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Waste Haven Transfer and Poverty-Environment Trap: Evidence from EU

Yanli Wang[1,2], Yi Liu[3], Wanyin Feng[4] and Shugui Zeng[5,*]

[1]*College of Art, Jiangxi University of Finance and Economics, China*

[2]*Media and Communications Department, Jiangxi University of Finance and Economics, China*

[3]*School of International Trade and Economics, Jiangxi University of Finance and Economics, China*

[4]*School of Economics, Xiamen University, China*

[5]*School of Economics, Renmin University of China, China*

Abstract: This paper tests the extent to which the migration of "waste haven" causes a "poverty-environment trap." That is to say, imported waste caused the mid-income trap of the less-developed European countries. Using Spatial Durbin Model on waste carbon dioxide emission of 28 EU countries from 2001 to 2018, we estimate the carbon footprint of imported wastes of the European Union (EU) members. The result shows an inverted "U-" shape curve between GDP per capita and imported waste carbon footprint, confirming an Environment Kuznets Curve of "waste haven" transfer. It hinders the inbound of high-quality FDI. In the further mechanism test, we found industrial structure, FDI, industrialization, and urbanization are responsible for the spatial-temporal transfer of "pollution haven" and "environmental-poverty trap." The results also show that "waste haven" may accelerate the economic growth of less-developed countries to some extent; however, with a higher percentage of dirty industries, FDI in the pollution-intensive sectors of these countries worsens their environmental conditions. It reinforces pollution haven effects and created a vicious circle of "poverty-environment trap" for low-income countries in the EU.

Keywords: the carbon footprint of imported waste, environment Kuznets curve, Spatial Durbin Model, pollution haven effects, poverty-environment trap, mid-income trap

Highlights:

(1) Result of the Spatial Durbin Model shows that the Environmental Kuznets Curve exists in the relation between the carbon footprint of imported wastes and the GDP per capita of EU member countries.
(2) The transfer of recycling sectors confirmed the Pollution Haven Hypothesis.
(3) Foreign Direct Investment (FDI), urbanization, and industrialization in comparatively low-income nations facilitate the transfer of recyclable resources from rich countries.
(4) The transfer of pollution-intensive industries reinforced the pollution caused by the increasing import of recyclable waste, forming a "poverty-environment trap" in the comparative low-income countries in the EU.

1. Introduction

In March 2020, the European Commission launched a new Circular Economic Action Plan (CEAP) to reduce the waste of raw materials and achieve "Zero Waste." The application of CEAP will add 0.5% to the GDP growth rate by 2030, creating around 700,000 new jobs. More importantly, a circular economy's vigorous promotion will further increase the recycling rate and promote waste trade. However, an important issue has long been ignored. Namely, how does the policy shock impact members' environment under interaction, especially the comparatively less-developed nations? This paper first measures carbon emission embodied in imported waste from four industries, namely plastic, paper, metal, and non-ferrous metal, using a specific energy/carbon method[1]. Secondly, using the Spatial Durbin Model and panel data of 28 EU countries from 2001 to 2018, we found an inverted "U-" shape curve between the carbon emissions of imported wastes and economic growth in the EU. The inflection point is between $22,824 per capita and $52,459 per capita. Besides, there is a

*Corresponding author: Shugui Zeng, School of Economics, Renmin University of China, China. Email: zengshugui@alu.ruc.edu.cn

[1]CO_2 emission of each sector is the sum of total CO_2 embodied in the waste import of that sector.

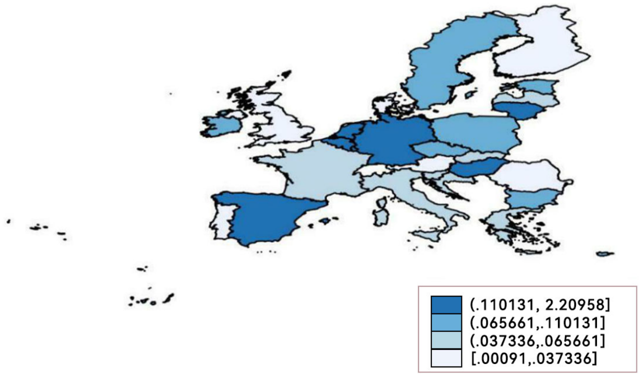
significant spatial-temporal dependence on the transfer of imported carbon footprint of waste in EU members. The spatial-temporal transfer of waste carbon footprint is likely to be affected by neighboring economic activities such as industrialization, FDI, and urbanization. As such, worsening environmental conditions reinforced the less-developed nations' pollution haven status, creating a vicious circle of "poverty-environment trap" for the EU's low-income countries. This research extends the Pollution Haven Effects (PHE) by introducing the "poverty-environmental trap" in PHE. Additionally, this research explains why certain countries with rich neighbors can hardly escape from the "mid-income trap."

Recyclable waste has advantages in cost and energy efficiency over original materials. The application of a circular economic system is essential in achieving sustainable growth of resource consumption. Recycling helps to maximize the added value and extend the lifespan of the utilization of end-life products. Waste recycling is a critical approach to reducing the exploration of virgin resources. Around 40% of manufacturing production cost comes from material inputs. The world's consumption of materials and minerals is projected to double in the upcoming four decades. In the mid-21st century, waste generation is expected to increase by 70% annually. Due to waste recycling, the EU's import demand for raw materials can be effectively reduced by 17% to 24% by 2030, saving 630 billion Euros in industrial raw material import per year (Innova, 2012).

Although recyclable waste is an essential intermediate input, the waste-related environmental problem is a significant challenge for human beings. Various toxic gases are produced in the process of recycling and disposal in the waste importing nations, such as methane, carbon dioxins, and furans (Awasthi et al., 2016; Gu et al., 2017). The recycling process produces toxic substances that are likely to pollute the nearby surface water and soil (Awasthi et al., 2016; Kiddee et al., 2013). Proper disposal and utilization of waste greatly reduce its negative impacts. However, developing countries may not have the skills and capability to deal with waste properly (Higashida & Managi, 2014). Although recycling is essential, in the long run, various types of recycled products will eventually become residues and be released into the atmosphere (Kneese, 1971). Different kinds of waste generate different degrees of carbon dioxide emissions (CO_2) in the process of recycling[2]. Through offshoring, pollution-intensive sectors transferred to the low-income nations together with pollution-intensive wastes. As such, the "North" is the major waste producer, but the responsibility of waste recycling and carbon emission mitigation is mainly taken by the "South" (Brian & Taylor, 2019; Geng et al., 2013; Stahel, 2016). Consequently, understanding the waste carbon footprint of recyclable waste imports helps to know the relationship between trade and global warming.

International trade optimally allocates resources in the process of economic globalization. Through international trade, the responsibility of carbon mitigation related to waste treatment has been transferred from the producers to the consumers. The international trade of recyclable waste is an indispensable part of input in the global manufacturing production network. The industrial structure decides the type of resources to be imported, including recyclable wastes. Through deindustrialization and offshoring, the share of secondary industries in the developed nations is likely to be smaller; meanwhile, less-developed countries tend to have larger manufacturing sectors and more pollution-intensive sectors. The high-income nations, such as the UK, France, Netherlands, and Belgium, are more likely to import less pollution-intensive wastes. Comparatively speaking,

Figure 1
Hotspots and cold spots of waste import carbon emission



less-developed countries such as Poland, Hungary, Sweden, and Czech prefer to import more pollution-intensive recyclable wastes (see Figure 1). Although extracting wastes from waste generates less pollution than virgin resources, we cannot deny that waste treatment is a pollution-intensive sector that has always been offshoring from the "North" to the "South" (Brian & Taylor, 2019; Kellenberg, 2009). We propose that the transfer of pollution haven also happens in a more developed region. This evidence might help to understand why less-developed areas in the EU cannot get much more prosperous.

According to the "poverty-environmental trap" theory, environmental degradation reinforces poverty. Environmental quality plays a significant role in deciding labor productivity and wealth distribution. Regions with better environmental quality are more likely to attract agents with more capital and advanced technology to reinforce environmental evolution; meanwhile, environmental quality continues to degrade for regions with low environmental quality. The interaction between poverty and environmental degradation forms a "poverty-environment trap" (Ikefuji & Horii, 2007). Our research might be a novel study that provides empirical evidence with pollution haven transfer evidence for the "poverty-environment trap" theory. This probably is the first study that examines the existence of the "poverty-environment trap" using spatial econometrics. It is much easier to understand the forming process of heterogenous poverty and environmental quality through the interaction among nations with different income levels.

A difference between this research and the previous research is that the former can hardly accurately investigate the impact of waste import on the environment. Previous research emphasizes the total amount of waste imported rather than the environmental impact of imported waste. Previous publications mainly use trade-in total value and weight. For example, the top three waste importers of the EU were Germany, Belgium, and the Netherlands, representing 17.57%, 13.55%, and 11.37% of total EU waste import in value; however, we can hardly say that the industrial sector in these countries is dirtier than the rest of EU members. In this research, we use the LCA approach to measure CO_2 emission embodied in waste to quantify the impact of waste import in the EU and investigate the driving forces of migration of import waste carbon emission.

Our study may have the following potential contributions. First, few scholars have linked the EKC and waste trade-related emissions together. By measuring the carbon emissions of imported waste recycling based on CO_2 footprint in EU countries, EKC's existence in waste carbon emission is detected. Second, we also explore the spatial spillover effect of imported waste carbon emissions. Compared with wastewater, solid waste, SO_2, and other pollutants, carbon emissions

[2]According to the specific energy/carbon method, CO_2 emission of recycling specific waste material can be calculated according to British carbon and energy list of ICE (Dong et al. 2018).

have more spatial diffusion and cross-border hazards, so the EKC of carbon emissions estimated by the spatial panel model is more robust. SDM is used to study EU economic integration on the Environmental Kuznets Curve interdependence of EU economies. Third, this research helps to understand better the impact of waste trade on the environment and how pollution interacts with international waste trade. It further analyzes whether the disparity of EU countries' economic growth will lead to the transfer of "Pollution Haven" from wealthier EU members to lower-income EU members. It is thus providing new evidence for the "poverty-environment trap" and PHH.

2. The Spatial Dependence of EU Carbon Emission Embodied in Waste Import

There is a strong spatial-temporal effect of waste trade due to economic integration in the EU. EU integration allows countries to have spillover impacts of similar waste imports and related pollution. Due to their geographical location proximity, member countries often lead to closer bilateral ties and states frequently interact through various channels such as commodity trade, capital flows, technology diffusion, and standard environmental policies. These can have a positive or negative impact on the reduction of carbon dioxide emissions.

First, an intensive production network helps to promote the sourcing of recyclable waste materials within the EU. There are three major regional production networks within the global value chain, including the EU, Asia-Pacific, and North America. International fragmentation of production networks and labor divisions creates stronger connections between countries within a region than between regions. Second, since waste is a low-value but bulky commodity, a country is more likely to import waste from its closest neighbor to save cost, conditional at the same price. Waste is bulky with a low unit price. As such, waste trade is more likely to happen between nearby nations.

Third, economic integration encourages waste trade between member countries by reducing trade and transaction costs. EU is a common market with a free flow of labor, capital, and resource materials. As such, a regional free trade agreement between EU member countries further reduces friction costs related to trade.

Fourth, according to the Similarity of Preferences Theory, consumers are more likely to have overlapping tastes if countries have similar per capita incomes. EU is one of the most integrated production networks due to economic integration and policy harmonization. Most EU countries are members of the OECD. Consumers from countries with similar income levels create similar consumer preferences and environmental regulation stringency. Identical consumer preferences produce similar wastes that help to generate a regional recyclable waste supply chain. Countries with equivalent income levels are more likely to adopt similar technology and environmental regulations and produce similar products that require identical recycling resources. As a result, the spatial dependence of waste trade is created.

As shown in Figure 1, the hotspots of waste carbon emission clusters in Central Europe (such as Germany, Holland, Belgium, Hungary, Sweden, Poland, and the Czech Republic) and Southwest Europe (such as Spain and Ireland). Cold areas include England, Portugal, Denmark, Italy, and France.

3. Methodology

3.1. Theoretical specification

EKC is one of the most long-lasting and extensive research topics in the empirical study of environmental and ecological economics. The EKC was proposed by Grossman & Krueger (1995). This hypothesis describes the inverted U-shaped relationship between economic development and its environmental impacts[3]. There are two mainly used conceptual models of EKC. One is the GK model from Grossman & Krueger (1995), and another is the BSS model from Bradford et al. (2005).

3.1.1. GK model

The basic EKC model (GK model) is written as:

$$\ln E_{it} = \beta_0 + \beta_1 \ln Y_{it} + \beta_2 (\ln Y_{it})^2 + \varepsilon_{it} \tag{1}$$

According to the EKC hypothesis, E_{it} represents the pollution emission of country i in year t. Y_{it} represents the productivity level of i country in the year t. If EKC exists, β_1 is significantly positive. In the meanwhile, β_2 is significant and negative. ε_{it} is a random disturbance term. We take logarithmic forms of all variables to reduce data volatility and the possible influence of heteroscedasticity. The relationships between environmental pollution of imported waste and economic growth are conditional on β_1 and β_2[4].

3.1.2. BSS model

According to Bradford et al. (2005), EKC's existence depends on the country's long-term economic growth and the level of development at different stages. The original BSS model is set up as follows.

$$\frac{dP}{dt} = \alpha (y - y^*) g \tag{2}$$

In formula (2), P represents the pollution level of a specific country, y represents the level of economic development, g represents the economic growth rate, α is a constant term. y^* is the inflection point of the EKC. The pollution level determines it. Equation (2) is equivalent to equation (3), where β is the term of intercept. As Figure 2 shows (Bradford et al., 2005), when $\alpha < 0$ an $y < y^*$, economic growth will lead to a faster increase in the pollution level; on the contrary, when y is more significant than y^*, the speed of economic growth delinks with the rate of pollution increase.

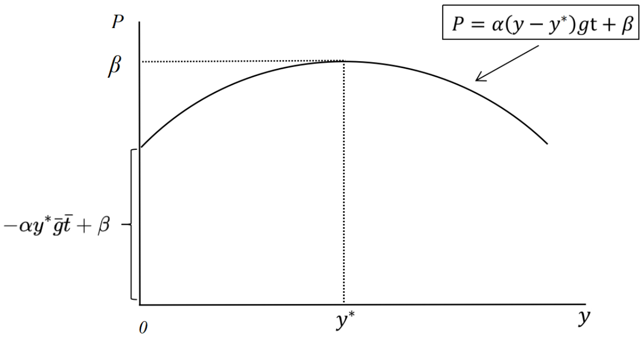
$$P = \alpha (y - y^*) gt + \beta \tag{3}$$

According to the Material Balance Theory (Kneese, 1971), under the condition of autarky, within a period, the size of residues discharged from the economic system into the natural environment must be roughly equal to the matter flowing into the economic system from the natural environment. That is to say, the increased emissions in the economic system will inevitably lead to an increase in the exploitation of natural resources. Suppose there is a material accumulation in the production and consumption

[3]Traditional EKC hypothesizes that the impact of economic growth on pollution depends on the stages of development. In the early stage, relatively disadvantageous industrial technology and low-resource utilization efficiency have led to the aggravation of environmental pollution. As the economy develops, the share of economic contribution from the tertiary industry is becoming more prominent, and people's environmental awareness also gradually strengthened environmental regulation. The rate of increase of pollutant discharge is gradually slowing down. As such, environmental quality starts to improve in the second stage.

[4]First, $\beta_1 = \beta_2 = 0$ indicating no relationship between CO2 emission of imported wastes and economic growth; if $\beta_1 > 0$ and $\beta_2 = 0$, indicating that CO_2 emissions of imported wastes increase linearly as economic develops; if $\beta_1 < 0$ and $\beta_2 < 0$, indicating that CO2 emissions of imported wastes decrease linearly as economic develops; if $\beta_1 > 0$ and $\beta_2 < 0$, indicating that there is an inverted U-shaped relationship between CO2 emissions of imported wastes and economic growth, indicating the existence of environmental Kuznets curve. Finally, if $\beta_1 < 0$ and $\beta_2 > 0$, CO2 emission of imported wastes and economic growth has a inverted U-shaped curve relationship.

Figure 2
EKC curve of BSS model



process of the economic system, pollutants may be returned to the production process for processing and reuse through recycling. In that case, pollutants may be returned to the production process for processing and reuse (Figure 3).

According to the general law of material balance, to reduce the environmental pollution caused by the modern economic system, we should reduce the pollution in the production process and recycle all kinds of waste to improve the utilization efficiency, recycling rate, and energy efficiency. However, the recycled products will eventually become residues and be released to nature in various forms, mainly as gases (Kneese, 1971).

3.2. Data

As an important type of renewable resource, waste is imported and recycled in a country; then, it is used as an input for production. As a result, all pollution remains in the country where waste is processed and recycled. We measure CO_2 emission embodied in waste import using the Specific Energy/Carbon Approach proposed by Dong et al. (2018).

$E_{waste,n,t}$ represents the CO_2 emission of the nth type of recyclable waste in year t, $M_{waste,n,t}$ is the amount of recyclable waste import of nth type waste in year t, $f_{waste,n}$ is the coefficient of the unit recyclable waste CO_2 emission. Among them, the carbon coefficient is obtained from the Inventory Carbon and Energy (ICE) database initiated by the University of Bath in the UK.

$$E_{\text{waste,n,t}} = M_{\text{waste},n,t} \times f_{\text{waste},n} \quad (4)$$

This paper extends the traditional EKC model by introducing other control variables such as trade openness, industrial structure, FDI, environmental regulations, and urbanization rate. Many factors may affect CO_2 emissions, such as trade openness (Birdsall & Wheeler, 1993) and population density. Many studies also find there is a positive linkage between urbanization and CO_2 emission (Madlener & Sunak, 2011; Zhang et al., 2014). We include industrial structure because the turning point of EKC arrives earlier in the countries that enter deindustrialization (Du & Xie, 2020). Besides, Birdsall & Wheeler (1993) approved that trade openness makes domestic production cleaner by adopting pollution standards from industrialized nations.

The value of CO_2 emission per capita is calculated according to the UNcomtrade database, and other data are from the World Development Index of the World Bank. Variable statistics are shown in Table 1.

3.3. Baseline model specification

CO_2 emission is also affected by other variables. The extended model of equation (1) is written as follows.

$$\ln PCO_{2\,it} = \beta_0 + \beta_1 PGDP_{it} + \beta_2 PGDP_{it}^{\;2}$$
$$+\beta_3 FDI_{it} + \beta_4 TR_{it} + \beta_5 INDUSTRY_{it} + \beta_6 ENR_{it} + \beta_7 \text{URB}_{it} + \varepsilon_{it} \quad (5)$$

PCO_2 represents the per capita carbon emissions of imported waste. It is measured by the CO_2 emissions embodied in imported waste divided by the size of the population; Y_{it} represents GDP per capita; TR_{it} represents trade openness. It is measured by the share of total imports and exports as a percentage of GDP; FDI_{it} is the intensity of FDI. It is measured by the proportion of foreign direct investment in GDP; $INDUSTRY_{it}$ stands for industrial structure. It is reflected by the ratio of industrial added value in GDP; ENR_{it} stands for environmental regulation. The unit energy consumption

Figure 3
Material flow relationship after recycling

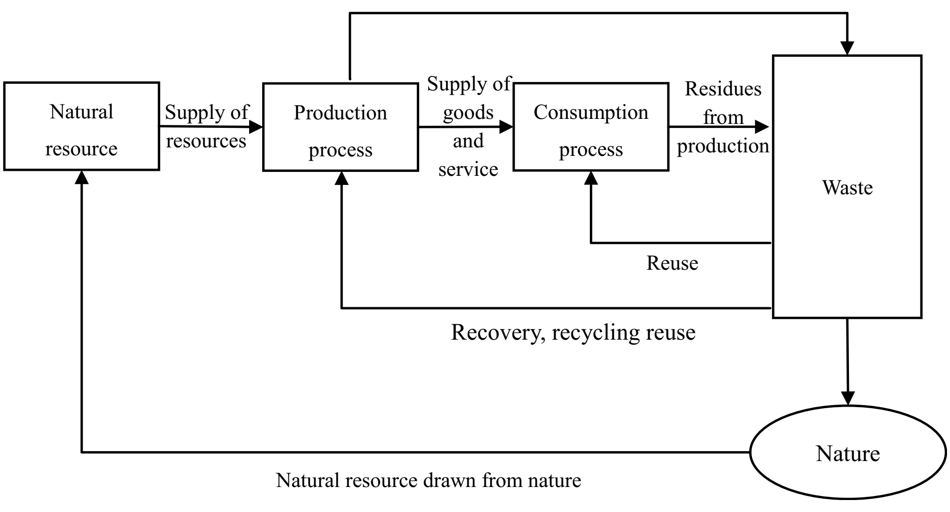


Table 1
Variable descriptive statistics

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
PCO_2	Per capita CO_2 emission embodied in waste Export (ton)[b]	504	−3.115	1.956	−9.803	1.512
PGDP	ln per capita GDP[a]	504	10.155	0.677	8.339	11.626
$PGDP^2$	ln square of per capita GDP	504	103.597	13.660	69.551	135.163
TR	Trade openness[a]	504	0.841	0.384	0.272	1.821
FDI	FDI[a]	504	0.161	0.802	−0.279	11.519
Industry	Industrial structure[a]	504	0.237	0.056	0.099	0.385
URB	Urbanization rate[a]	504	0.722	0.125	0.508	0.980
ENR	Environmental regulation stringency[a]	504	0.094	0.042	0.033	0.271

Notes: World Development Index, World Bank. b: calculated according to the UNcomtrade database. To reduce heteroscedasticity, logarithm of moment invariant was taken.

of GDP measures it; URB_{it} stands for urbanization level. It is the urban population ratio to the total population (Wang et al., 2019). ε_{it} is a random disturbance item.

3.4. Econometric models

3.4.1.. Spatial weight matrix

It is crucial to specify the spatial weights matrix in spatial econometrics. The three most used spatial weight matrixes are the distance weight matrix, adjacent binary matrix, and economic weight matrix. First, two regions are considered adjacent if they have a common boundary. In the adjacent matrix, the element on the main diagonal is 0. If country i is adjacent to country j, W_{ij} is marked as 1; otherwise, it is 0.

Second, the geographic weight matrix d_{ij} records the geographic distance between locations i and j, which is calculated as the great circle distance based on the latitude and longitude coordinate data of states in the EU. The spatial weights can be defined as $W_{ij} = \frac{1}{d_{ij}}$.

The economic weight matrix uses the difference in per capita GDP between countries as an indicator to measure the regional economic distance. All the main diagonal elements of the matrix are 0, and non-main diagonal elements are $w_{ij} = \frac{1}{|GDP_i - GDP_j| + 1}$. Besides, we standardize three spatial weight matrices by dividing each element by the row sum of the elements, the sum of the elements in each row is 1.

3.4.2. Spatial panel models specification

Three spatial panel data models are commonly used to describe spatial correlation. They are the spatial autoregressive model (SAR), spatial error panel data model (SEM), and spatial Durbin model (SDM) (Elhorst, 2012). The SAR model hypothesizes that the dependent variable's value is decided by the spatial lag effects of the dependent variable (Lee & Chen, 2010). That is, the waste carbon emission of a region is affected by that of its neighbors. The SAR model is specified as follows:

$$\begin{aligned} \ln PCO_{2it} &= \lambda W \ln PCO_{2jt} + \beta_1 PGDP_{it} + \beta_2 PGDP_{it}{}^2 \\ &+ \beta_3 FDI_{it} + \beta_4 TR_{it} + \beta_t INDUSTRY_{it} + \beta_6 ENR_{it} + \beta_7 URB_{it} + \varepsilon_{it} \end{aligned} \tag{6}$$

λ is the spatial autoregressive coefficient, reflecting the spatial correlation between the explained variables; the space W is the spatial weight matrix of $n \times n$ order; β is the regression coefficient, reflecting the influence of the independent variable on the dependent variable; and ε_{it} is the random disturbance term.

The SEM aims to fix the spatial autocorrelation among the error terms. The interaction between regions is different due to their different relative positions. SEM is specified as follows:

$$\begin{aligned} \ln PCO_{2it} &= \beta_0 + \beta_1 PGDP_{it} + \beta_2 PGDP_{it}{}^2 + \beta_3 FDI_{it} \\ &+ \beta_4 TR_{it} + \beta_5 INDUSTRY_{it} + \beta_6 ENR_{it} + \beta_7 URB_{it} + \rho W \mu_{it} \end{aligned} \tag{7}$$

ρ is the explained variable's spatial error coefficient, indicating the influence degree of the error impact of the neighboring area on the observed value of the local area; W is the spatial weight matrix; β is the regression coefficient; and μ_{it} is the random disturbance term. The spatial autoregression model explores the spillover effect of a region's economic behavior on other regions with similar spatial characteristics. SAR might ignore omitted variables and spatial heterogeneity. SDM can overcome this disadvantage. SDM is an extension of the SAR model, and it includes spatial lag terms of both the independent and dependent factors (LeSage & Pace, 2009). The expression of the Spatial Durbin model is written as:

$$\begin{aligned} \ln PCO_{2it} &= \beta_0 + \lambda W PCO_{2jt} + \beta_1 PGDP_{it} + \beta_2 PGDP_{it}{}^2 \\ &+ \beta_3 FDI_{it} + \beta_4 TR_{it} + \beta_5 INDUSTRY_{it} + \beta_6 ENR_{it} \\ &+ \beta_7 URB_{it} + \theta \sum_{j=1}^{n} WX_{jt} + \varepsilon_{it} \end{aligned} \tag{8}$$

λ is the spatial autoregressive coefficient, W is the spatial weight matrix, WX_{jt} is the spatial lag terms of explanatory variables and explanatory variables; Xi includes the second power of economic growth ($PGDP_{it}{}^2$), industrial structure ($INDUSTRY_{it}$), the intensity of foreign direct investment (FDI_{it}), degree of Trade Openness (TR_{it}), urbanization level (URB_{it}) and environmental regulation (ENR_{it}); β and θ are regression coefficients; ε_{it} is a random disturbance term.

4. Estimation Results and Discussion

4.1. Spatial dependence test

In this step, we test the spatial correlation of the spatial panel data; the global spatial autocorrelation of the CO_2 emissions of imported waste from 28 EU member states is calculated based on three different weight matrixes. Table 2 shows the results. Among them, if Moran's $I > 0$, it indicates that there is a positive spatial correlation between the observations; the larger the value, the more obvious the spatial correlation. If Moran's $I < 0$, there is a negative spatial correlation; the smaller the value, the greater the spatial difference. If Moran's $I = 0$, it indicates that the space is random. The results of Table 2 show that no matter which form of spatial weight matrix is used for measurement, CO_2 emissions among EU member states have significant positive spatial agglomeration characteristics.

Table 2
2001–2018 Moran' *I* statistics of Global CO_2 emission

	Binary adjacent matrix		Geographic weight matrix		Economic weight matrix	
	Moran's I	Z-score	Moran's I	Z-score	Moran's I	Z-score
2001	0.202***	2.429	0.104***	3.468	0.210***	0.008
2002	0.141**	1.821	0.079***	2.874	0.201***	0.009
2003	0.122*	1.613	0.082***	2.909	0.187**	0.014
2004	0.109*	1.484	0.085***	3.004	0.192**	0.012
2005	0.120*	1.596	0.071***	0.001	0.149**	0.033
2006	0.120*	1.636	0.070***	0.001	0.183**	0.013
2007	0.100*	1.435	0.064***	0.002	0.144**	0.034
2008	0.106*	1.520	0.062***	0.002	0.130**	0.043
2009	0.087*	1.315	0.055***	0.004	0.127**	0.047
2010	0.064	1.049	0.058***	0.004	0.196***	0.009
2011	0.091*	1.333	0.064***	0.002	0.152**	0.028
2012	0.087*	1.310	0.059***	0.003	0.138**	0.037
2013	0.082	1.262	0.063***	0.002	0.206***	0.006
2014	0.064	1.075	0.062***	0.002	0.201***	0.007
2015	0.090*	1.322	0.075***	0.001	0.137**	0.040
2016	0.068	1.100	0.071***	0.001	0.159**	0.023
2017	0.030	0.705	0.055	0.004	0.132	0.042
2018	0.066	1.048	0.065	0.002	0.067	0.152

Notes: "***", "**", "*" indicates statistical significance at 1%, 5%, 10%, respectively.

4.2. Regression results

In the spatial autocorrelation analysis, we have concluded that imported waste carbon emission has significant spatial autocorrelation. At the same time, the fixed effects model or the random-effects model should be considered in the process of selecting the spatial panel. In the spatial Durbin model, the explanatory variable includes the deformation of the explained variable, contrary to the assumption that the explanatory variable is strictly exogenous in the traditional model regression. Therefore, the results obtained by the ordinary least squares estimation (OLS) method are biased and do not meet the consistency requirements. According to Lee & Yu (2010), we adopt the maximum likelihood estimation method (Elhorst, 2003) to estimate the parameters of Equation (8).[5]

We assume the CO_2 embodied in the country's waste import tends to have an inverted U-shape curve relation with GDP per capita. That is, in the early stage of economic development, total CO_2 emission embodied in the waste import of a country tends to increase since the country is more likely to be a passive job taker under the global international division of labor. The poorer country is more likely to have weaker environmental regulation and become a net recipient of pollution-intensive FDI. Thus, this makes the country to be a net importer of pollution-intensive recyclable waste. As the GDP per capita of a country started to increase, the country's industrial structure tended to upgrade. Environmental regulation stimulates the transfer of pollution-intensive sectors to even less-developed countries. Total CO_2 emission embodied in waste import tends to decrease.

[5]To test which spatial econometric model is the best to fit the data, in this study, we follow the specification tests outlined by Anselin and Rey(1991) and Elhorst (2012). The result shows both the SAR model and SEM model have passed the significance level of 1% based on the three spatial weight matrices. Therefore, it is appropriate to choose the spatial Durbin model (SDM).

Table 3
Spatial Durbin Model (SDM)

	Binary adjacent matrix	Geographic distance weight matrix	Economic distance weight matrix
PGDP	13.858***	20.394***	20.521***
	(4.68)	(6.56)	(5.82)
PGDP ^{2}	−0.637***	−1.016***	−0.978***
	(−3.94)	(−6.09)	(−5.36)
FDI	0.083***	0.090***	0.069**
	(2.70)	(2.86)	(2.42)
TR	0.643***	0.998***	0.507***
	(3.64)	(5.61)	(2.77)
Industry	2.904**	2.131*	2.840**
	(2.12)	(1.70)	(2.24)
URB	4.172**	2.034	5.352***
	(1.99)	(0.99)	(3.22)
ENR	−0.028	−0.046	−0.008
	(−0.83)	(1.57)	(0.32)
W * PGDP	7.098	47.917**	43.399***
	(1.08)	(2.56)	(−3.97)
W * PGDP ^{2}	−0.284	−2.741***	−2.482***
	(−0.76)	(−2.67)	(4.24)
W * FDI	−0.165	0.006	−0.111**
	(−0.92)	(0.02)	(−2.32)
W * TR	2.612***	5.977***	1.092**
	(3.36)	(5.84)	(2.40)
W * Industry	−10.221***	−29.206***	−9.249***
	(−2.70)	(−3.07)	(−3.02)
W * URB	29.390***	24.084*	29.899***
	(4.09)	(−1.71)	(4.99)
W * ENR	0.033	0.726***	0.439***
	(0.42)	(4.01)	(−5.96)
λ	−0.201**	−0.846***	−0.2888***
R^2	0.406	0.390	0.413
LogL	−241.327	−245.186	−239.261
Sigma^2	0.148***	0.137***	0.1298***
Obs	504	504	504
Turning point (USD)	52,459	22,824	35,670

Notes: "***", "**", "*" indicates statistical significance at 1%, 5%, 10%, respectively.

As Table 3 shows, judging from the shape of the estimated curve, the regression coefficients of economic growth under the three spatial weights are all positive. The quadratic terms of economic growth are all negative. Both are significant at the 1% level. Therefore, an inverted U-shaped relationship between the EU's per capita imported waste carbon emissions and economic growth can verify the traditional environmental Kuznets curve hypothesis. Furthermore, the inflection point of the EKC curve of the EU's imported waste carbon emissions is calculated to be between \$22,824 per capita and \$52,459 per capita.

The spatial lag coefficients of economic growth are positively correlated with imported waste carbon emissions. Spatial lag coefficients of the quadratic terms of economic growth are negatively correlated with waste carbon emissions. Both coefficients are statistically significant at 1% level. It indicates that there is significant spatial dependence between the per capita waste carbon emissions in EU countries. Namely, the waste carbon emission of a country is affected by its neighbors' waste carbon emissions.

The estimated coefficients of trade openness, industrial structure, FDI, and urbanization are positive. Among them, trade openness and FDI are significant at 1% level. The industrial structure has passed the 10% significance test. Urbanization and its lagged spatial term are significant at the 1% and 5% levels. Regulations have a positive impact on the waste carbon emission of its neighbors. It may indicate that when the environmental regulation strengthens, its neighbors' waste carbon emission tends to increase.

Interestingly, the industrial development and FDI inflow of a nation are likely to increase the waste carbon emission of a country but decrease the waste carbon emission of its neighbors. It provides further evidence of pollution haven effects. The industrial development of a nation tends to increase its demands on recyclable waste material and waste carbon emissions. Besides, the environmental regulation of a nation is not a key determinant of waste carbon emission. Still, more stringent environmental regulation is likely to increase the waste carbon emission of its neighbors. It implies that there is a strong pollution haven effect of waste CO_2 emission within the EU.

We further decompose the total spatial effect to obtain the direct effect, indirect effect, and total effect of each variable. The results are shown in Table 4.

As Table 4 shows, under the three spatial weight matrices, the influence of economic growth on the carbon emissions of imported wastes is 13.51, 19.39, and 23.26, respectively, and all have passed the 1% significance test, indicating that a country's economic growth has an impact on the carbon emission of imported waste. Besides, the direct effect under the economic weight matrix is the largest, indicating that economic growth has a more obvious promotion effect on the carbon emissions of domestic imported waste after considering economic factors. The main reason may be that the expansion of economic activities has led to an impact on the need for raw materials and renewable resources. With increasing demand, waste imports can alleviate the contradiction of insufficient materials for industrial development and reduce the damage to the ecological environment caused by over-development.

The spatial spillover effects of economic growth are negative under three spatial models. It implies that EU member states' economic growth decreases neighboring CO_2 emissions embodied in waste imports. This finding is consistent with that of Maddison (2006). The direct and indirect effects of trade openness are positive under three matrices. This finding is consistent with the hypothesis. It implies that trade openness's stimulation of waste trade significantly increases carbon emission embodied in waste import in both domestic and foreign countries.

The direct effect of FDI will increase the CO_2 emission embodied in waste import. Nevertheless, the indirect effects of FDI have negative effects but are only significant using the economic matrix. It implies that CO_2 emission embodied in waste import will increase in the FDI recipient country but decrease in other nations with similar economic development levels. The direct effects of the industrial structure are positive but negative in all three matrixes, implying industrialization increases CO_2 emission embodied in waste import but decreases that of its neighbors. That approves this finding of Du et al. (2018). That is, industrializing slows down the arrival of peaks in EKC, but deindustrialization is faster.

The direct and indirect effect of urbanization is positive, implying speeding up urbanization will increase CO_2 emission embodied in the waste import of a nation and its neighbors. A possible explanation can be that urbanization supplies more recyclable resources and needs more recyclable waste for manufacturing production. Urbanization itself will have spillover effects on its neighbors, making CO_2 emission embodied in waste import increase. This finding confirms that urbanization is a major cause of pollution (Du et al., 2018; Wang et al., 2019). The main reason lies in a series of resource demands brought about by population growth and industrial agglomeration.

Besides, environmental regulation has no direct effect. However, the indirect impact under the geographical weight and economic weight was significantly positive, showing that if countries strengthen their environmental regulation, the geographic and economic neighbors' CO_2 embodied in waste import is likely to increase.

Table 4
Direct, indirect, and total Spatial Effects of SDM

		Binary adjacent matrix	Geographic distance weight matrix	Economic distance weight matrix
Direct effects	GDP	13.851***	19.395***	23.263***
		(4.51)	(5.39)	(5.71)
	GDP^2	−0.640***	−0.954***	−1.132***
		(−3.82)	(−4.98)	(−5.39)
	FDI	0.092***	0.095***	0.079***
		(2.99)	(3.11)	(2.84)
	TR	0.571***	0.803***	0.457***
		(3.23)	(4.47)	(2.61)
	Industry	3.233**	2.7818**	3.381***
		(2.45)	(2.34)	(2.69)
	URB	3.392*	1.822	3.915**
		(1.72)	(0.97)	(2.49)
	ENR	−0.027	0.022	0.033
		(−0.78)	(0.69)	(1.18)
Indirect effects	GDP	3.500	17.39*	41.1746***
		(0.66)	(1.53)	(−4.28)
	GDP^2	−0.121	−1.066*	−2.309***
		(−0.40)	(−1.72)	(4.52)
	FDI	−0.148	−0.021	−0.106***
		(−0.97)	(−0.09)	(−2.71)
	TR	2.1107***	2.9681***	0.7747**
		(3.30)	(4.97)	(2.15)
	Industry	−9.2621***	−16.9083***	−8.2564***
		(−2.73)	(−2.78)	(−3.03)
	URB	24.4668***	−12.50	23.4693***
		(4.06)	(−1.54)	(4.68)
	ENR	0.0334	0.3994***	0.3656***
		(0.47)	(3.20)	(5.86)
Total effects	GDP	17.3516***	36.7881***	17.9116**
		(3.11)	(3.87)	(−2.41)
	GDP^2	−0.7611**	−2.0206***	−1.1764***
		(−2.36)	(−3.82)	(2.87)
	FDI	−0.0562	0.0741	−0.0275
		(−0.38)	(0.32)	(−0.64)
	TR	2.6825***	3.7715***	1.2319***
		(4.06)	(6.26)	(2.92)
	Industry	−6.6819*	−15.4480**	−4.8747*
		(−1.86)	(−2.53)	(−1.78)
	URB	27.8593***	−14.52	27.3846***
		(4.02)	(−1.60)	(5.15)
	ENR	0.0060	0.4214***	0.3987***
		(0.10)	(3.58)	(5.42)

Notes: "***", "**", and "*" indicates statistical significance at 1%, 5%, and 10%, respectively.

4.3. Heterogenous test

To further test the spillover effects of CO_2 emissions in waste import and EKC, we separate 28 EU member counties into two groups: high-income and low-income. We run SDM again using the economic matrix. The result is shown in Table 5.

Interestingly, FDI inflow is likely to increase CO_2 emission embodied in the waste import of low-income countries but decrease the FDI inflow of high-income countries. Possibly because FDI attracted by high income are more capital and technology-intensive while the media and low-income countries are labor and resource-intensive. FDI in low-income countries is more likely to be pollution-intensive and thus attracts more pollution-intensive FDI. FDI from economic neighbors ($W * FDI$) negatively impacts imported waste carbon emission in high-income countries, implying environment-friendly FDI inflow convergence in high-income countries, improving the environment of the high-income countries. Such a convergence effect is insignificant in low-income countries. It means that low-income countries are more likely to become the sacrifice of pollution haven transfer through FDI inflow.

Table 5
SDM in high and media income

	GDP per capital < 40,000 USD	GDP per capital > 40,000 USD
PGDP	19.6929***	28.6847**
	(3.22)	(2.22)
$PGDP^2$	−0.8981***	−1.2936**
	(−2.81)	(−1.55)
FDI	0.0769**	−0.1689**
	(2.02)	(−2.12)
TR	0.219	0.9430***
	(0.68)	(4.85)
Industry	1.254	−0.188
	(0.59)	(−0.13)
URB	11.1693***	2.7799*
	(3.62)	(1.74)
ENR	−0.0084	0.0283
	(−0.14)	(1.47)
W * PGDP	−63.9253***	97.46
	(−3.74)	(1.62)
W * $PGDP^2$	3.6813***	−4.436
	(4.07)	(−1.62)
W * FDI	−0.0157	−1.6850**
	(−0.24)	(−2.34)
W * TR	0.266	1.545
	(0.40)	(1.42)
W * Industry	−4.834	−0.349
	(−1.04)	(−0.07)
W * UBR	48.1151***	17.8224***
	(5.22)	(3.18)
W * ENR	6.2962**	0.2166***
	(−2.37)	(−2.83)
λ	−0.3160***	−0.6010***
R^2	0.4327	0.4195
LogL	−198.4118	70.2258
$Sigma^2$	0.1754***	0.0246***
Obs.	306	198
Turning point(USD)	57,734	65,326

Notes: Countries with GDP per capita between $8,000 and $40,000 are in group one. Countries include Bulgaria, Poland, Italy, Spain, Croatia, and other 17 countries. There are 11 countries with per capita GDP above $40,000. We designate them in group two, including the United Kingdom, France, Germany, Denmark, and the Netherlands. "***", "**", and "*" indicates statistical significance at 1%, 5%, and 10%, respectively.

The marginal impacts of urbanization on CO_2 embodied in low-income countries triple that of high-income countries. It implies that low-income countries need more pollution-intensive recyclable waste to accelerate urbanization. Besides, facing the strengthening of environmental regulation in neighbors, low-income countries' waste carbon import increases much more than that of high-income neighbors.

This finding confirms the finding of Völlmecke et al., (2016). That is, income convergence across all European regions is weak in the process of economic integration. The poverty trap appears in some Central and Eastern European countries because FDI and human capital inflow are always in favor of high-income countries. Our study found that the differences in-country resources endowment might also cause such a poverty trap, and the types of FDI low-income countries can attract. The inflow of pollution-intensive industries has a negative impact on the environment of low-income countries, making environmentally friendly FDI escape from it. Thus, worsening environmental conditions strengthens a vicious circle of a "poverty and environment trap." This is important evidence that extends the "pollution-poverty trap" by considering the PHH.

5. Conclusion

Based on the EKC assumption and the panel data of 28 EU countries from 2001 to 2018, using the spatial Durbin model, this paper firstly tested empirically the existence of EKC in CO_2 emission embodied in imported waste. We further explained the mechanism of the imported waste carbon emission transfer between countries. The results show that (1) the relation between CO_2 emission embodied in waste import and GDP per capita shows an inverted U-shape curve in both low-income and high-income EU countries. The inflection point of GDP per capita is between $22,824 and $52,459. (2) There is a significant spillover effect on carbon emissions embodied in imported wastes among EU member states. (3) Imported waste carbon is not only affected by economic growth but also affected by trade openness, industrial structure, FDI intensity, urbanization level, and environmental regulations. We also find evidence of pollution haven transfer to low-income countries, confirming a vicious circle of "poverty-environment trap." The existence of pollution haven transfer among high-income and middle-income nations is new evidence for the PHH. This phenomenon may help us understand the "poverty-environment trap" and the "mid-income trap" in the world's developed regions. Further studies are suggested to investigate the possible existence of the "poverty-environment trap" using immigrant data.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

References

Anselin, L., & Rey, S. (1991). Properties of tests for spatial dependence in linear regression models. *Geographical Analysis*, *23*(2), 112–131. https://doi.org/10.1111/j.1538-4632.1991.tb00228.x

Awasthi, A. K., Zeng, X., & Li, J. (2016). Environmental pollution of electronic waste recycling in India: A critical review. *Environmental Pollution*, *211*, 259–270. https://doi.org/10.1016/j.envpol.2015.11.027

Birdsall, N., & Wheeler, D. (1993). Trade policy and industrial pollution in Latin America: where are the pollution havens? *The Journal of Environment & Development*, *2*(1), 137–149. https://doi.org/10.1177/107049659300200107

Bradford, D. F., Fender, R. A., Shore, S. H., & Wagner, M. (2005). The environmental Kuznets curve: exploring a fresh specification. *Contributions in Economic Analysis & Policy*, *4*(1), 1–28. https://doi.org/10.2202/1538-0645.1073

Brian, R. C., & Taylor, M. S. (2019). North-South Trade and the Environment. In Judith M. Dean (Ed.), *International Trade and the Environment*, (p. 34). Routledge. https://doi.org/10.4324/9781315201986

Dong, H., Geng, Y., Yu, X., & Li, J. (2018). Uncovering energy saving and carbon reduction potential from recycling wastes: A case of Shanghai in China. *Journal of Cleaner Production*, *205*, 27–35. https://doi.org/10.1016/j.jclepro.2018.08.343

Du, G., Liu, S., Lei, N., & Huang, Y. (2018). A test of environmental Kuznets curve for haze pollution in China: Evidence from the penal data of 27 capital cities. *Journal of Cleaner Production*, *205*, 821–827. https://doi.org/10.1016/j.jclepro.2018.08.330

Du, X., & Xie, Z. (2020). Occurrence of turning point on environmental Kuznets curve in the process of (de) industrialization. *Structural Change and Economic Dynamics*, *53*, 359–369. https://doi.org/10.1016/j.strueco.2019.06.003

Elhorst, J. P. (2012). Dynamic spatial panels: models, methods, and inferences. *Journal of Geographical Systems*, *14*(1), 5–28. https://doi.org/10.1007/s10109-011-0158-4

Elhorst, J. P. (2003). Specification and estimation of spatial panel data models. *International Regional Science Review*, *26*(3), 244–268. https://doi.org/10.1177016001760325379l

Geng, Y., Sarkis, J., Ulgiati, S., & Zhang, P. (2013). Measuring China's circular economy. *Science*, *339*(6127), 1526–1527. https://doi.org/1227059

Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. *The Quarterly Journal of Economics*, *110*(2), 353–377. https://doi.org/10.2307/2118443

Gu, F., Guo, J., Zhang, W., Summers, P. A., & Hall, P. (2017). From waste plastics to industrial raw materials: A life cycle assessment of mechanical plastic recycling practice based on a real-world case study. *Science of the Total Environment*, 601–602, 1192–1207. https://doi.org/10.1016/j.scitotenv.2017.05.278

Higashida, K., & Managi, S. (2014). Determinants of trade in recyclable wastes: evidence from commodity-based trade of waste and scrap. *Environment and Development Economics*, *19*(2), 250–270. https://doi.org/10.1017/S1355770X13000533

Ikefuji, M., & Horii, R. (2007). Wealth heterogeneity and escape from the poverty–environment trap. *Journal of Public Economic Theory*, *9*(6), 1041–1068. https://doi.org/10.1111/j.1467-9779.2007.00344.x

Innova, E. (2012). Guide to resource efficiency in manufacturing: Experiences from improving resource efficiency in manufacturing companies. *Greennovate Europe EEIG*, 8–13.

Kellenberg, D. K. (2009). US affiliates, infrastructure and growth: A simultaneous investigation of critical mass. *The Journal of International Trade & Economic Development*, *18*(3), 311–345. https://doi.org/10.1080/09638190902986488

Kiddee, P., Naidu, R., & Wong, M. H. (2013). Electronic waste management approaches: An overview. *Waste Management*, *33*(5), 1237–1250. https://doi.org/10.1016/j.wasman.2013.01.006

Kneese, A. V. (1971). Environmental pollution: Economics and policy. *The American Economic Review*, *61*(2), 153–166. https://doi.org/10.2307/1816988

Lee, L. F., & Yu, J. (2010). Estimation of spatial autoregressive panel data models with fixed effects. *Journal of Econometrics*, *154*(2), 165–185. https://doi.org/10.1016/j.jeconom.2009.08.001

Lee, S. M., & Chen, L. (2010). The impact of flow on online consumer behavior. *Journal of Computer Information Systems*, *50*(4), 1–10.

LeSage, J., & Pace, R. K. (2009). *Introduction to Spatial Econometrics*. UK. Chapman and Hall/CRC.

Maddison, D. (2006). Environmental Kuznets curves: A spatial econometric approach. *Journal of Environmental Economics and Management*, *51*(2), 218–230. https://doi.org/10.1016/j.jeem.2005.07.002

Madlener, R., & Sunak, Y. (2011). Impacts of urbanization on urban structures and energy demand: What can we learn for urban energy planning and urbanization management?. *Sustainable Cities and Society*, *1*(1), 45–53. https://doi.org/10.1016/j.scs.2010.08.006

Stahel, W. R. (2016). The circular economy. *Nature*, *531*(7595), 435–438. https://doi.org/10.1038/531435a

Völlmecke, D., Jindra, B., & Marek, P. (2016). FDI, human capital and income convergence—Evidence for European regions. *Economic Systems*, *40*(2), 288–307. https://doi.org/10.1016/j.ecosys.2015.11.001

Wang, Z., Bu, C., Li, H., & Wei, W. (2019). Seawater environmental Kuznets curve: evidence from seawater quality in China's coastal waters. *Journal of Cleaner Production*, *219*, 925–935. https://doi.org/10.1016/j.jclepro.2019.02.012

Zhang, Y. J., Liu, Z., Zhang, H., & Tan, T. D. (2014). The impact of economic growth, industrial structure and urbanization on carbon emission intensity in China. *Natural Hazards*, *73*, 579–595. https://doi.org/10.1007/s11069-014-1091-x

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