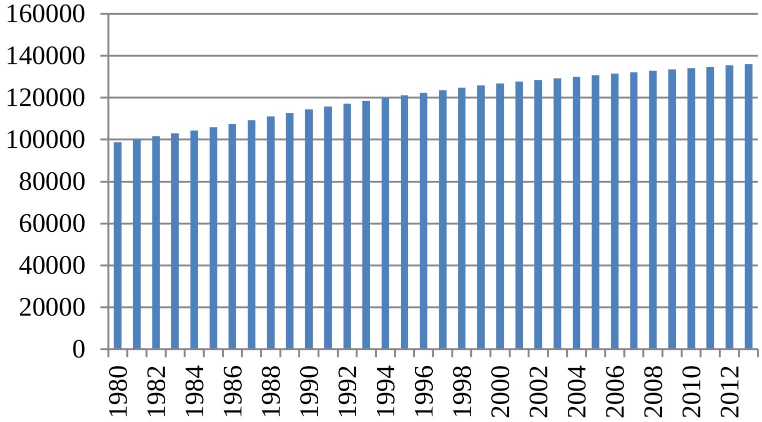

Figure 3. The growth of population in China during 1980 to 2013

4.2.4 Urban Citizen's Per Capita Disposable Income

Because of the fast economy development, the urban citizen's per capita disposable income had obviously increased from 1980 to 2013, which was 477.6 Yuan RMB in 1980 and 26955.1 Yuan RMB in 2013, nearly overfolded 56 times. The sharp increase in urban citizen's per capita disposable income did not obviously increase the generation of MSW, since statistics shows that every 1% increase in urban citizen's per capita disposable income will result in 0.378% increase in MSW, which means that the growth of MSW is not very sensitive to the increase of urban citizen's per capita disposable income. So, although in the future the urban citizen's per capita disposable income is anticipated to keep on increase greatly, this will not obviously increase the generation of MSW.

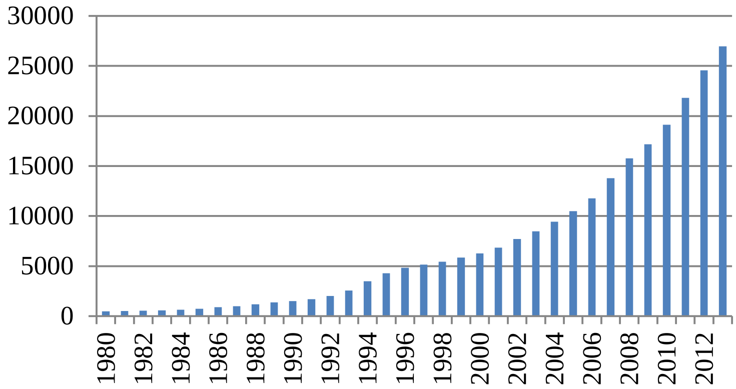

Figure 4. The development of urban citizen's per capita disposable income from 1980 to 2013 in China (Yuan RMB)

5. Conclusion

Because of the ever fast growing in economy, people's living standard in China had been greatly improved, and the consumption had been vastly activated. As a result, the growth of MSW in China was fast accelerated, so identify the main factors that contribute to the fast growing in MSW is the key for future MSW management. This work uses the STIRPAT model to examine the different roles of population, affluence, urbanization and development of tertiary industry on the generation of MSW. The results show that, among all these factors, the increase in the share of the tertiary industry in overall economy and urbanization rate are much more sensitive to the growth of MSW, and only the effect of urbanization rate is negative on the generation of MSW, all the other 3 factors positively contribute to the growth of MSW.
Meanwhile, by analyzing the future developing trend of the factors that contribute to the growth of MSW, it is found that basically the future growing trend of MSW generation is

still very obvious because of the continuing prosperity of tertiary industry and the growth in people's income. In order to reduce the overall final treatment of MSW, the related management department should put more efforts in improving the efficiency in reducing MSW after its generation and before final treatment process, such as encouraging people to classify MSW and thus make full use of the classified waste to reproduction, only by this way can really reduce the negative environmental impacts caused by waste treatment.

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References

1. Rotchana I. P., Abdul S., Kumar S., Akarapong U. (2015) Forecasting of municipal solid waste quantity in a developing country using multivariate grey models. *Waste Management*, Vol. 39, p.p.3-14
2. Buenrostro, O., Bocco, G., Vence, J. (2001) Forecasting generation of urban solid waste in developing countries-A case study in Mexico. *Journal of the Air & Waste Management Association*, Vol. 51, p.p.86–93
3. Lebersorger, S., Beigl, P. (2011) Municipal solid waste generation in municipalities: quantifying impacts of household structure, commercial waste and domestic fuel. *Waste Management*, Vol. 31, p.p.1907–1915.
4. Purcell, M., Magette, W.L. (2009) Prediction of household and commercial BMW generation according to socio-economic and other factors for the Dublin region. *Waste Management*, 29, p.p.1237–1250
5. Liu, G., Yu, J. (2007) Gray correlation analysis and prediction models of living refuse generation in Shanghai city. *Waste Management*, Vol. 27, p.p.345–351
6. Rimaityte, I., Ruzgas, T., Denafas, G., Racys, V., Martuzevicius, D. (2011) Application and evaluation of forecasting methods for municipal solid waste generation in an eastern-European city. *Waste Management and Resource*, Vol. 30, p.p.89–98
7. Skovgaard, M., Moll, S., Andersen, F.M., Larsen, H. (2005) Outlook for waste and material flows: baseline and alternative scenarios, Working Paper 1. *Proc. Conf. on. European Topic Centre on Resource and Waste Management*, Copenhagen, Denmark
8. Brantley L. (2013) Urban density and climate change: a STIRPAT analysis using city-level data. *Journal of Transport Geography*, Vol. 28, p.p.22-29
9. Wang P., Wu W. S., Zhu B. Z., et. al. (2013) Examining the impact factors of energy-related CO_2 emissions using the STIRPAT model in Guangdong province China. *Applied Energy*, Vol. 106, p.p. 65-71
10. Wang M. W., Che Y., Yang K., et al. (2011) A local-scale low-carbon plan based on the STIRPAT model and the scenario method: the case of Minhang district, Shanghai, China. *Energy Policy*, 39(11), p.p. 6981-6990
11. Ming M., Niu D. X., Wei S. (2012) CO_2 emissions and economic development: China's 12th five-year plan. *Energy Policy*, 42, p.p.468-475
12. Beigl, P., Lebersorger, S., Salhofer, S. (2008) Modelling municipal solid waste generation: a review. *Waste Management*, Vol. 28, p.p.200–214
13. Ehrlich, P., Holdren, J. (1971) The impact of population growth. *Science*, 171, p.p.1212–1217
14. Dietz, T., Rosa, E. (1997) Effects of population and affluence on CO2 emissions. *National Academy of Sciences of the USA*, Vol. 94, p.p.175–179
15. Phillips P. C. B., Moon H. R. (1999) Linear regression limit theory for nonstationary panel data. *Econometrica*, Vol. 67, p.p.1057–1112